

Decentralized Flight Path Planning for Air Traffic Management

Wei Zhang, Maryam Kamgarpour, Dengfeng Sun, and Claire J. Tomlin

Abstract—This paper studies the flight path planning problem for a large-scale air traffic management (ATM) system. The goal is to find the optimal 4D path plan, represented by a sequence of waypoints and the corresponding time stamps, for each individual flight subject to weather and sector-capacity constraints of the overall system. We decompose the overall functionality of the ATM system into two interactive stages: traffic regulation and performance optimization. In the first stage, the ATM system, based on the existing flight plans, sets up traffic rules, namely, decides which sectors are still open to use over each future time slot, while in the second stage it optimizes the path plans for new flights subject to these traffic rules as well as the weather constraints. Through this decomposition, the performance optimization task can be done in a fully decentralized way and can be easily solved using dynamic programming. Such a decentralized strategy can handle a large number of flights, respects the structure of the current ATM system, and has a great potential to improve its performance with safety guarantees. The proposed algorithm is validated through a simulation based on real traffic data over the entire US airspace.

I. INTRODUCTION

Air Traffic Management (ATM) is responsible for sustainable, efficient, and safe operation in civil aviation. A substantial change in the current ATM paradigm is needed in order to improve its capacity, efficiency, environmental impact, and flexibility. One of the main constraints in airspace allocation is sector capacity. A sector is a pre-defined region of airspace in which the traffic is monitored and controlled by human operators. For each sector the number of aircraft per time unit are restricted due to air traffic controllers' workload and safety of flights. Currently, such capacity constraints are mainly handled through flight re-routes or the Ground Delay Program (GDP) [1]. For aircraft en-route, speed adjustments and flight re-routes can be applied to redirect traffic to meet the sector and route capacity constraints [2], [3], [4]. These two methods do not consider design of the flight plans prior to aircraft take-off in order to respect the airspace capacities. To take into account the constraints prior to planning, the authors in [5] consider scenarios in which users specify a few possible routes with varying preferences. Then, a centralized system evaluates and accepts the ones that meet capacity limits with high preferences.

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In addition to the constraints imposed due to airspace capacity and route restrictions, the hazardous weather imposes constraints on the aircraft trajectories. In recent years weather forecasts with increasing accuracy and resolution for the national airspace have become available, and their utilization in air traffic control has been extensively studied. The use of weather information in terminal airspace operation was considered in [6], [7], while re-routing existing flight plans during adverse weather in the en-route portion of the flight was addressed in [8], [9], [10]. Most of these approaches compute the re-routing paths by solving certain centralized optimization or optimal control problems, which may not be numerically tractable when the number of aircraft is large.

In this paper, we study a large-scale air traffic management problem subject to both the capacity and hazardous weather constraints. We aim to design 4D path plans, represented by sequences of waypoints and the corresponding time stamps, that optimize individual aircraft performance metrics while satisfying the constraints of the overall system. A hierarchical decentralized approach is proposed, in which the capacity constraints that couple the aircraft are evaluated at the ATM layer and the resulting traffic restriction information is communicated to the user layer that consists of individual flights. Each individual flight then plans its 4D paths by optimizing its own objective function, while respecting the traffic restrictions imposed by the ATM layer as well as the weather constraints. Through this hierarchical decomposition, the path planning problem is fully decoupled and can be solved efficiently using dynamic programming.

Compared with many existing results in the literature, the proposed hierarchical ATM strategy together with the decentralized path planning algorithm has several distinctive features. First of all, the paths generated by the proposed planning algorithm are guaranteed to be safe (satisfying all the constraints) and optimal for each individual flight under the given traffic and weather restriction rules. In addition, the complexity of such a decentralized planning algorithm does not depend on the number of aircraft in the system, and thus the algorithm will be able to handle an increasing air traffic volume as predicted by FAA [11]. Furthermore, the algorithm gives each user full freedom to optimize its own cost function subject to traffic restrictions, which may greatly improve its operation efficiency and passenger satisfaction. Lastly, the proposed hierarchical ATM strategy respects the structure of the current ATM system and will not be affected by the existence of non-participating users, that is, the users not following the proposed planning algorithm. This allows the current ATM system to be gradually transformed into the new framework.

This paper unfolds as follows. The general 4D path

planning problem is formulated in Section II. A decentralized solution to this problem is developed in Section III. Simulation results based on real air traffic data of the US airspace is presented in Section IV and some concluding remarks are given in Section V.

II. 4D FLIGHT PLANNING PROBLEM

A. Graph Model of En-Route Airspace

Let $X^3 \subset \mathbb{R}^3$ denote a bounded and connected subregion of the en-route airspace, which can represent a Center, a collection of Centers or the entire en-route airspace of the US. Let $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ be an undirected graph describing the airways within X^3 . Each node on the graph, $v_i \in \mathcal{V}$, represents a waypoint with a given latitude and longitude; each link $link(v_i, v_j) \in \mathcal{E}$ represents an airway (or jet route at high altitudes) joining the two waypoints v_i and v_j . The waypoints we consider in this paper include both *named waypoints* that appear on aviation charts, as well as (*virtual*) *geographical waypoints* with temporary positions introduced to assist flight planning or monitoring. A $link(v_i, v_j)$ is called outside a bounded set $B \subset X^3$, denoted by $link(v_i, v_j) \notin B$, if the line segment joining v_i and v_j does not cross B , i.e.,

$$\{v_i + \gamma \cdot (v_j - v_i) : \gamma \in [0, 1]\} \cap B = \emptyset.$$

Suppose that the region X^3 is covered by n_s sectors $\{S_m\}_{m \leq n_s}$, i.e., $X^3 = \cup_{m=1}^{n_s} S_m$ and $S_i \cap S_j = \emptyset$, for any $i \neq j$. Denote by $\mathcal{I}_s = \{1, \dots, n_s\}$ the index set for the sectors. Let $\beta : \mathcal{V} \rightarrow \mathcal{I}_s$ be the function that assigns each node on the graph to its corresponding sector, i.e., for any $v \in \mathcal{V}$, $\beta(v) = m$ if and only if $v \in S_m$. Each sector S_m is a bounded subset of X^3 and is associated with a maximum capacity $c_m \in \mathbb{Z}_+$. It is required that the number of aircraft within each sector be less than or equal to the corresponding sector capacity at any time instant. This will be referred to as the *traffic constraints* in the rest of this paper.

Consider a finite discrete planning horizon $\mathcal{T} \triangleq \{0, \dots, T\}$ with $T \in \mathbb{Z}_+$. For each $x \in X^3$ and $t \in \mathcal{T}$, let $w_t(x) \in \mathbb{R}_+$ represent the level of weather hazard at time t and location x , which is often characterized by a combination of certain measurements, such as Vertically Integrated Liquid (VIL), Lightning rate, etc. At the initial time, we are given a probabilistic prediction of the weather data w represented by a distribution function $p_t(a; x) = \text{Prob}\{w_t(x) \leq a\}$, $\forall a \in \mathbb{R}_+$, and $t \in \mathcal{T}$. Define the weather forbidden zone at time $t \in \mathcal{T}$ as

$$W(t) = \{x \in X^3 : 1 - p_t(\hat{w}; x) \geq \hat{p}\},$$

where \hat{w} and \hat{p} are given threshold constants according to certain regulation rules. In other words, the set $W(t)$ contains points at which there is more than \hat{p} percentage of chance that the predicted weather hazardous level at time t is larger than \hat{w} . Define $W_+(t) = W(t) \cup W(t+1)$ as the union of the two forbidden zones at time t and $t+1$.

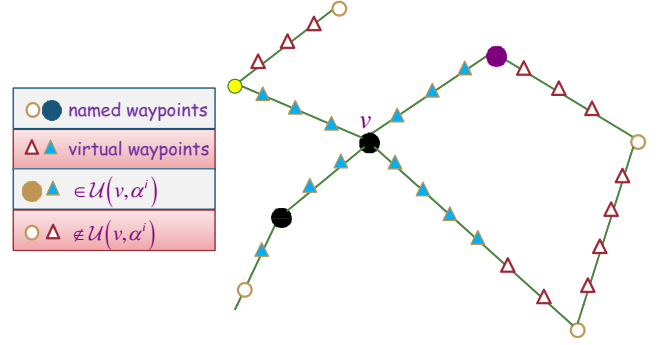


Fig. 1. Illustration of the set of reachable waypoints over one time unit

B. Simplified Model for High-level Planning

Let $\mathcal{A} \triangleq \{1, \dots, n_a\}$ be the set of available aircraft types. Each type of aircraft $\alpha \in \mathcal{A}$ is characterized by its corresponding maximum/minimum speeds s_α^+ / s_α^- and minimum turning radius r_α^- . Consider $N \in \mathbb{Z}_+$ flights to be completed within the discrete time interval \mathcal{T} . Let $\mathcal{I}_F = \{1, \dots, N\}$ denote the index set for the flights. Each flight $i \in \mathcal{I}_F$ is associated with an aircraft type $\alpha^i \in \mathcal{A}$, a scheduled departure time $t_0^i \in \mathcal{T}$, a maximal allowable flight time $\tau^i \in \mathcal{T}$, an initial location $x_0^i \in \mathcal{V}$ and a destination location $x_f^i \in \mathcal{V}$. Let $x^i(t) \in \mathcal{V}$ denote the location of flight i at time $t \in \mathcal{T}^i \triangleq \{t_0^i, \dots, t_0^i + \tau^i\}$. For the flight planning problem, the decision to be made at each time step is the waypoint to reach at the next time step. Different types of aircraft may have different sets of reachable waypoints over one unit of time. Let $\mathcal{U}(v, \alpha)$ be the set of reachable waypoints at the next time step if the aircraft type is $\alpha \in \mathcal{A}$ and the current flight location is $v \in \mathcal{V}$. Assume that $v \in \mathcal{U}(v, \alpha)$, namely, an aircraft can always stay at the same waypoint over two consecutive time steps, which corresponds to a holding pattern. In addition, assume that $\mathcal{U}(v, \alpha)$ always contains waypoints other than v , i.e., $\mathcal{U}(v, \alpha) \setminus \{v\} \neq \emptyset$. This can always be satisfied by inserting virtual waypoints when needed. For example, suppose that flight i is at waypoint v at time t and the airway structure around v is shown in Fig. 1 with circles representing the named waypoints and triangles representing the virtual waypoints. Then due to the maximum speed of aircraft α^i , the set of reachable waypoints at time step t may only contain the ones corresponding to the shaded circles and triangles.

With these notations, the evolution of the path trajectory of flight i is given by:

$$\begin{aligned} x^i(t+1) &= f^i(x^i(t), u^i(t)) \\ &\triangleq \begin{cases} u^i(t), & \text{if } x^i(t) \neq x_f^i \\ x_f^i(t), & \text{if } x^i(t) = x_f^i \end{cases}, \quad (1) \\ &\text{with } x^i(t_0^i) = x_0^i \text{ and } u^i(t) \in \mathcal{U}(x^i(t), \alpha^i). \end{aligned}$$

At each time before reaching the destination, the control $u^i(t) \in \mathcal{U}(x^i(t), \alpha^i)$ specifies the next waypoint along the

path. Notice that the flight may land at some time before the deadline time $t_0^i + \tau^i$.

C. Problem Statement

There are usually multiple paths connecting the origin and destination airports. Suppose that flight i prefers the path that minimizes the following cost function:

$$J^i(x_0^i, u^i) = \phi^i(x^i(t_0^i + \tau^i)) + \sum_{t=t_0^i}^{t_0^i + \tau^i - 1} L^i(t, x^i(t), u^i(t)),$$

where for any $v \in \mathcal{V}$, the function ϕ^i is the terminal cost function, defined by

$$\phi^i(v) = \begin{cases} 0 & \text{if } v = x_f^i \\ \infty & \text{otherwise} \end{cases},$$

and L^i is the running cost function, given by

$$L^i(t, v, u) = \begin{cases} 0 & \text{if } v = x_f^i \\ e^i(v, u) + \bar{r}(t, v, u) & \text{otherwise} \end{cases}$$

with $e^i(v, u)$ accounting for the cost penalizing the traveling time and/or fuel consumption for traveling from waypoint v to $f^i(v, u)$ and

$$\bar{r}(t, v, u) = \mathbb{E}(w_t(f(v, u))) = \int a \frac{\partial p_t(a; f(v, u))}{\partial a} da, \quad (2)$$

being the average weather hazardous level at waypoint $f(v, u)$. Incorporating the term \bar{r} into L^i takes advantage of the stochastic nature of the predicted weather data and allows us to penalize the path that is close but not inside the weather forbidden zone. Notice that there are many other ways to quantify the weather risk.

We now assume that each flight has chosen its own running cost function L^i based on its preference of different factors. Let $u^i = [u^i(t_0^i), \dots, u^i(t_0^i + \tau^i)]$ be the sequence of inputs for flight i . The overall flight planning problem can be formulated as the following optimal control problem subject to state and control constraints.

Problem 1 (Centralized Planning Problem): Find the control sequences $\{u^i\}_{i=1}^N$ for all the flights that minimize $\sum_{i=1}^N J^i(x_0^i, u^i)$ subject to

$$\text{(Dynamics): } \begin{cases} x^i(t+1) = f^i(x^i(t), u^i(t)) \\ u^i(t) \in \mathcal{U}(x^i(t), \alpha^i) \end{cases} \quad (3a)$$

$$\text{(Weather): } \text{link}(x^i(t), x^i(t+1)) \notin W_+(t) \quad (3b)$$

$$\text{(Traffic): } \sum_{i=1}^N \mathbf{1}_{S_m}(x^i(t)) \leq c_m \quad (3c)$$

for all $t \in \mathcal{T}^i$, $i \leq N$, and $m \leq n_s$, where $\mathbf{1}_{S_m}(\cdot)$ denotes the indicator function which equals to 1 if its argument is inside S_m and equals to 0 otherwise.

III. DECENTRALIZED PLANNING ALGORITHM

The optimal centralized solution to Problem 1 is intractable for large flight numbers N . More importantly, even if such a solution is available, its application in the ATM system would be rather limited because the optimality and safety (satisfying the constraints) for one flight would be immediately lost if some other flights deviate from their optimal paths, or a new flight enters the system. With these concerns in mind, we propose a decentralized solution to Problem 1, which, although may not achieve the global minimum, can handle a large number of aircraft and be easily employed in the current ATM system.

A. Decentralization Through Traffic Regulation Function

The main challenge for solving Problem 1 lies in the traffic constraints (3c) which involve couplings among the paths of different flights. Conflicts of interest arise if more than c_m flights want to use the same sector S_m over the same period of time. The main task of ATM is to properly resolve these conflicts. In the current ATM system, when a potential traffic jam is identified, certain ATM actions will be taken, e.g., the en-route flights can be controlled through speed variation, vector for spacing (VFS), holding pattern (HP) or redirecting to other sectors, to avoid entering the overly-used sectors, while the flights that are still on the ground may be delayed or required to modify their paths. All of these forms of control can be essentially viewed as particular ways of preventing some affected flights from entering the congested sectors. This general goal can be encoded into a so-called *traffic regulation function*

$$\lambda : \mathcal{I}_F \times \mathcal{I}_S \times \mathcal{T} \rightarrow \{0, \infty\},$$

where the control $\lambda(i, m, t) = 0$ permits flight i to use sector m over time slot $[t, t+1]$ (if it desires to do so), while $\lambda(i, m, t) = \infty$ disallows the use of sector m over $[t, t+1]$ by flight i .

The role of the traffic regulation function is to specify which flights can use which sectors at different time steps. One can think of it as a way to assign priorities to different flights for using congested sectors. The current ATM system in general assigns priorities according to flight departure times. This corresponds to an iterative way of designing the regulation function λ . At the beginning, all the sectors over all the time slots are open. After accepting more and more flight plans, a certain sector S_m may reach its capacity limit over a certain future time slot $[t, t+1]$. In this case, the regulation function $\lambda(i, m, t)$ is set to infinity for any future flight i that has not departed yet.

The above discussion indicates that the traffic regulation function is a reasonable abstraction of the regulation role of the ATM system. We now assume that λ has already been specified by the ATM system and must be obeyed by each future flight. Then if a new flight $i \in \mathcal{I}_F$ wants to plan (or replan) its path x^i , to respect the traffic rule λ , the following condition must be satisfied:

$$\lambda(i, \beta(x^i(t)), t) = 0, \quad \text{whenever } x^i(t) \neq x_f^i. \quad (4)$$

Roughly speaking, this is to require that the new plan x^i should not travel through sectors over their congested time. If this condition is satisfied, then adding this new plan to the system will not violate the traffic constraints of the entire system.

Therefore, under a given traffic regulation rule λ , the best flight i can do is to solve the following decoupled planning problem.

Problem 2 (Decentralized Planning Problem): Find the control sequence $\{u^i\}$ that minimize $J^i(x_0^i, u^i)$ subject to constraints (3a), (3b) and (4).

The solution of the above problem will produce the optimal path x^i for flight i under the current ‘‘traffic condition’’ λ . Once the path plan x^i is filed, then some sectors may become fully used over certain time slots and the function λ will be updated accordingly.

B. Decentralized Planning Algorithm

We now describe an algorithm to solve the decentralized 4D path planning problem (Problem 2).

The weather constraint (3b) can be easily addressed by introducing a penalty term in the running cost function. Let $L_w : \mathcal{T} \times \mathcal{E} \rightarrow \{0, \infty\}$ be the weather penalty function defined by:

$$L_w(t, v_1, v_2) = \begin{cases} 0 & \text{if } \text{link}(v_1, v_2) \notin W_+(t) \\ \infty & \text{otherwise} \end{cases}$$

For flight i , if its location and control at time t are $x^i(t)$ and $u^i(t)$, respectively, then the weather penalty incurred over $[t, t+1]$ is $L_w(t, x^i(t), f^i(x^i(t), u^i(t)))$.

To respect both the weather constraints and the traffic regulation rule λ , we define a new running cost function for flight i as

$$\begin{aligned} \hat{L}^i(t, x^i(t), u^i(t)) &= L^i(t, x^i(t), u^i(t)) \\ &+ L_w(t, x^i(t), f^i(x^i(t), u^i(t))) + \sum_{m=1}^{n_s} \lambda(i, \beta(x^i(t)), t). \end{aligned}$$

With the new running cost function \hat{L} , Problem 2 can be transformed into the following unconstrained problem.

Problem 3: Find the control sequence u^i that minimizes the cost function

$$\hat{J}^i(x_0^i, u^i) = \phi^i(x^i(t_0^i + \tau^i)) + \sum_{t=t_0^i}^{t_0^i + \tau^i - 1} \hat{L}^i(t, x^i(t), u^i(t)).$$

It is clear that the set of all the control sequences u^i with finite $\hat{J}^i(x_0^i, u^i)$ coincides with the set of feasible solutions to Problem 2. Therefore, Problems 3 and 2 must have the same set of optimal solutions.

Proposition 1: The optimal solution u^i to Problem 3 is also optimal for Problem 2.

Problem 3 can be viewed as a shortest path problem with time-dependent link cost. Such a problem has been studied extensively for vehicle transportation applications [12], [13] and is often referred to as the Time-Dependent Shortest Path (TDSP) problem. A standard way to solve the TDSP problem

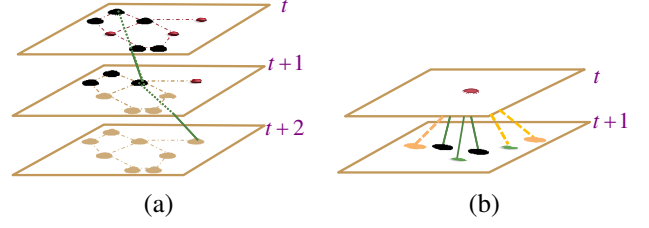


Fig. 2. (a) Spatial-Temporal graph. (b) Illustration of aircraft-dependent links of graph $\tilde{\mathcal{G}}$

is to expand the state space to include the time component as well. Following this idea, for each $i \in \mathcal{I}_F$, we extend the spatial graph \mathcal{G} to a spatial-temporal graph $\tilde{\mathcal{G}}_i = (\tilde{\mathcal{V}}_i, \tilde{\mathcal{E}}_i)$, where

$$\begin{aligned} \tilde{\mathcal{V}}_i &= \{(v, t) : v \in \mathcal{G}, t \in \{t_0^i, \dots, t_0^i + \tau^i\}\} \\ \tilde{\mathcal{E}}_i &= \{((v_1, t), (v_2, t+1)) : v_1 \in \mathcal{G}, \\ &t \in \{t_0^i, \dots, t_0^i + \tau^i\}, v_2 \in \mathcal{U}(v_1, \alpha^i)\} \end{aligned}$$

The construction of graph $\tilde{\mathcal{G}}_i$ is illustrated in Fig. 2-(a), where a copy of the spatial graph \mathcal{G} is made at each time step, and every link starts and ends at two adjacent time layers. The set of links $\tilde{\mathcal{E}}_i$ may vary with aircraft type α^i . For example, as shown in Fig. 2-(b), the node at time t may be associated with 3 downward links (solid lines) for one type of aircraft, but 5 downward links (solid and dashed lines) for another type of aircraft with larger maximum speed and smaller turning radius.

For each flight $i \in \mathcal{I}_F$, let $\tilde{x}^i(t) = (x^i(t), t)$ be the extended state, which evolves according to

$$\tilde{x}^i(t+1) = \tilde{f}^i(\tilde{x}^i(t), u^i(t)) = (f^i(x^i(t), u^i(t)), t+1),$$

for $t \in [t_0^i, t_0^i + \tau^i]$ under the control sequence u^i . Let $\tilde{x}_0^i = (x_0^i, t_0^i)$ and $\tilde{x}_f^i = (x_f^i, t_0^i + \tau^i)$. For any $\tilde{v} = (v, t) \in \tilde{\mathcal{V}}_i$ and $u \in \mathcal{U}(v, \alpha^i)$, define the extended terminal and running cost functions as

$$\tilde{\phi}^i(\tilde{v}) = \begin{cases} 0 & \text{if } \tilde{v} = \tilde{x}_f^i \\ \infty & \text{otherwise,} \end{cases}$$

$$\tilde{L}^i(\tilde{v}, u) = \begin{cases} \hat{L}^i(t, v, u) & \text{if } v \neq x_f^i \\ 0 & \text{otherwise} \end{cases}$$

Problem 3 can be solved using dynamic programming. For each $k = 0, \dots, \tau^i$, let $V_k^i : \tilde{\mathcal{V}}_i \rightarrow \mathbb{R}_+ \cup \{\infty\}$ be the k -step value function (minimum cost-to-go function). Initially set $V_0^i(\tilde{v}) = \tilde{\phi}^i(\tilde{v}), \forall \tilde{v} \in \tilde{\mathcal{V}}_i$. Then, for $k = 0, \dots, \tau^i - 1$, evolve the value function according to the value iteration formula:

$$V_{k+1}^i(\tilde{v}) = \min_{u \in \mathcal{U}(\tilde{v}, \alpha^i)} \left\{ \tilde{L}^i(\tilde{v}, u) + V_k^i(\tilde{f}^i(\tilde{v}, u)) \right\}, \forall \tilde{v} \in \tilde{\mathcal{V}}_i.$$

As long as there is a feasible 4D path, we will have $V_{\tau^i}^i(\tilde{x}_0^i) < \infty$, and the corresponding optimal path can be obtained easily as follows:

$$\begin{cases} u^i(t) = \arg \min_{u \in \mathcal{U}(\tilde{x}^i(t), \alpha^i)} \left\{ \tilde{L}^i(\tilde{x}^i(t), u) + V_k^i(\tilde{f}^i(\tilde{x}^i(t), u)) \right\} \\ \tilde{x}^i(t+1) = \tilde{f}^i(\tilde{x}^i(t), u^i(t)), \end{cases}$$

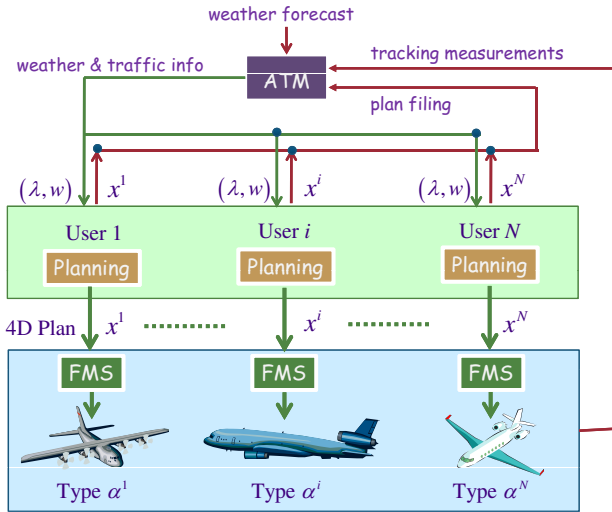


Fig. 3. Proposed hierarchical structure for Air Traffic Management, where the users of the system include the pilots in command as well as the flight dispatchers at some Airline Operations Center (AOC).

which is guaranteed to satisfy all the constraints.

C. Practical Interpretations

The decentralized flight planning algorithm developed in this section leads to a hierarchical framework for the overall air traffic management system as illustrated in Fig. 3. The framework contains three interacting layers consisting of the air traffic management (ATM), air traffic users (individual flights), and the flight management system (FMS). The role of each layer is described below.

The role of ATM is to, in real time, gather various measurements, update detailed weather and traffic forecasts accordingly, and distribute these informations to the end users (individual flights). At the beginning of each time period, the ATM receives new weather forecast data and new filing requests of flight plans. For each proposed flight plan, the ATM will check whether it satisfies all the weather and traffic constraints, namely, whether it passes through certain weather forbidden zone (based on the updated forecast) or some congested sectors (based on the traffic regulation function of the previous step). If the constraints are all satisfied, then the plan will be accepted and the traffic regulation function λ will be updated by, for example, setting the entries corresponding to the “overly-booked” sectors for each time slot to infinity. These updated weather and traffic predictions (λ, w) will then be distributed to the second layer consisting of individual flights.

At the second layer, each flight, before taking off, receives the weather and traffic information from FAA, and regards these information as traffic rules. Subject to these rules, the user optimizes its path plan using the algorithm described in Section III-B. Each individual flight formulates its own cost function in order to optimize for its preferences. If the optimal cost is infinite, then the flight has to delay its departure time; otherwise, it will file the flight plan with FAA. It is guaranteed that the plan satisfies all the

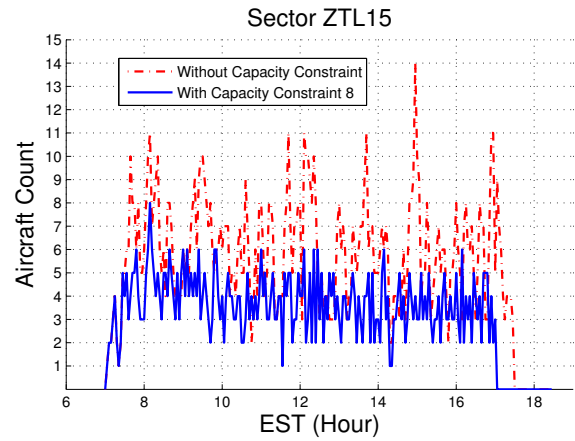


Fig. 4. Comparison of aircraft counts in Sector ZTL15 with and without capacity constraints

constraints and is optimal under the current weather and traffic restrictions.

The bottom layer can be viewed as a “physical layer”, where the on-board FMS receives the high-level (waypoint-based) path and designs a detailed flight trajectory according to the plan. Since our planning algorithm respects the underlying aircraft dynamics, it is guaranteed that the 4D paths generated by the algorithm can be carried out by the aircraft.

IV. SIMULATION RESULTS

The proposed planning framework is tested through a large-scale simulation motivated by real traffic data of the continental NAS of the United States. The origin-destination pairs and the departure times of the flights that travel among the 34 continental airports in the FAA’s Operational Evolution Plan (OEP)¹ are extracted from the ETMS data of Aug 24th, 2005. We consider all the flights whose departure times are between 12 p.m. GMT (7 a.m. EST) and 10 p.m. GMT (5 p.m. EST) and use them as our testing data set, which consists of 5419 flights.

We first use the decentralized planning algorithm to compute the optimal path for each of the flights in the data set without considering any traffic constraints. Based on these paths, the average sector count over the time window between 12 p.m. EST and 5 p.m. EST is calculated for each of the 284 high-altitude sectors in the continental US, and their values, in normalized scale, are shown in Fig. 5. It can be seen that without any regulation, the traffic tends to concentrate on a few sectors and the majority of the rest of the airspace remains under-utilized.

To demonstrate the proposed ATM strategy, all the sector capacities are set to 8 and the flight plans are recomputed subject to these constraints with priorities assigned according to their departure times². The obtained paths satisfy the

¹There are 35 airports in the OEP plan, which account for about 69% of total operations in the NAS [14]. Our simulation is based on 34 of them, except HNL (Honolulu International Airport)

²Here the number 8 was chosen artificially to illustrate the algorithm. Normal capacities typically range from 10 to 20.

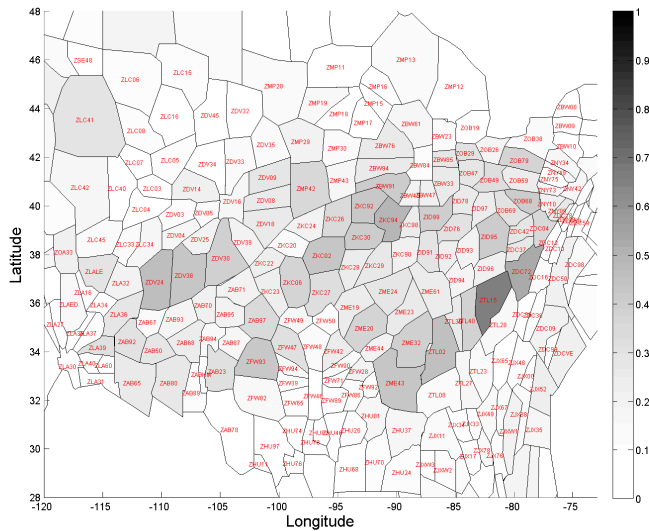


Fig. 5. Average sector counts between 12 p.m. EST and 5 p.m. EST corresponding to the unconstrained path plans.

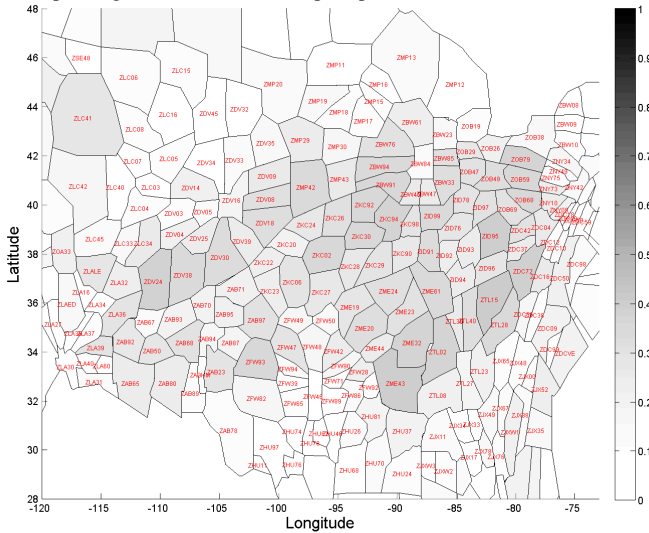


Fig. 6. Average sector counts between 12 p.m. EST and 5 p.m. EST corresponding to the path plans computed using the proposed algorithm with sector capacities set to 8.

capacity constraints at all times, while the previous unconstrained paths result in 40 sectors exceeding the capacity over some time period during the planning interval. An example of aircraft-count improvements is illustrated in Fig. 4 for Sector ZTL15. Fig. 6 shows the average sector counts based on the constrained flight plans under the same condition as described in the last paragraph. In comparison to Fig. 5, it is clear that the proposed planning strategy yields a better utilization of the airspace over time with the traffic volume in the congested sectors properly diffused into their neighbors. It is remarkable that this is achieved by only a 0.71% increase of the average traveling distance of all the flights.

V. CONCLUSION

A hierarchical decentralized framework has been developed to tackle a large-scale air traffic control problem. Under

this framework, the role of the ATM is to evaluate the traffic and weather conditions and distribute the information to the end users; the users, on the other hand, optimize flight paths according to their own cost functions while respecting the received traffic and weather restrictions. Simulation results based on real air traffic data indicate potential applications of the proposed framework on regulating air traffic with safety guarantees. An immediate step of our future work is to further validate our strategy by incorporating real weather forecast data.

REFERENCES

- [1] D. Sun. *Large-scale modeling and optimization of en route air traffic flow*. PhD thesis, University of California at Berkeley, 2008.
- [2] A. M. Bayen, R. L. Raffard, and C. J. Tomlin. Eulerian network model of air traffic flow in congested areas. In *Proceedings of the 2004 American Control Conference*, Boston, Massachusetts, June 2004.
- [3] P. K. Menon, G. D. Sweriduk, and K. Bilimoria. A new approach for modeling, analysis and control of air traffic flow. In *AIAA Conference on Guidance, Navigation, and Control*, Monterey, CA, August 2002.
- [4] S. L. Waslander, R. L. Raffard, and C. J. Tomlin. Market-based air traffic flow control with competing airlines. *AIAA Journal of Guidance, Control and Dynamics*, 31(1):148–161, Jan. – Feb. 2008.
- [5] S. Gutierrez-Nolasco and K. S. Sheth. Analysis of factors for incorporating user preferences in air traffic management: A users’ perspective. In *AIAA Conference on Aviation Technology, Integration, and Operations*, Forth Worth, Texas, September 2010.
- [6] D. Michalek and H. Balakrishnan. Building a stochastic terminal airspace capacity forecast from convective weather forecasts. In *Proceedings of the Aviation, Range and Aerospace Meteorology Special Symposium on Weather-Air Traffic Management Integration*, 2009.
- [7] H. Balakrishnan. Techniques for reallocating airport resources during adverse weather. In *Proceedings of the 46th IEEE Conference on Decision and Control*, pages 2949–2956, New Orleans, LA, December 2007.
- [8] J. Prete and J. S. B. Mitchell. Safe routing of multiple aircraft flows in the presence of time-varying weather data. In *AIAA Guidance, Navigation, and Control Conf*, 2004.
- [9] J. J. Pannequin, A. M. Bayen, I. M. Mitchell, H. Chung, and S. Sastry. Multiple aircraft deconflicted path planning with weather avoidance constraints. In *AIAA Guidance, Navigation and Control Conference*, 2007.
- [10] M. Kamgarpour, V. Dadok, and C. Tomlin. Trajectory Generation for Multiple Aircraft Subject to Dynamic Weather Uncertainty. In *IEEE Conference on Decision and Control*, 2010. To appear.
- [11] D. Bhadra. Demand for air travel in the united states: Bottom-up econometric estimation and implications for forecasts by origin-destination pairs. *Journal of Air Transportation*, 8(2), 2003.
- [12] A. K Ziliaskopoulos and H. S Mahmassani. Time-dependent, shortest-path algorithm for real-time intelligent vehicle highway system applications. *Transportation Research Record*, (1408):94–100, 1993.
- [13] I. Chabini. Discrete dynamic shortest path problems in transportation applications: complexity and algorithms with optimal run time. *Transportation Research Record*, 1645:170–175, 1998.
- [14] D. Bhadra and P. Texter. Airline networks: An econometric framework to analyze domestic US air travel. *Journal of Transportation and Statistics*, 7(1):87–102, 2004.