

Strategic Flight Cancellation under Ground Delay Program Uncertainty

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Abstract— Under certain capacity constraints, flight operators will strategically cancel flights to improve their overall operating schedule. However, the benefits of such cancellations are best realized if made early, often before any traffic flow rate limitation is imposed. With improved weather forecasts, the need for early action is more apparent; however, determining the correct actions – in this case, flight cancellations – is still challenging. This paper proposes a framework for optimizing an adaptive decision strategy based on the evolution of the forecast uncertainty. Using an ensemble forecast, a scenario tree is generated to highlight both key planning scenarios and the likelihood of these scenarios developing over the forecast horizon. By aligning decision points at the initial and intermediary nodes in the tree, strategies are optimized to capture the timing of relevant decisions with respect to the forecast uncertainty. Using flight cancellation under Ground Delay Program uncertainty as an example, the paper will analyze the recommended cancellations over the forecast horizon, against different predicted scenarios as well as how these recommendations adapt as new forecast information is made available. The results will show that by directly planning for adaptation, improved outcomes can be obtained.

Keywords- Traffic flow management; decision support; flight-operator priorities; traffic management initiatives

I. INTRODUCTION

The forecast uncertainty inherent to Air Traffic Management (ATM) compounds the already challenging task of designing effective strategies in a complex, dynamic system. Recent advances in decision support capabilities - developed for both Air Navigation Service Providers (ANSPs) and flight operators - have enabled predictive performance of decisions to be assessed prior to action under deterministic conditions. As such, these tools require human expertise to adjust for variations induced by forecast uncertainty. However, as humans have difficulty factoring uncertainty into decision making, the predictability desired from incorporating automation isn't fully realized.

To address this problem, this paper proposes an Adaptive Planning Framework (APF), derived from a forecast ensemble, to directly capture the evolution of uncertainty over the forecast horizon and identify key planning scenarios for consideration. A decision tree is overlaid to capture not only the initial recommendation for action, but subsequent contingency plans for each scenario represented. By optimizing the sequence of actions under multiple scenarios simultaneously, both the cost of incorrect action and the risks of delayed decisions can be explicitly assessed through the cost function evaluation.

This paper will demonstrate the potential value of APF through examination of the strategic flight cancellation problem. When a flight operator is faced with significant delays due to a large-scale Traffic Management Initiative (TMI), it is potentially desirable to strategically cancel some flights to improve their overall schedule performance. To minimize the disruption caused – to both the operation and passengers – early cancellation is best; however, the impact of the TMI (e.g., timing, rate, etc.) is generally not known at these times.

Focusing on LaGuardia Airport (LGA) in New York, the paper will demonstrate how the forecast information on a historical day could be used to identify opportunities for a major flight operator to strategically cancel flights. The analysis will compare the recommendations generated by APF – which permits incremental decision making – to those generated when only a single decision point is defined. Finally, the paper will analyze the performance of both approaches as time advances and new forecast information is obtained.

This paper is structured as follows. First, we review relevant literature in forecast translation, TMI prediction and strategic decision making under uncertainty. Section III outlines the construction of the APF while Section IV describes the optimization problem formulated for the strategic cancellation problem. Section V presents the results and analysis for the historical example problem considered. Section VI discusses key findings and their relationship to continuing work.

II. LITERATURE REVIEW

Predicting airport capacity at longer planning horizons (greater than two hours) is challenging as the primary weather forecast variables – convection, winds, ceilings, and visibility – exhibit high uncertainty at these times. Airport capacity predictions may forecast the hourly operation limit, the Airport Arrival Rate (AAR) or the specific runway configuration, which has associated rate limits under different meteorological conditions. Multiple studies have proposed models tuned to the operations of a single airport [1-5], using both operational rules and/or historical data-driven models. Recently, researchers have developed generic models, parameterized by historical data [6-9], to avoid the challenges of site-specific adaptation.

As the example pursued herein is tailored to LGA, we leverage the method proposed in [10], which explicitly captures the uncertainty of AAR predictions for LGA. Specifically, a non-parametric discrete choice algorithm, tailored to LGA operations is derived from fine-resolution (5-minute) observed

meteorological conditions, captured by the Automated Surface Observation System (ASOS). Coupled with National Traffic Management Log (NTML) data and site-specific adaptation, this new model has demonstrated great skill [10].

While the predominant cause for a Ground Delay Program (GDP) is terminal weather-induced AAR reductions, other constraints (e.g., en route capacity reduction, staffing shortages, etc.) can precipitate issuance of a controlled rate into the airport. Furthermore, as a GDP delays flights on the surface at their respective departure airports, these decisions must be made with sufficient lead time – and thus greater forecast uncertainty -- to capture the targeted aircraft. Coupling these challenges with the required human interpretation of data reduces the obvious correlative influence of AAR on specific GDP parameters, such as start time, hourly rate, and scope.

GDP prediction approaches have evolved significantly with improved AAR forecasting methods based on historical data learning algorithms [11-15]. Leveraging historical data and capturing behavior trends over the time horizon, Ref. [10] leverages the probabilistic AAR forecast model to provide GDP predictions for LGA. While the current instantiation of the model is limited to winds, ceiling, and visibility events, additional events are being explored.

Leveraging the probabilistic, time-series information provided by the AAR and subsequent GDP predictions, the APF seeks to assess the overlaying sequential decision-making problem [16, 17] inherent to cancellation under GDP uncertainty. 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 [18-20]. While the applications are diverse, they share the challenge of optimizing a high-dimensional, dynamic decision space subject to uncertain information.

Recently, sequential decision-making approaches have been proposed to address challenges in the ATM space [21-24]. In our previous work [25], we developed an initial version of the APF and examined its utility for designing TMIs. While the preliminary results showed promise, the investigation was limited to a single weather forecast due to computational considerations. In this paper, we mature and extend the APF to a more computationally-tractable problem – flight cancellation under GDP uncertainty – which permits this paper to analyze the evolution of incremental decisions under updating impact forecasts.

III. CONSTRUCTING THE ADAPTIVE PLANNING FRAMEWORK

The APF employs a decision tree that is generated by evaluating the similarity between members of an ensemble forecast. Figure 1 illustrates how the uncertainty evolves over the planning horizon. This section describes the method for generating the APF and notes assumptions specific to this application.

A. Ensemble Forecast

An ensemble forecast is a collection of deterministic projections that are assumed to be equally likely and span the space of future outcomes [26]. We note that although an ensemble forecast often refers to a weather product, we

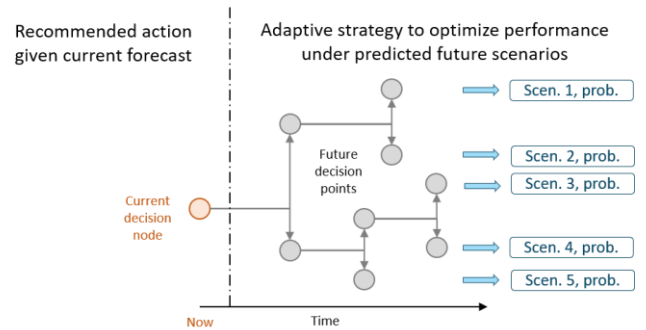


Figure 1. The Adaptive Planning Framework

generalize the terminology here to capture any forecast of information (e.g. traffic demand, rate constraint). For this application, an ensemble weather forecast is translated into an ensemble of AAR probability distributions developed from historical data analysis [10].

At time t , the ensemble forecast E^t is generated where we denote e_i^t as the i th member of E^t for $i = 1, 2, \dots, E = |E^t|$ and ρ_i^t as the probability of the i th member of E^t . Nominally, we assume that each member is equally probable ($\rho_i^t = \frac{1}{E^t}$). However, this assumption can be readily relaxed.

Each member in the ensemble forecast defines a trajectory of forecast variable(s) at discrete times $h = (0, 1, 2, \dots, H)$ where $h = 0$ corresponds to the initial time of the forecast, t . The horizon discretization δt and the forecast horizon T are defined as:

$$h(i + 1) - h(i) = \delta t \quad (1)$$

$$T = t + H * \delta t \quad (2)$$

Note the distinction between clock time, t , and forecast time, h . Beyond the assumed discretization of forecast time, we further assume that the forecast time resets to $h = 0$ each time a forecast is issued. However, the underlying members will change both in time as well as in the forecasted variables. As such, we do not assume that $e^{t+\delta t} = e^t$ or that $e^{t+\delta t}(h) = e^t(h + \delta t)$.

B. Learning Forecast Similarity

While it is unlikely that two forecast members are identical over the entire forecast horizon, some differences will be more significant than others. Of interest in this application are differences which distinguish between different GDPs. To identify these trends in the forecast variable (AAR distributions) a learning model is trained to identify critical trajectory differences between the forecast members. Details on the methods used to learn similarity can be found in [27].

C. Partitioning the Ensemble

When a new forecast ensemble is issued, the learned similarity is applied to partition the forecast into a tree. Specifically, at time $h = 0$, all members are assumed to be sufficiently similar and are clustered together. At subsequent times ($h > 0$), the similarity of each forecast member to all other members over the trajectory from h through H is evaluated. If at time h a subset of ensemble members is sufficiently dissimilar in the future, the ensemble is partitioned into two or more

subsets. As such, we define $E^{t,h}$ to be the set of partitioned ensemble members sets of forecast ensemble E^t present at time h , where $E^{t,h} = \{E_1^{t,h}, E_2^{t,h}, \dots, E_{k_h}^{t,h}\}$ and k_h is the number of partitioned sets defined at time h . As a partition, the following constraints apply.

$$\bigcup_{k=1}^{k_h} E_k^{t,h} = E^t \quad \forall h, t \quad (3)$$

$$\bigcap_{k=1}^{k_h} E_k^{t,h} = \emptyset \quad \forall h, t \quad (4)$$

$$E_k^{t,h} \neq \emptyset \quad \forall k, h, t \quad (5)$$

Equations 3 and 4 state that all ensemble members are included in exactly one sub-set at any time while Equation 5 states that no subset is empty at any time.

Finally, we require that a partition at time h contains only ensemble members that belonged to a subset at the previous time step.

$$\begin{aligned} \exists \bar{k} \text{ s. t. } E_{\bar{k}}^{t,h} &\subseteq E_q^{t,h-1} \\ &\& E_{\bar{k}}^{t,h} \cap E_r^{t,h-1} = \emptyset \quad \forall t, h, k, q \neq r \end{aligned} \quad (6)$$

The probability of each subset is defined as

$$\rho_k^{t,h} = \frac{|E_k^{t,h}|}{|E^{t,0}|} \quad (7)$$

where $|\cdot|$ denotes the cardinality of the set.

Furthermore, we identify a prototype ensemble member to represent each subset, where the prototype is selected based on the centrality of its similarity metric to those in the subset. We define $\hat{e}_k^{t,h} \in E_k^{t,h}$ to be the representative member of the subset $E_k^{t,h}$. Finally, the partitioning can occur at either any forecast time $h > 0$ or at specified forecast times. We use the latter approach in the example presented in Section V.A to generate trees that reflect the operational decision timeline.

D. Generate the Decision Tree

The forecast tree defined by the ensemble partitioning is used to construct the decision tree. The tree is defined as a directed graph of nodes and arcs with the following properties. The set of nodes \mathcal{N}^t contains nodes $n = \{1, 2, \dots, N\}$ where each split between forecast ensemble members is captured as a node in the network. In addition, a node is defined for each subset at time T . For convenience, we assume $n = 1$ corresponds to the initial grouping at $h = 0$.

This selection of decision nodes captures two critical properties: 1) generating a single recommendation at the current time, considering the known uncertainty, and 2) identifying future recommendations associated with different outcomes of the forecast, which can advise future actions as new information is obtained. Put another way, the decisions defined at each node in the APF network are optimal decisions, given the uncertainty characterized by the subset of ensemble members associated with that node.

Each node $n \in \mathcal{N}^t$ has the following properties:

- h_n corresponds to the forecast time h at which the forecast ensemble is partitioned
- E_n^t corresponds to the subset of forecast ensembles associated with node n , which is defined as the subset at the time immediately preceding the partition (i.e., $E_n^t = E_k^{t,h_{n-1}}$)

The set of directed arcs in the network, \mathcal{A}^t , are defined to represent the ensemble partitioning over the forecast horizon, as defined in Equation 8.

$$(i, j) \in \mathcal{A}^t \text{ iff } E_j^t \subset E_i^t \quad \forall i, j \in \mathcal{N}^t \quad (8)$$

The resulting tree graph implies that each node has a single incoming arc and therefore a uniquely defined *predecessor* node [28]. For convenience, we define $\text{pred}(\cdot)$ to return the predecessor of n . Note that the root node, with no incoming arc, has no predecessor and therefore denote $\text{pred}(n = 1) = 0$. The leaves of the tree are defined as nodes that have no outgoing arcs. We denote the set of leaf nodes as L where

$$l \in L \text{ iff } \nexists j \in N \text{ s. t. } (l, j) \in \mathcal{A}^t \quad (9)$$

For each leaf node we define the branch (b_l) as the sequence of nodes connecting the root node to that leaf node.

$$b_l = \{l, n = \text{pred}(l), \text{pred}(n), \dots, 1\} \quad (10)$$

IV. OPTIMIZING FLIGHT CANCELLATION DECISIONS

This section presents the formulation for designing strategic cancellation decisions under GDP uncertainty. We begin with a summary of the GDP prediction method and then present the cost formulations considered in this work. Next, the decision variables and constraints are defined, resulting in the overall optimization formulation. The section concludes with algorithmic considerations for solving the resulting problem.

A. Define GDP Constraint Scenarios

For each leaf node, $l \in L$, we leverage the associated prototype ensemble forecast member to predict the GDP scenario using the method developed in [10]. The prototype member for leaf node l is translated into a GDP scenario, $S_l \in S^t$, where S^t represents the set of GDP scenarios derived from each leaf node $l \in L \in \mathcal{N}^t$. Each GDP scenario defines the start time, end time and hourly rates, which in turn is processed by an algorithm that mimics Flight Schedule Monitor (FSM) to produce assigned arrival slots and delays for impacted flights. Note that the current approach assumes the scope is to all departure airports within 1425 miles.

B. Identifying Candidate Flights

Each GDP scenario, S_l , defines the set of flights that are impacted by the constraint, which we denote as F_l , as they may be different for each scenario. The total set of flights F is the union of these sets (i.e., $F = \bigcup_{l \in L} F_l$).

For each flight $f \in F$, we denote the following properties, which are provided as input to the model:

- td^f is the originally scheduled departure time of flight f

- ta^f is the originally scheduled arrival time of flight f
- o^f is the origin airport for departure of flight f
- a^f is the arrival airport of flight f
- b^f is the aircraft type of flight f

C. Evaluating Decision Costs

Two types of cost are considered in this application: Cancellation and Delay. The authors readily note that the models considered are simplistic, especially with respect to the representation of relative flight priority. While ongoing research seeks a more-nuanced model [29, 30], ultimately the data to populate such a model is known only to flight operators. However, we argue that the simplified cost model considered here is not a limitation of the APF, as the true cost function, if known, could be substituted.

1) Cancellation costs

Each flight has an associated cost of cancellation, determined by factors that reflect its importance to achieving the business objective. To estimate these costs, we leverage published averages from masFlight [31] which distinguish the average cost (USD 2014) per cancelled flight segment by aircraft type and carrier operations. In the example pursued, we consider a major airline's decisions regarding GDPs at LaGuardia airport, a hub for the carrier. As such, we are limited to two cancellation cost values:

- Regional Jets: \$1050
- Legacy Narrowbodies: \$4930

To illustrate how a flight's relative importance to the operation can be captured within the APF framework, we assume a uniform distribution around these published means with bounds of $\pm 10\%$. The cancellation cost of flight f , denoted as cx^f , is stochastically defined through random sampling (from the appropriate aircraft type distribution), but remains constant for all evaluations. We note that if more accurate, flight-specific data was available, these costs could be readily incorporated as input into the APF.

The permuted values provide a baseline cancellation cost for each flight; however, based on discussions with flight operators, we know that the timing of the cancellation (relative to the departure time), further modulates this cost. Specifically, if cancellations are made earlier, there is perceived benefit (e.g., easier to reschedule, improved customer satisfaction, etc.). To

$$\alpha_n^f = \begin{cases} 1.5; & h_n - td^f < 2 \\ 1; & 2 \leq h_n - td^f < 4 \\ 0.9; & 4 \leq h_n - td^f < 8 \\ 0.8; & 8 \leq h_n - td^f < 12 \\ 0.7; & 12 \leq h_n - td^f < 16 \\ 0.6; & 16 \leq h_n - td^f \end{cases} \quad (11)$$

capture this behavior, we define a timing penalty α_n^f associated with each node $n \in \mathcal{N}^t$.

2) Delay costs

While the delay associated with a given GDP scenario can be computed directly from the initial slot assignment, this delay does not account for the operational benefit of swapping slots between lower/higher priority flights or the use of slots for cancelled flights¹. To capture the potential for delay reduction, we model the slot assignment using a network model [28]; see Figure 2.



Figure 2. Slot Assignment Network

For GDP scenario S_l , the associated set of arrival slots is denoted as Z_l . For each flight $f \in F_l$ and arrival slot $z \in Z_l$ we define the graph $\mathcal{G}_l = \{(f, z) \mid f \in F_l, z \in Z_l\}$ such that

$$\exists (f, z) \text{ iff } ta^{z,l} \geq ta^f \quad (12)$$

where $ta^{z,l}$ is time of slot z under scenario S_l and ta^f is the original arrival time of flight f . This constraint implies that a flight in the scenario can utilize a slot if the flight's original arrival time is at or before the slot time. Note that this constraint represents the minimal feasibility requirement; additional constraints (e.g., crew scheduling, passenger connectivity, etc.) could be incorporated to further limit network connectivity.

D. Decision Variables

The primary decision of this application is whether and when to cancel flights, given the uncertainty of future GDP constraints. As such, for each $f \in F$, we define a decision variable, $x_n^f = \{0, 1\}$, for each node $n \in \mathcal{N}^t$, to represent whether flight f is cancelled at node n ($x_n^f = 1$) or not ($x_n^f = 0$). We further constrain the independence of x_n^f such that once a flight is cancelled at a given node, all subsequent nodes in that branch maintain the flight's cancellation status.

$$x_j^f \geq x_i^f \forall (i, j) \in A \quad (13)$$

We further add the constraint that no flight can be cancelled after its departure time.

$$(h_n - td^f) * x_n^f \leq 0 \forall n \in \mathcal{N}^t f \in F \quad (14)$$

However, to assess the cost of a potential flight cancellation, it is also necessary to determine how the vacated slot, as allocated under a given GDP scenario, is best used. As such, we define $y_l^{f,z} \in \{0, 1\}$ as the decision to assign flight $f \in F_l$ to slot $z \in Z_l$ as allowable by the connectivity defined in \mathcal{G}_l , where $y_l^{f,z} = 1$ denotes an assignment and $y_l^{f,z} = 0$ denotes no assignment. We further add the constraints that: 1) only a flight that is not cancelled at the leaf node (l) can be assigned to at most one slot (Eq. 15) and that at most one flight can be assigned to a slot (Eq. 16).

¹ Note that the terminology referenced here is from the perspective of the flight operator. Once a flight is cancelled, as recorded by the ANSP, the slot is no longer available for swap. For the purpose of

this paper, we refer to the recommendation of cancelling a flight and the use of its current slot for delay reduction purposes.

$$\sum_{z \in Z_l \text{ s.t. } (f,z) \in G_l} y_l^{f,z} = 1 - x_l^f, \forall f \in F_l, l \in L \quad (15)$$

$$\sum_{f \in F_l \text{ s.t. } x_l^f = 0} y_l^{f,z} \leq 1, \forall z \in Z_l, l \in L \quad (16)$$

Note that the cancellation decisions are evaluated with respect to the subset of GDP scenarios downstream of the decision node, whereas the slot decisions are unique to each scenario, implying that the optimal swap can be defined later in the decision-making process.

E. Optimization Formulation

In general, the APF assumes no structure to the cost function, permitting a wide-range of applications, including simulation-in-the loop [25] to be evaluated. However, to enable such flexibility, a heuristic solver such as a Multi-Objective Genetic Algorithm, must be used [32]. While these solvers have demonstrated promising performance for solving a wide-range of problems, exact algorithms designed to solve a linear formulation will both guarantee solution optimality and generate solutions quickly.

As the problem formulation described thus far can be written as an integer optimization model and because the model is almost exclusively defined as a network, the linear program relaxation is extremely efficient. The complete optimization problem is expressed as:

$$\begin{aligned} \min C = & \sum_l \rho_l * [2 \sum_{n \in b_l} \sum_f c x^f * \alpha_n^f * (x_n^f \\ & - x_{pred(n)}^f) \\ & + \sum_{z \in Z_l} \sum_{f \in F_l} (ta^{z,l} - ta^f) * y_l^{f,z} * w^f] \end{aligned} \quad (17)$$

subject to:

$$x_j^f \geq x_i^f \forall (i,j) \in A \quad (18)$$

$$(h_n - td^f) * x_n^f \leq 0 \forall n \in N^t f \in F \quad (19)$$

$$\sum_{z \in Z_l \text{ s.t. } (f,z) \in G_l} y_l^{f,z} = 1 - x_l^f, \forall f \in l, l \in L \quad (20)$$

$$\sum_{f \in F_l \text{ s.t. } x_l^f = 0} y_l^{f,z} \leq 1, \forall z \in Z_l, l \in L \quad (21)$$

$$x_n^f \in \{0,1\} \forall f \in F, j \in N \quad (22)$$

$$y_l^{f,z} \in \{0,1\} \forall f \in F_l, z \in Z_l, l \in L \quad (23)$$

where we define $x_{pred(1)}^f = \emptyset$ and w^f to be a flight-specific weight on the impact of delay. In this example, we set w^f to be the average number of seats for the aircraft type to capture the higher passenger delay costs associated with larger aircraft.

V. RESULTS AND ANALYSIS

This section presents and analyzes the results generated by the APF using a historical scenario and the associated GDP uncertainty predicted. The recommendations generated by the APF will be compared to solutions generated under the same uncertainty, but without the explicit allowance for future

adaptation. Furthermore, we evaluate how the recommendations evolve as updated forecast information is provided.

A. Historical Example

The example considers flights into LaGuardia Airport in New York on 13, November 2018. Using an experimental 100-member ensemble of ceiling and visibility, provided by The Weather Company [33], and augmented with wind gust forecasts from the Localized Aviation Model Output Statistics (MOS) Program (LAMP) [34], 100 trajectories of AAR are produced using the model developed in [10] for each forecast issuance. The ensemble forecast tree is generated by evaluating the similarity of these trajectories, where similarity is learned through analysis of a nine-month period of the same data, as described in [27]

From an operational perspective, strategic cancellations can be made as early as the evening before and therefore we begin the analysis with the 22Z forecast on 12 November 2018. We repeat the analysis overnight (at 02Z) and at the start of shift (09Z). We similarly align the forecast clustering to these times and continue using 3-hour intervals thereafter.

B. Single Decision Point Optimization

To compare results generated by the APF, we consider the optimal decisions generated under uncertainty, but without explicit modeling of future decisions under updated information. Specifically, we compute the expected value of the cancellation cost under GDP uncertainty. Note the delay cost is computed for each scenario individually.

C. Strategic Cancellations at 22Z

Beginning with the 22Z forecast on 12 November 2018, a decision tree is constructed, as shown in Figure 3 where the

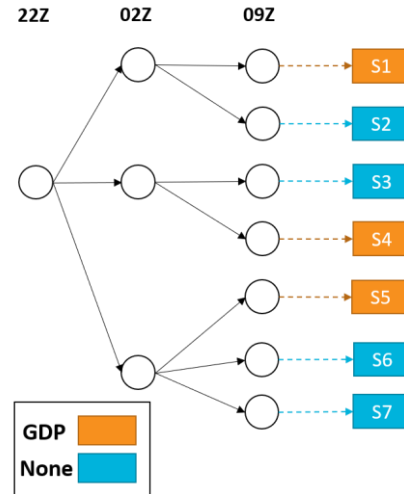


Figure 3. Decision Tree for 22Z Forecast

corresponding GDP scenarios are listed in Figure 4. Each circle in Figure 3 corresponds to a cancellation decision node. Each leaf node in the tree is associated with a GDP scenario. Note that a GDP scenario can have no GDP, as indicated by the blue scenario boxes. Orange scenario boxes indicate a predicted GDP constraint. Figure 4 lists the probabilities of each scenario as well as the timing and rates, as denoted by the color legend. Taken

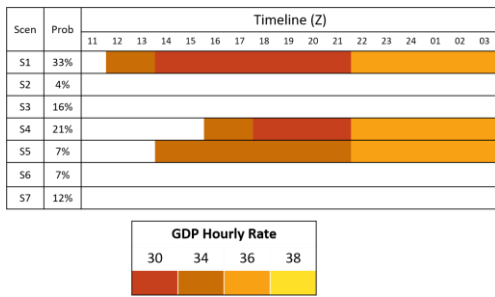


Figure 4. GDP Scenarios and Probabilities for 22Z Decision Tree together, we note that there is a 62% likelihood of future GDP; however, the severity varies across scenarios.

Before analyzing solutions generated under uncertainty we first optimize the recommendations for each GDP independently. Table 1 provides the results for each scenario assuming three cases: no action (i.e., delays in response to the GDP), slot assignment only (i.e., minimum delay), and optimal cancellation and slot assignment. Viewing Table 1, we see that the severity of Scenario 1 results in the highest delays, and while slot assignment can reduce the delay significantly, the combination of cancellations and slot assignment provides the most benefit. Both Scenarios 4 and 5 perform best when cancellations are considered with slot assignment optimization, but the benefits are less pronounced.

Using the APF, the cancellation and slot assignment recommendations are computed, as shown in Figure 5, where a red circle indicates the number of cancellations defined at each decision node. For clarity, the cumulative cancellations for each scenario are placed above the arrows connecting the leaf node to the scenario boxes and the numbers to the right correspond to the number of swaps for each scenario.

Table 1. Optimization without Uncertainty

		Cancellation Cost	Delay Cost
S1	No Action	0	365385
	Slot Assignment Only	0	226330
	Cancellation and Slot Assignment	27166	42488
S4	No Action	0	136262
	Slot Assignment Only	0	78971
	Cancellation and Slot Assignment	14641	24376
S5	No Action	0	113278
	Slot Assignment Only	0	70470
	Cancellation and Slot Assignment	8870	37373

The solution depicted in Figure 5 has an expected cost of \$36,913; however, no cancellations are defined at the root node (22Z). Thus, while S1 is the most impactful, the risk of an incorrect decision at 22Z is too high to warrant immediate action. Instead 21 cancellations are defined at 02Z, where the

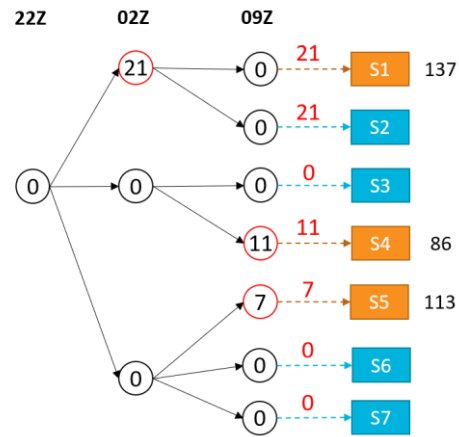


Figure 5. APF Solution for 22Z

low risk (4%) of incorrect action if S2 occurs is outweighed by the rewards for strategic action in response to S1.

For comparison, we optimize the same set of GDP scenarios using the single decision point (SDP) approach. Figure 6 presents the solution which results in an expected cost of \$46,331. In Figure 6 we observe that 17 cancellations are recommended at 22Z, incurring a cost of \$20,740. Despite the 38% chance of not having a GDP, this costly decision aims to mitigate costs associated with S1 (see Table 1 and the limitations of solely using slot assignment to reduce cost).

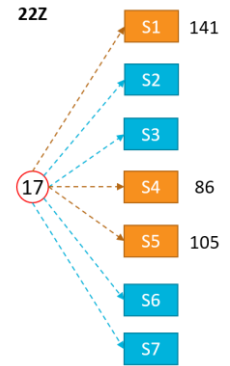


Figure 6. SDP solution at 22Z

The authors readily concede that a flight operator is unlikely to strategically cancel 17 flights the night before, given these forecast probabilities. However, without the appropriate decision support, the alternative is to either wait until more certain information is made available or to heuristically identify a subset of flights to cancel. The value of the APF is that it explicitly provides this recommendation by differentiating between the actions to take now and the actions which should be postponed until further information is obtained.

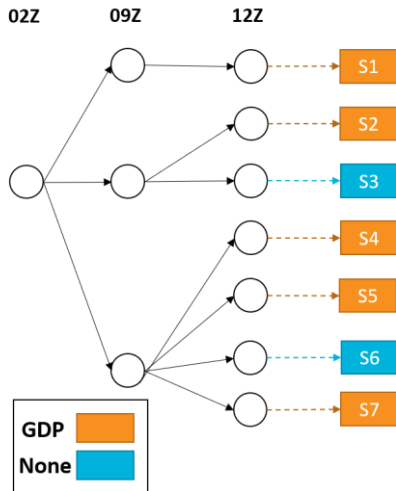


Figure 7. Decision Tree for 02Z Forecast

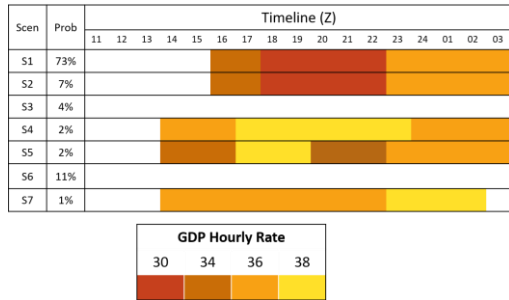


Figure 8. GDP Scenarios and Probabilities for 02Z Decision Tree

D. Strategic Cancellations at 02Z

Next, we examine the 02Z forecast, where the decision tree is shown in Figure 7 and the corresponding GDP scenarios are listed in Figure 8.

With the updated forecast, there is now an 85% chance for a future GDP, but more importantly, the GDP defined by S1 and S2 has an 80% likelihood. Note that it is possible to predict the same GDP from two different AAR trajectory evolutions; however, refining these results is a subject of continuing research, as is discussed in Section VI.

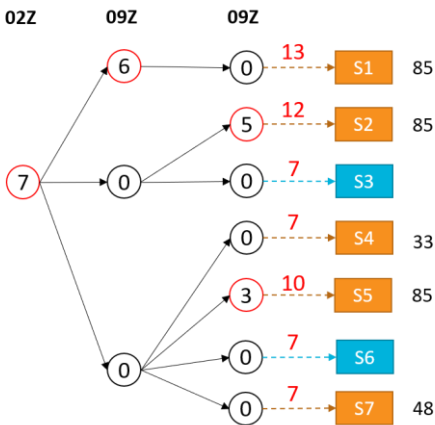


Figure 9. APF Solution for 02Z

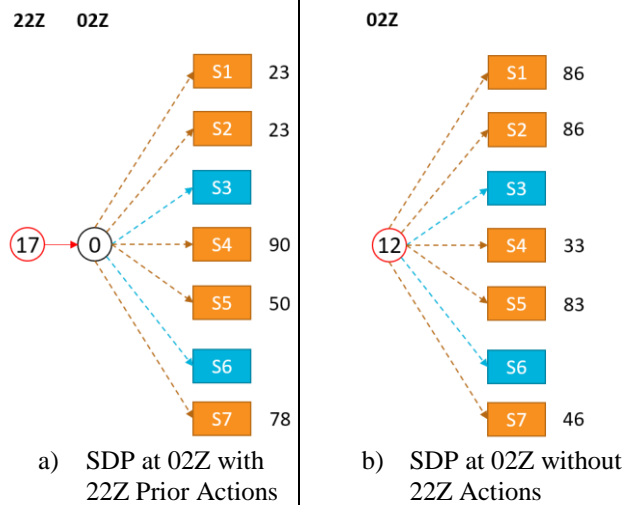


Figure 10. SDP Solutions at 02Z

The APF recommendations are optimized using this updated GDP forecast tree and the results are presented in Figure 9. The solution depicted in Figure 9 has an expected cost of \$38,543, where the 7 recommended cancellations at 02Z incur a cost of \$8,618. Note, however, that additional cancellations are defined, at later decision points, even for S1. As such, the APF identifies cancellations at 02Z that are most likely to be beneficial and defers action on a complete solution.

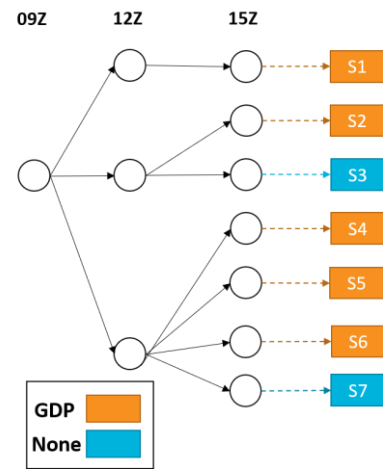


Figure 11. Decision Tree for 09Z Forecast

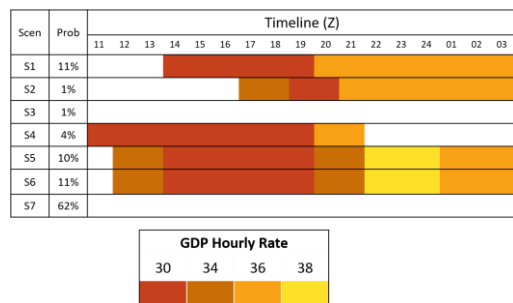


Figure 12. GDP Scenarios and Probabilities for 09Z Decision Tree

Figure 10 presents the results of the SDP with (Fig. 10.a) and without (Fig. 10.b) implementation of the actions recommended at 22Z. For SDP with the prior actions defined at 22Z recommends no additional cancellations and has an expected cost of \$48,884, of which \$20,740 has already been incurred. Alternatively, if no previous cancellations had been taken, the SDP solution recommends 12 cancellations to be taken at 02Z. The expected cost of this solution is \$38,842, where \$14,717 represents the recommended 02Z cancellation cost.

E. Strategic Cancellations at 09Z

The final forecast time analyzed corresponds to 09Z, where Figure 11 depicts the decision tree and Figure 12 identifies the corresponding GDP scenarios. While the decision tree in Figure 11 is similarly-structured to that of the one at 02Z, the corresponding GDP scenarios, and more importantly the probabilities associated with GDP-impact scenarios have changed significantly. Specifically, the 09Z forecast tree indicates that there is a 63% likelihood of no GDP impact. Furthermore, upon reviewing the specifics of the GDPs predicted over the forecast evolution, we note that the timing and rates are not consistent. While some degree of fluctuation is expected, given the underlying weather uncertainty, this scenario variation is problematic for strategic planning.

Recall that the APF recommended 7 cancellations at 02Z and as such we optimize the 09Z recommendations both with (Fig. 13.a) and without (Fig. 13.b) these prior actions. Figure 14 provides the same analysis for the SDP results, again with 22Z actions (a) and without (b).

The APF recommendation, assuming prior actions (Fig. 13.a) suggests that no additional cancellations be made at 09Z. The expected cost for this solution is \$34,624; however the incurred cost is only \$8,618 from the 7 cancellations at 02Z. In

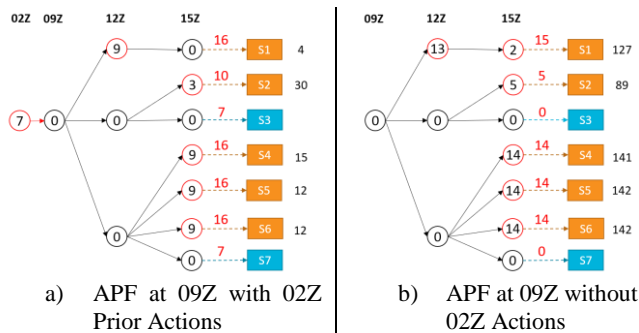


Figure 13. APF Solutions at 09Z

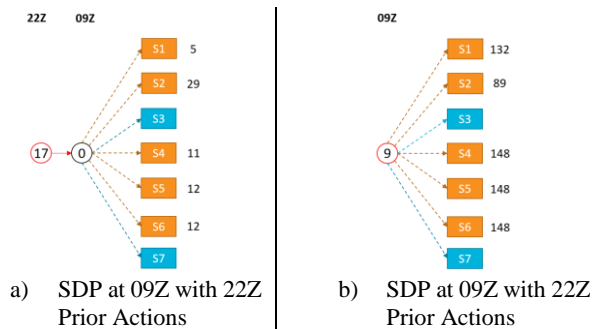


Figure 14. SDP Solutions at 09Z

contrast, the APF solution without prior cancellations (Fig. 13.b) has an expected cost of \$29,247 but this is all projected, not incurred cost.

In comparison, the SDP solution with prior action (Fig. 14.a) has an expected cost of \$36,848; however, the 17 prior cancellations have already incurred a cost of \$20,740. Had no previous action been taken, the SDP still results in an expected cost of \$37,608, higher than both the APF with and without prior action. Furthermore, the recommendation for this case is 9 cancellations at 09Z, incurring a cost of \$15,204.

F. Actual GDP issued at 11Z

On 13 November 2018, a GDP for LGA was issued at 11Z for a program beginning at 1230Z; Figure 15 provides the initial rates and times for the TMI.

Scen	Prob	Timeline (Z)																
		11	12	13	14	15	16	17	18	19	20	21	22	23	24	01	02	03
Actual GDP	100%																	

Figure 15. Actual GDP issued 13 November 2018

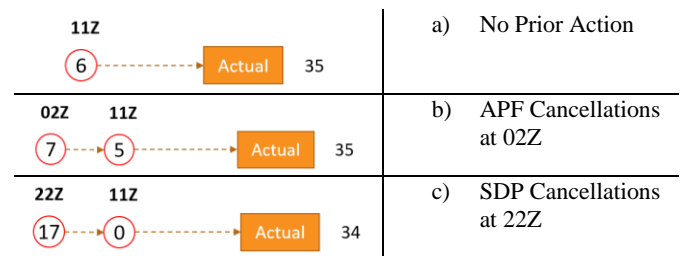


Figure 16. Recommendations under GDP issued 11Z

Based on the issue time, we conduct one final analysis, comparing the recommendations optimized under three cases: no prior actions, prior APF actions and prior GDP actions. Figure 16 depicts the recommendations for each of these cases.

With the issuance of the GDP, there is no longer uncertainty and therefore no need to compute expected cost. In this example, had no prior actions been taken, the cost of the 6 recommended cancellations plus 35 slot assignments for delay reduction is \$48,316. In comparison, had the 7 cancellations recommended by the APF been acted upon, the overall cost is \$53,212. Note that this sum includes the \$8,618 for the previously cancelled flights. Finally, the cost for having already cancelled the SDP-recommended 17 flights remains \$20,740 but an additional cost of \$35,472 is incurred from the resulting delay.

G. Discussion

The scenarios predicted by the forecasts tree over the planning horizon exhibit little consistency in terms of GDP-impact probabilities as well as the specifics of the GDPs. Thus while the 09Z forecast tree specifies four different GDP-impact scenarios with a cumulative probability of 37%, the actual GDP is much less severe than any 09Z scenario and is instead closest to the 02Z scenarios S4, S5, and S7 which have a cumulative probability of 5%.

While this result points to a need for additional research in forecast tree generation, the nature of probabilistic decision

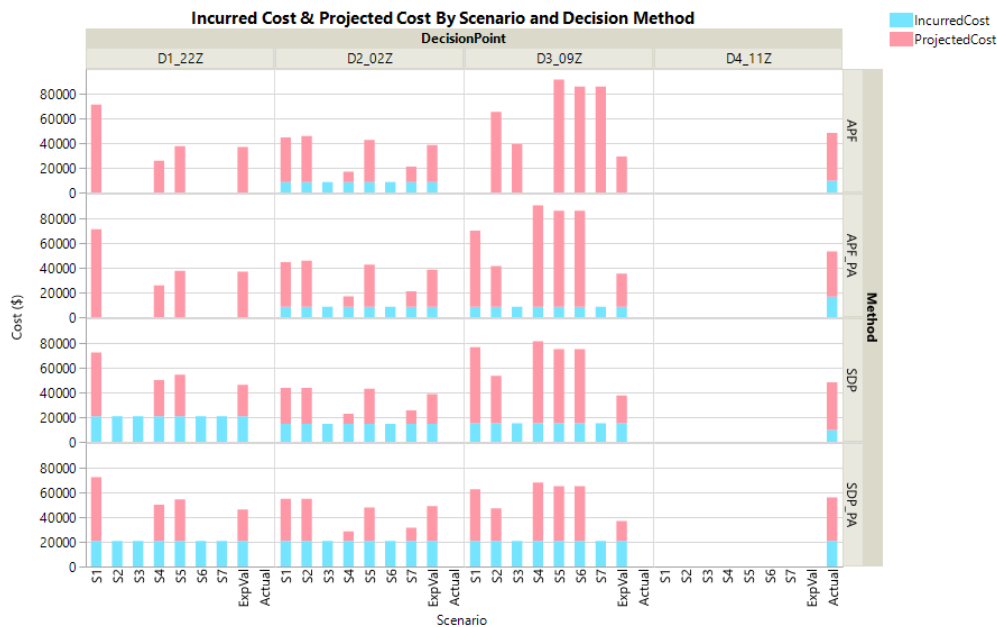


Figure 17. Incurring and Projected Costs, by Scenario, under each Method over the Decision Time Horizon

making is that there will be instances when the outlier scenarios occur. Thus, while for this example it would have been better (in terms of the simple cost function assumed) to wait until the 11Z GDP was enacted it is necessary to repeat this experiment over many operational days to determine if the APF produces a lower expected cost value than waiting.

That said, the results still highlight the value of incremental planning under uncertainty, as compared to a single decision approach, as it can mitigate the risk of incorrect action. Figure 17 summarizes the costs – broken out by incurred (blue) and projected (pink) cost -- for each scenario. Viewing Figure 17 we compare the 2nd and 4th row, corresponding to the APF prior action and the SDP prior action, respectively. Leveraging the APF framework, the only cost incurred prior to the 11Z event is \$8,618 at 02Z. Comparing this to the incurred cost of \$20,740 at 22Z from the SDP prior action approach highlights the ability of the APF framework to mitigate decision risk more effectively.

VI. CONCLUSIONS

This paper outlined a framework for mitigating decision risk under forecast uncertainty. The APF described herein is defined by the evolution of forecast uncertainty and can thus identify critical decisions times in order to capture the trade-off between waiting for updated information and acting strategically, reducing the cost of the decision. In fact, the APF explicitly identifies which decisions are best to take and which are best to defer. Furthermore, as the APF is generic in structure, it permits consideration of a wide range of domain-specific applications.

In this paper, the APF was constructed for the problem of strategic airline cancellation under GDP uncertainty and evaluated against a historical day. The models for AAR forecasting and GDP prediction were generated from real-time ensemble forecast data for LGA. Furthermore, the APF required only a few minutes to solve – a number that could be improved through allocation of additional computation resources. As

such, the model derived is viable for real-time decision-making applications.

However, to become an accepted method for decision making additional research is needed. First, additional study is required to assess whether the underlying forecast trees cluster ensemble members correctly for this application. However, this requires multiple sample days be evaluated with Subject Matter Experts to ensure that the clustering and identification of prototype ensemble members are relevant, based on the forecast.

Furthermore, the authors explicitly noted that the cost cancellation model was simplistic at best. Thus, while the example case illustrated indicates that no strategic action would have been best, the result would have been last-minute cancellations to short-haul flights. If the stated objective of strategic cancellation is to avoid such outcomes, where possible, it is necessary to evaluate whether the current objective function adequately represents these considerations.

Finally, this is a single case day. With probabilistic decision-making approaches, benefits must be assessed over a wide range of examples. Once the above two questions are addressed, statistical analysis over a multitude of days is needed.

NOTICE

Approved for Public Release 19-0503; Distribution Unlimited.

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