

Optimizing Airspace Sectors for Varying Demand Patterns using Multi-Controller Staffing

Shin-Lai (Alex) Tien
University of Maryland
College Park, Maryland, U.S.A.
Alextien(at)umd.edu

Robert Hoffman, Ph.D.
Metron Aviation, Inc.
Dulles, Virginia, U.S.A.
Hoffman(at)metronaviation.com

Abstract—A variety of design concepts have been implemented in sectorizing en route airspace, e.g. balancing controller workload, aligning sector shape with flow, and maintaining minimum dwell time. To efficiently serve demand variation over time and space and to increase efficiency, models for dynamic airspace management, e.g. frequently changing sector boundaries or re-organizing jet routes, have also been envisioned. In the U.S., a common way to deal with temporary demand peaks in a sector is to use multiple controller teams, e.g. a Radar-side controller plus a Data-side controller. In this study, we propose an optimization model to create airspace sector boundaries that takes traffic demand variations and multi-controller teams into account. We improve upon existing sectorization techniques by acknowledging that sector capacity can be increased by adding auxiliary controllers. By comparing a multi-controller policy with a single-controller policy, our numerical results confirm that when traffic demand patterns are steady over time, a single-controller policy is satisfactory. But when demand varies over time, sectors can be designed in a way that allows for strategic use of multi-controller teams. This makes effective use of controller workforce and circumvents the need to perform disruptive sector boundary changes during busy periods.

Key Words – *optimization, mixed integer program, fixed-charge problem, airspace partitioning, sectorization, multi-period design, traffic patterns, variable sector capacity, controller staffing, controller cost, controller workload, dynamic airspace configuration, dynamic airspace and capacity management.*

I. INTRODUCTION

Dynamic airspace and capacity management, also known as dynamic airspace configuration (DAC), addresses the need to adapt the airspace to changing needs and demands of the airspace users. A question of particular concern has been how to design airspace sectors, which human controllers would work, to accommodate selected design objectives, e.g. alignment with traffic flow or buffering for aircraft maneuvering. This is known as *airspace partitioning* or *sectorization*. The overarching assumption is that if sectors are designed to be more efficient (i.e. reduce controller workload), they can handle more traffic, thereby reducing air traffic control (ATC) delays on airspace users.

Air traffic control capacity can perhaps be increased by adding controllers. But unlimited controller staffing would be

an expensive policy. In the U.S., controller labor costs have increased from \$82.98 per flight in FY1998 to \$137.81 per flight in FY2006 [1]. The Federal Aviation Administration will hire and train more than 15,000 controllers over the next decade, in response to controller attrition and an anticipated increase in air travel [2]. There is a strong need in both the U.S. and Europe to take controller costs into account when designing sector boundaries.

An important DAC research issue addressed by this paper is how to accommodate spatial and volume variations in traffic demand – the dynamic part of dynamic airspace configuration. Our focus is on demand variations that occur throughout the day, rather than over the course of months or years. Sectorization methods in the literature (see Section II) address demand variation by reapplication of a static sectorization method. For instance, if traffic demand in the 12:00 – 14:00 time period were significantly different than the demand pattern in the 10:00 – 12:00 time period, than a resectorization would be proposed at 12:00.

Dynamic resectorization is common practice in U.S. air traffic operations today. However, it is difficult for controllers to make staffing or boundary changes during intense activity. Significant sector boundary changes are made only in the hours when traffic levels are low. Given limitations of the system, en route computers, etc., it is reasonable to assume that for the foreseeable future, wholesale resectorization during “the heat of battle” will remain impractical. Under our sectorization approach, we design sector boundaries that can remain in place throughout the day.

We address demand variability by varying the number of controllers working each sector. This capitalizes on the existing practice of multi-controller teams. When traffic is slow, one controller can perform all three basic functions for a sector: ATC-to-pilot communication, data processing and management (e.g. handling flight strips), and coordination with other air traffic controllers. But during high demand periods, these responsibilities are often spread among multiple controllers. A common configuration is to augment the primary Radar (R-side) controller working a given sector with a second controller (Data or D-side). In addition to sector boundaries, an output of our model is a least-cost staffing assignment (i.e. number of controllers assigned to each sector throughout the day). Current

models in the literature either ignore this capacity control mechanism or are in conflict with it by assuming a uniform number of controllers per sector.

In Section II, we review state-of-the-art sectorization techniques, we provide other operational information (e.g. controller practices) necessary to appreciate the relevance of this work, and we further motivate the need to consider multiple controllers per sector through a small sectorization example. In Section III, we formulate a mixed integer program (MIP) that outputs quality airspace sectors while minimizing controller staffing levels. In Section IV, we confirm via real traffic data that the MIP performs as claimed. And in Section V, we summarize our work, its applicability, and possible research extensions.

II. BACKGROUND

There are numerous considerations in design of radar-controlled sectors. Controllers have indicated that aligning sectors with traffic flows is a paramount concern in sector design. To the extent possible, sector boundaries should minimize coordination and promote overall system flexibility to support user preferred trajectories. Flow alignment reduces workload in the form of handoffs. The problem with today's system is that sectors are aligned with static jet routes; hence, the airspace is rigid. DAC must consider future user-preferred demand patterns. In this paper, we assume that user-preferred trajectories are input to our model, no matter how they were generated. These can be historical patterns or forecasted.

Sector design should afford optimum flight profile procedures that enable flights to reach desired altitudes, optimum speeds, and climb/descent rates without interruption for ATC operational or organizational reasons. Other (secondary) sector design considerations include equipment and spectrum constraints (e.g. radio coverage), local boundary constraints (e.g. reserved airspace), aircraft performance mix, shallow-angle boundary crossings, and room for controller maneuvering of aircraft (e.g. keep intersection points away from the boundary).

These sector design criteria often interact or conflict with one another, so it would be ambitious to meet all objectives in one modeling effort. In order to implement the designed airspace in practice, Conker et al. [3] proposed a framework for clean-sheet airspace design, consisting of three important aspects: 1) airspace partitioning, 2) controller workability evaluation, and 3) sector boundary evaluation and improvement. Since each aspect is addressed by an individual module separately developed, favorable modeling techniques can be applied in order to incorporate more realistic or comprehensive design concerns.

Various methods and models have been developed for airspace partitioning. Delahaye et al. [4] [5] proposed genetic algorithms to obtain sectors with well-balanced workload. Trandac and Duong [6] also considered workload balancing and proposed a two-phase approach using graph partitioning heuristics to find an initial sectorization and employing constraint programming techniques to locally optimize based on a set of geometric constraints. Klein [7] proposed an algorithm for Center boundary formation by iteratively

combining hex-cells in order to achieve well-balanced workload among Centers.

In Basu et al. [8], airspace is partitioned using computational geometry (CG) algorithms. The primary advantage of CG over classical optimization techniques is that virtually any computable design criteria can be incorporated. Mitchell et al. [9] incorporated metrics on workload variation into CG algorithms. Xue [10] applied optimization algorithms to improve the solutions from the CG paradigm in order to meet various objectives in airspace design.

The use of optimization techniques (network flow structure with side constraints) to sectorize airspace was pioneered by Yousefi [11] [12] [13] and later improved and reformulated by Hoffman et al. [14] and Drew [15]. The polygonal cells used to tile airspace were clustered into a pre-determined number of sectors, constrained by a workload balancing criterion. As will be seen in Section III, our model also clusters cells via optimization techniques inspired by [11] and [14].

A common technique found in previous studies is to design airspace for forecasted workload aggregated over one planning horizon (e.g. one day or week). However, this is too granular in time to capture the traffic variations that occur throughout the day. Some of the techniques can accommodate peak workload, but then the sectorization tends to cater to those peaks, rather than the variance. If demand variation is not considered, the resulting boundary design might end up using controller resources inefficiently.

As stated in the introduction, one can always keep pace with demand variation by resectorizing more frequently. But this practice is highly disruptive to controller workflow, as sector boundary changes can be problematic. Controllers tell us that it can take several minutes or longer to "get the picture". The effect of wholesale boundary changes while aircraft are being actively separated is uncharted territory that would require extensive human factors and safety studies to evaluate. Moreover, a controller has to be familiar with (and certified on) sector boundaries in his or her area of specialization, so frequently introducing new boundaries is impractical [16]. Although temporary adjustment of sector control areas (e.g. combining quiet sectors or splitting busy sectors) is commonly seen in practice, the potential sector boundaries, once determined, will last for months or years. In this paper, we address the need for optimizing fixed sector boundaries against traffic patterns over time.

Existing sectorization techniques in the literature place heavy emphasis on balancing workload across sectors (in addition to other sector design objectives). The idea is that prevention of sector overloads will reduce the need for controllers to apply en route flow restrictions. But workload balancing tacitly presumes that sectors have (or should have) equivalent capacity across the planning horizon. To the contrary, sector capacity varies with the number of controllers working that piece of airspace. An en route sector in the United States is managed by a team of up to four controllers. Therefore, capacity of a given sector increases step-wise with the number of controllers assigned to that sector. Fig. 1 gives an example of sector capacity estimation based on controller staffing.

Number of Controllers by Function and Number of Aircraft Worked		
Function	Number of Aircraft Worked During 15-Minute Interval	Number of Controllers
High Altitude Radar Sector	0	0
	1 - 12	1
	13 - 17	2
	18 - 29	3
	30+	4
Low/Both Altitude Radar Sector	0	0
	1 - 10	1
	11 - 14	2
	15 - 24	3
	25+	4
A-Side	0	0
	1 - 73	1
	74+	2

NOTE: For application, count aircraft worked for radar sector controller positions during current 15-minute interval. Count aircraft worked for A-side positions at +30 minutes from current 15-minute interval.

Figure 1. Effect of number of controllers on sector capacities [17]

The assumption of equal sector capacity across the day or week can result in an inefficient allocation. For a given sector, workload (as measured, say, by aircraft counts or radar hits) may equal or be below the single-controller level *on average* over a planning horizon, but there may be shorter periods of time in that horizon when demand slightly exceeds the single-controller capability, necessitating a second controller. In principle, controller assignments could be highly dynamic (e.g. add a second controller for 45 minutes, off for 10 minutes, then on again), but the cost would not be; controllers cannot necessarily be taken on and off the clock that sporadically. In this paper, our surrogate metric for controller cost is total controller shifts needed to work the airspace of concern. These are integer values which are easily converted to controller-hours by multiplying by hours per shift. (Actual costs vary by controller pay scale, classification of airspace, specialization, etc.)

Next, we construct a simple example to illustrate that the detrimental effects of balancing workload in a dynamic traffic setting can be mitigated by capitalizing on multiple controller positions. Consider a portion of airspace decomposed into seven atomic cells, 1 through 7, as in Fig. 2. Suppose we wish to partition these cells into two sectors to be maintained over the entire planning horizon. (Since the sectors must be contiguous, there are only six ways to do this.)

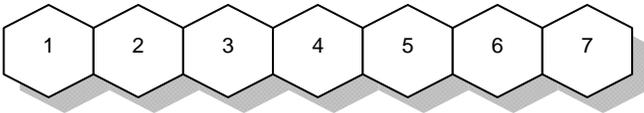


Figure 2. Airspace cells to be grouped into two sectors

Table 1 shows hypothetical controller workload values for each cell over three time periods spanning the planning horizon. (The workload units are irrelevant to this illustration.) Note the demand spikes in cell 5. Optimal workload balance (across the entire planning horizon) is achieved by grouping cells 1,2,3,4 and cells 5,6,7. Suppose a single controller can handle 10 workload units in a given time period, while the addition of a second controller raises that capacity to 18 units. Table 2 shows the number of controllers required in each time

period under this sectorization. Note the three instances (highlighted cells) in which two controllers are required, for a total of 9 controller-periods.

Table 3 shows controller staffing requirements for an alternate sectorization in which cell 5 is now grouped in the first sector rather than the second (i.e. 1,2,3,4,5 and 6,7). Now, two controllers are required in only two time periods (highlighted cells). The total number of controller-periods is reduced to 8. (In fact, this is minimal for a two-sector design.)

Table 1: Workload across cells and time periods

Cell:	1	2	3	4	5	6	7
<i>T=1</i>	2	3	0	2	4	2	5
<i>T=2</i>	5	3	3	1	5	3	5
<i>T=3</i>	0	2	1	2	1	3	2
<i>Sum</i>	7	8	4	5	10	8	12

The principle at work is as follows. Though total workload is the same across the two sectorizations (64 units), the inefficiency of the sector-balancing solution resulted from requiring *slightly* more than one controller in the first sector in period 2 (12 units of demand, when a single controller can handle only 10). On the other hand, the optimal sectorization reduces controller cost by deliberately shifting workload excesses created by cell 5 to the first sector in period 2. This raises workload from 12 to 17 units, but this is still under the 2-controller workload level of 18 units. (Note: A comparable example can be constructed even when workload is not additive across cells.)

The point of this stylized example is that human controllers come in discrete quantities and that the resulting variance in sector capacity should be acknowledged (and capitalized on) in sector boundary design.

Table 2: Balanced sectors induce three instances of 2-controller teams

Controller Usage	Partition	
	[1,2,3,4]	[5,6,7]
<i>T=1</i>	1	2
<i>T=2</i>	2	2
<i>T=3</i>	1	1
<i>Total</i>	9	

Table 3: Imbalanced sectors incite only two instances of 2-controller teams.

Controller Usage	Partition	
	[1,2,3,4,5]	[6,7]
<i>T=1</i>	2	1
<i>T=2</i>	2	1
<i>T=3</i>	1	1
<i>Total</i>	8	

In the next section, we extend the scope of existing airspace design work by presenting a sectorization model that accommodates multi-period demand patterns and that employs step-wise sector capacity values as a decision variable. A

mixed-integer programming model is proposed to find optimal sector boundaries across the design horizon while considering efficient controller assignment strategy at individual periods.

III. MULTI-PERIOD VARIABLE CONTROLLER (MPVC) MIXED INTEGER PROGRAM

Like references [14] and [11], we partition the airspace into atomic polygonal cells, which will be grouped into sectors by our mixed integer program. The flight data input is demand at each cell. We assume that sector demand and sector capacity levels are measured in the same unit, e.g. number of aircraft, radar hits, or a composite metric estimated from traffic complexity analysis during a certain period. We also assume that traffic demand is additive across cells. (We elaborate on these assumptions in Section IV.) The optimization problem we solve is to group cells into contiguous sectors so that they tend to align with traffic flows, thereby increasing sector dwell time and minimizing controller handoffs. The Yousefi model also solves this problem, but it balances workload among the sectors. We will deliberately manipulate imbalances, as in the motivating example.

A. Network Structure

We formulate our multi-period variable controller (MPVC) mixed integer program as a variant of the fixed-charge network flow problem with side constraints. To account for demand variations over time, we divide the planning horizon into a set of contiguous time periods. Each cell corresponds to a node in the network, and if two cells are adjacent, there will be two directed links connecting them. The network structure is created via the parameters below.

- i : index of nodes (or cells), $i \in \{1, \dots, I\}$.
- t : index of periods, $t \in \{1, \dots, T\}$.
- A_i : set of neighbor nodes (or cells) of i .
- S : set of nodes specified as “seed” for candidate sector locations; $S \subseteq \{1, \dots, I\}$.
- k : index of sector capacity values offered, $k \in \{1, \dots, K\}$.
- b_i^k : label of dummy node associated with each value of sector capacity k offered at $i \in S$.
- B_i : set of dummy nodes associated with $i \in S$; $B_i = \{b_i^k \mid k = 1, \dots, K\}$ for $i \in S$.
- d_i^t : demand (or workload metric) of i at t .

The demand at node i in period t is denoted $d_i^t \geq 0$. This is the amount of workload (e.g. aircraft count) demand at cell i by the input data. Conceptually, this demand will flow along the network through a series of contiguous cells to exactly one sink. Each sink determines a sector, and all cells contributing to that sink belong to that sector. (These cell-to-sector relations are determined by tracing paths in post-optimization processing.) To reduce problem size, only a subset of cells S ,

called “seeds”, are considered for selection as sinks by the optimization process.

We modify this seed and demand-flow technique (taken from [14] and [11]) as follows. We augment each cell $i \in S$ with a set of dummy nodes $b_i^k \in B_i$, as shown in Fig. 3. If seed i is selected as a sink, then we pass its accumulated flow to exactly one of the dummy nodes, which indicates a level of workload employed at the seed. (So, strictly speaking, the dummy node becomes the sink.) This creates the fixed charge network structure. The non-seed nodes ($i \notin S$) are not connected to dummy nodes.

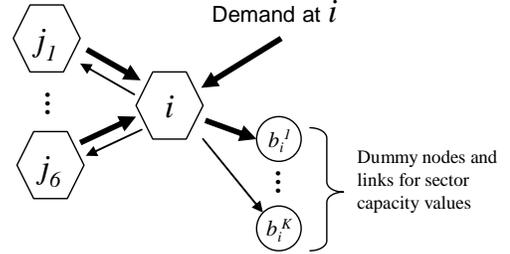


Figure 3. Underlying network structure at a seed node

B. Decision Variables

The decision variables are as below. The flow along the link from i to j at period t is denoted x_{ij}^t . This is the demand originating at node i plus any demand passed into i from its neighbors. The q variables determine which cell-to-cell links will be active; the p variables determine which seed-to-dummy nodes will be active.

- x_{ij}^t : decision variable of flow on link from i to node j at t ; for $i \in S$, $j \in A_i \cup B_i$; for $i \notin S$, $j \in A_i$.
- q_{ij} : binary decision variable. $q_{ij} = 1$ whenever $x_{ij}^t > 0$ for any $t \in \{1, \dots, T\}$, $i \in \{1, \dots, I\}$, $j \in A_i$; $q_{ij} = 0$ otherwise.
- p_{ik}^t : binary decision variable. $p_{ik}^t = 1$ whenever $x_{ik}^t > 0$ for $t \in \{1, \dots, T\}$, $i \in S$, $k \in B_i$; $p_{ik}^t = 0$ otherwise.

C. Cost Parameters and Bounds

The per-unit flow cost on the cell-to-cell links, the sector-level links, and the bounds on the links are shown below.

- c_{ij}^t : unit cost of flow on link from i to $j \in A_i$ at t
- f_{ik}^t : fixed cost for dummy link (which takes effect only if $x_{ik}^t > 0$), for $t \in \{1, \dots, T\}$, $i \in S$, $k \in B_i$.
- M_{ij} : upper bound of flow on link from i to j ; for $i \in S$, $j \in A_i \cup B_i$; for $i \notin S$, $j \in A_i$.

D. Constraints

We establish the following constraints.

$$\sum_{j \in A_i} x_{ji}^t + d_i^t = \sum_{j \in A_i} x_{ij}^t \quad \text{for all } i \notin S, t \in \{1, \dots, T\} \quad (1)$$

$$\sum_{j \in A_i} x_{ji}^t + d_i^t = \sum_{j \in A_i \cup B_i} x_{ij}^t \quad \text{for all } i \in S, t \in \{1, \dots, T\} \quad (2)$$

$$x_{ij}^t \leq M_{ij} q_{ij} \quad \text{for all } i \in \{1, \dots, I\}, j \in A_i, t \in \{1, \dots, T\} \quad (3)$$

$$M_{i, b_i^{k-1}} p_{i, b_i^k}^t \leq x_{i, b_i^k}^t \leq M_{i, b_i^k} p_{i, b_i^k}^t \quad \text{for all } i \in S, \\ k \in \{1, \dots, K\}, \\ t \in \{1, \dots, T\} \quad (4)$$

$$\sum_{j \in A_i} q_{ij} \leq 1 \quad \text{for all } i \notin S \quad (5)$$

$$\sum_{j \in A_i} q_{ij} + \sum_{j \in B_i} p_{ij}^t \leq 1 \quad \text{for all } i \in S, t \in \{1, \dots, T\} \quad (6)$$

Constraint (1) conserves flow at each non-seed node, while constraint (2) conserves flow at each seed node.

Constraint (3) ensures that demand flows from a cell i to one of its neighbors j only if it has been allowed by binary decision variable q_{ij} . Parameter M_{ij} is chosen sufficiently large to maintain this relationship no matter how much flow the link carries. Note that q_{ij} has no time period index, so if $q_{ij} = 1$, the link is in use across all the time periods.

Constraint (4) defines the upper and lower bounds for $x_{i, b_i^k}^t$. For each link from $i \in S$ to dummy node b_i^k , where $k \in \{1, \dots, K\}$, at each period t , if $x_{i, b_i^k}^t > 0$, then its binary indicator $p_{i, b_i^k}^t$ equals 1, and 0 otherwise. The practical meaning of $p_{i, b_i^k}^t = 1$ is that at period t the k^{th} capacity value is chosen to serve the demands that sink at i and pass volume $x_{i, b_i^k}^t$ to dummy node b_i^k . To ensure a bound on link capacity, we assume that the constant M_{i, b_i^k} is set to the k^{th} capacity value and that $M_{i, b_i^k} > M_{i, b_i^{k-1}}$ for each $k \in \{1, \dots, K\}$, where $M_{i, b_i^0} = 0$. Additionally, by setting sector capacity values to correspond with controller positions used, the number of controllers per sector per time period is determined.

Constraint (5) says that for each node $i \notin S$, at most one outbound link can have positive flow, as a positive value will be used to infer cell-to-sector assignment. Constraint (6) says that for each node $i \in S$ chosen as a seed, we force outbound flow to at most one of its sector capacity values, which tells us the number of controllers being used.

E. Objective Function

Our objective function (7) contains two cost terms. The first term, $f_{ij}^t p_{ij}^t$, represents total staffing cost. More precisely, this computes sector capacity cost.

$$\text{Minimize} \quad \sum_{\substack{i \in S, j \in B_i \\ t \in \{1, \dots, T\}}} \mu f_{ij}^t p_{ij}^t + \sum_{\substack{i \in \{1, \dots, I\} \\ j \in A_i \\ t \in \{1, \dots, T\}}} c_{ij}^t x_{ij}^t \quad (7)$$

By considering sector capacity as a step function of controller positions, the cost coefficients f_{ij}^t for dummy link can be set to represent the number of controller positions used or to reflect the monetary cost of controller positions. The second term, $c_{ij}^t x_{ij}^t$, controls sector shape. By making link cost inversely proportional to aircraft crossings between its nodes (cells), the model tends to connect cells with high aircraft transfer in the input data. This means that sectors tend to align with major traffic flows. (See [14] [11] [15] for further discussion of flow alignment.)

The parameter μ , which sets relative values of the two terms in the objective function, should be skewed toward staffing cost. Otherwise, the number of resulting sectors will be as many as possible. Note that by including sector capacity decision variables, the number of resulting sectors is output by the model rather than input to it.

In summary, MPVC minimizes (7) subject to constraints (1) through (6), where $x_{ij}^t \geq 0$ are free variables and where q_{ij} and p_{ij}^t are binary variables.

IV. EXPERIMENTAL RESULTS

We implemented our MPVC model on historical traffic data (1-minute radar positions) recorded in Washington DC en route Center (ZDC) on April 21, 2005 (in GMT). We tiled ZDC with 1043 hex cells of equal size, 41 of which are selected as seeds and evenly distributed within the design area, as in Fig. 4. The demand at each cell is measured as the number of the TZ radar hits between FL240 and FL360. For a given time period, the number of hits in a cell or a sector implies not only aircraft counts but also aircraft dwell time. To reduce problem complexity, we use aircraft position hits as a surrogate for workload. Analysis [11] shows that, for small airspace cells aircraft count is highly correlated to a composite workload measurement by more elaborate traffic complexity metrics. (In fact, before the airspace cells are clustered into sectors, there are very few options for complexity metrics.) For model demonstration, we used the number of radar hits as a surrogate for measuring sector demand and capacity.

Fig. 5 illustrates the temporal demand magnitude at ZDC every 2 hours. This is a series of histograms (each one running toward the reader) for various times of the day. Each histogram gives the frequency of radar hits. Fig. 6 shows the variation in traffic patterns (mainly intensity) in ZDC on that day.

From this single day, we created two demand data sets to show how MPVC performs when there is high demand variation and when there is low demand variation.

To demonstrate the multi-controller effect, at most two controller positions could be used at each resulting sector, i.e. $k \in \{1, 2\}$, so there are two dummy nodes for each seed $i \in S$.

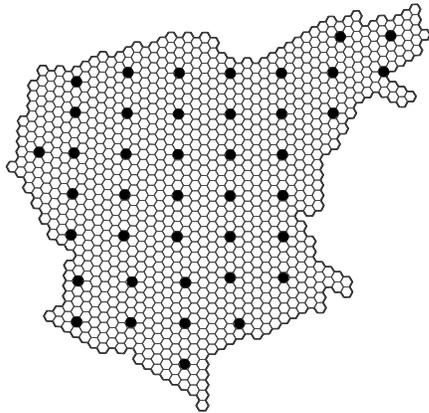


Figure 4. ZDC (without ocean) and seed locations

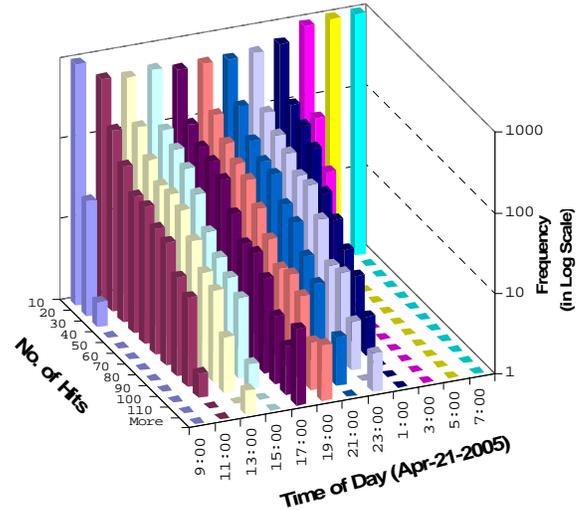


Figure 5. Period-wise histograms of radar hits at ZDC

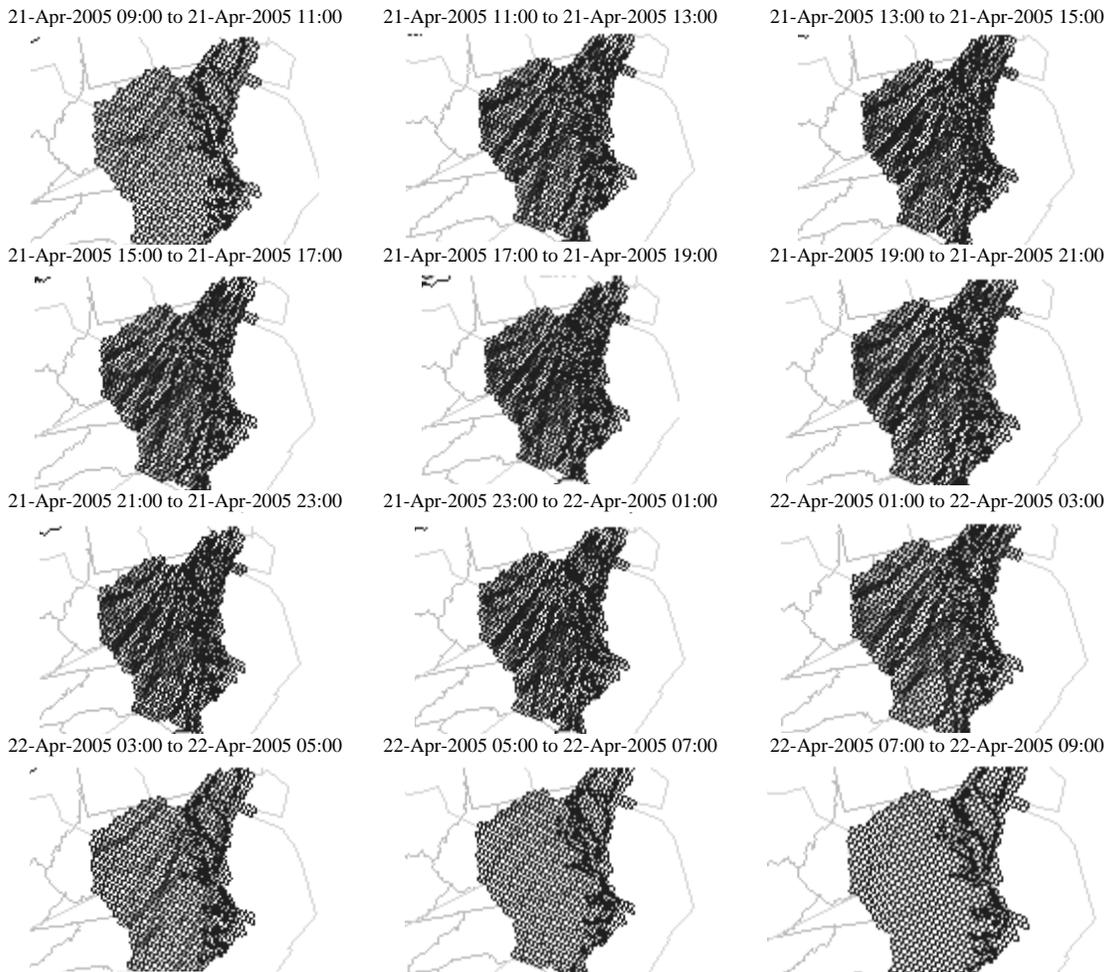


Figure 6. ZDC Traffic Patterns on April 21, 2005 (in GMT)

A. High-Demand Variation – 2 Positions and 4 x 4 Hours

For this case, we divided the 16-hour busy period of the day (11:00 to 03:00 the next day) into four 4-hour intervals. The fixed cost coefficients for dummy links in the objective function are set as $f_{i,b_1}^t = 1$ and $f_{i,b_2}^t = 1.9 < 2f_{i,b_1}^t$. As mentioned earlier, these coefficients should reflect the cost or quantity of controllers.

The assumption that a 2-controller team is less costly than two 1-controller teams is not necessary, but helpful for solving the integer program quickly. If there is a need for temporary capacity increase, then the tradeoff between cost and capacity gained will be determined through the optimization process. (Ideally, the sector capacity values should be estimated with controller capability, such as a step-wise relation in Fig. 1. But an estimation model for sector capacity is beyond the scope of this paper.) Given the 4-hour period length, precise estimates for sector capacity might be impractical and under large variation.

We approximated the capacity values from the current operational environment as follows. ZDC has about 17 en route sectors between FL240 and FL360 (this varies with time of day, and not all en route sectors lie in this altitude range). For the capacity provided by 1-controller team, we pick the highest total demand amongst the design periods and divide this number into total demand for each period:

$$M_{i,b_1} = \max \{ \text{total demand at period } t \} / 17$$

This is a very conservative estimate since it is implicitly assumed that at the busiest period one controller serves one sector in average. The capacity of a 2-controller team should incorporate the diminishing effect on productivity of an additional controller. In this study, we assume an additional controller brings 60% more capacity values, i.e.

$$M_{i,b_2} = M_{i,b_1} \times 160\%$$

To let sector shape align with air traffic flow, the cost of link between two cells at each period, c_{ij}^t , is defined as the inverse of the total number of aircraft crossings from both directions within the defined period, as suggested in Drew [15], in order to have better sector shape but without impacting design objective. We set the cost tradeoff parameter μ to a high value 10^6 , which allows controller cost to dominate the objective, flow alignment. Other parameter settings could be explored.

We solved this instance of MPVC with Xpress-Mosel solver software on a Dell PowerEdge 1900 with Intel Xeon 2.66Ghz processor and 12 GB memory. Solver time was 45,578 seconds (12.6 hours) for 12.17% optimality gap. Table 4 summarizes the controller requirements. The resulting sectors are visualized in Fig. 7, and demand distribution is displayed in Fig. 8 with dashed lines depicting the assumed capacity values.

Three of the 17 sectors formed in the optimization employed 2-controller teams. The total number of controller hours used was $(20+19+20+18) \times 4 = 308$.

To compare our MPVC results with a policy that balances average workload across the 16 hours, we modified our formulation and ran the Yousefi [14] et al. mixed integer program (YMIP) on the same data set with aggregated demand. YMIP accepts the number of sectors (17, in this case) as input. This is enforced by constraint (8). The primary objective of YMIP is to align sectors with flows. Workload balance is a secondary objective in YMIP, addressed in the constraints as maximum deviation from average workload across all sectors, as shown in constraint (9). Neither multi-period demand nor controller staffing are considered, so we set $T = 1$ and $K = 1$. The tolerance parameter for workload balancing is set to $\gamma = 0.05$, i.e. total workload in each sector for the planning horizon will be within 5% of the average over all sectors.

$$\sum_{i \in S, j \in B_i} p_{ij}^t = \text{Desired No. of Sectors} \quad (8)$$

$$p_{i,b_1}^t (1 - \gamma) W_{\text{target}} \leq x_{i,b_1}^t \leq p_{i,b_1}^t (1 + \gamma) W_{\text{target}} \quad \text{for all } i \in S \quad (9)$$

Fig. 9 shows resulting sectors from YMIP, while the demand distribution is shown in Fig. 10. Table 5 shows that $(24+24+26+17) \times 4 = 364$ controller-hours are required to serve the demand in the planning horizon. That is 56 more (worse) than the 308 required by MPVC. The less efficient use of controller-hours is attributable to the unacknowledged demand variation over time, as in the motivating example of Section II.

An alternate sector design strategy using YMIP would be to increase the number of sectors so that no sector workload level will exceed the 1-controller threshold of 2315, which is used in the previous MPVC example. We tested this and found that 20 sectors would be required (each with a one controller) for a total of 320 controller hours. This is better than the 364 controller-hours under the 17-sector YMIP policy, but still higher (worse) than the 308 achieved by MPVC under a multi-controller policy.

B. Low-Demand Variation Case

For this case, we divided the low-demand period of the day (17:00 to 01:00 the next day) into four 2-hour time intervals. This was constructed to confirm a hypothesis that when demand is steady (low variation), 1-controller teams make efficient use of controller resources.

We ran MPVC with the same settings as the high-demand case. The results in Table 6 suggest that the optimized number of sectors was 18. Note that this low-variation case created one more sector than the high-variation case. (18 versus 17.) When demand is steady (but high), creating two 1-controller sectors is more efficient than one 2-controller sector because the two sectors have greater capacity. (Recall that the second controller adds marginally less capacity than the first controller.) This principle, demonstrated by our model, captures the current practice of splitting sectors during busy periods.

Table 4: MPVC controller requirements for high-demand variation case

Resulting No. of Sectors	Resulting No. of Controller Shifts				Capacity Assumed	
	11:00 / 15:00	15:00 / 19:00	19:00 / 23:00	23:00 / 03:00	Using 1 Position	Using 2 Positions
	17	20	19	20	18	2315

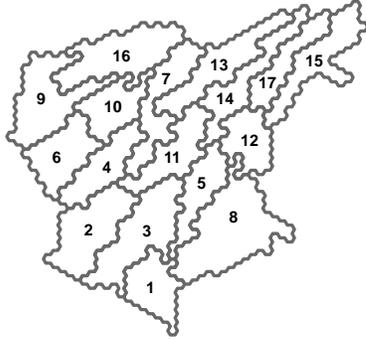


Figure 7. MPVC sector boundaries for high-demand variation

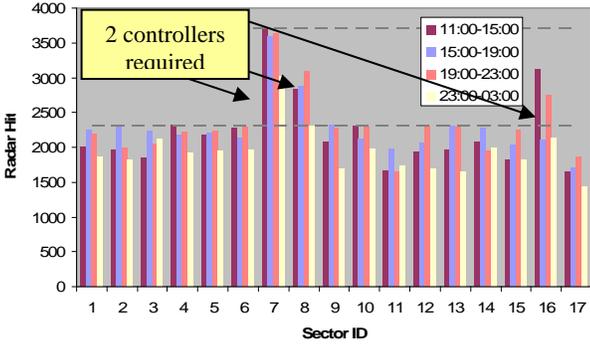


Figure 8. MPVC sector demand distribution for high-demand variation

The resulting sectors are depicted in Fig. 11, and demand distribution is displayed in Fig. 12. During this 8-hour planning horizon, the total number of controller hours required was $(19+18+18+18) \times 2 = 146$. Only one sector during one period required a 2-controller team. This confirms our hypothesis that one controller per sector suffices when the traffic is busy but less variable across the planning horizon.

Again for comparison purposes, we ran the YMIP model on this low-demand variation case, but this time calling for 18 sectors. Table 7 shows the controller requirements per time period. This sectorization requires $(23+21+19+18) \times 2 = 162$ controller-hours to serve the demand in the planning horizon. This is 16 more controller-hours than MPVC required. The YMIP sectors are shown in Fig. 13. Fig. 14 shows the demand distribution over time. Each bar over the lower dashed line indicates need for a 2-controller team.

C. Summary of Numerical Experiments

Table 8 summarizes the numerical results. The primary statistic is the number of controller-hours. The two optimal

Table 5: YMIP controller requirements for high-demand variation case

Resulting No. of Sectors	Resulting No. of Controller Shifts				Capacity Assumed	
	11:00 / 15:00	15:00 / 19:00	19:00 / 23:00	23:00 / 03:00	Using 1 Position	Using 2 Positions
	17	24	24	26	17	2315

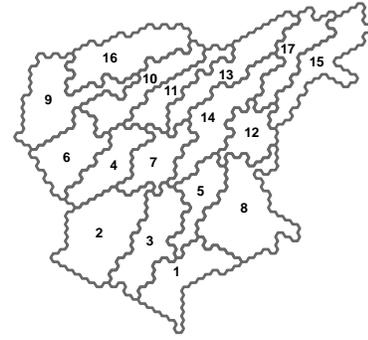


Figure 9. YMIP sector boundaries for High-demand Case

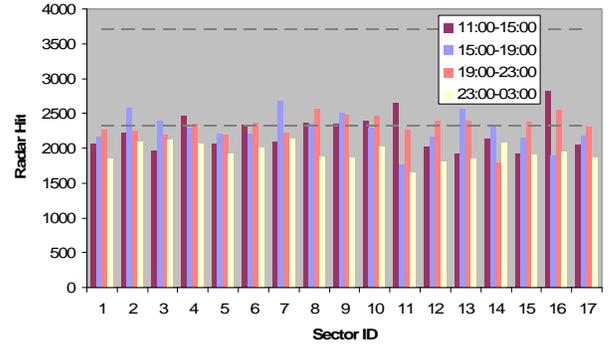


Figure 10. YMIP sector demand distribution for high-demand variation

(minimal) values for the two test cases are highlighted. In addition, we show the average aircraft dwell time by using whole day traffic. For each sector, we computed average dwell time of the aircraft trajectories, then averaged over all sectors. Based on [14], this is a simple but reasonable surrogate for flow alignment (alignment with traffic flows tends to increase sector dwell time). We merely wish to point out that the two models are comparable in flow alignment, a common objective of the two models. For YMIP, this is traded off with workload balancing; for MPVC, this is traded off with controller cost. The tradeoff in each model can be controlled by parameter settings.

The balance deviations are shown in the last two rows of Table 8. These are, respectively, the maximum (positive) deviation and minimum (negative) deviation from average workload (radar hits) computed across all sectors over the planning horizon. This is simply confirmation that YMIP has balanced workload to within its reasonable tolerance, but that MPVC has deliberately unbalanced sectors to allow for larger sectors that require multiple controllers.

Table 6: MPVC controller requirements for low-demand variation case

Resulting No. of Sectors	Resulting No. of Controller Shifts				Capacity Assumed	
	17:00	19:00	21:00	23:00	Using 1 Position	Using 2 Positions
	/ 19:00	/ 21:00	/ 23:00	/ 01:00		
18	19	18	18	18	1272	2035

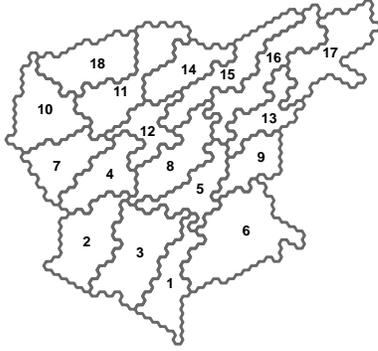


Figure 11. MPVC sector boundaries for low-demand variation

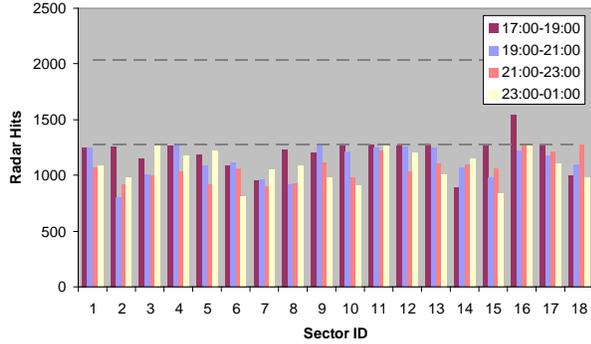


Figure 12. MPVC sector demand distribution for low-demand variation

Table 7: YMIP controller requirements for Low-Demand Variation Case

Resulting No. of Sectors	Resulting No. of Controller Shifts				Capacity Assumed	
	17:00	19:00	21:00	23:00	Using 1 Position	Using 2 Positions
	/ 19:00	/ 21:00	/ 23:00	/ 01:00		
18	23	21	19	18	1272	2035

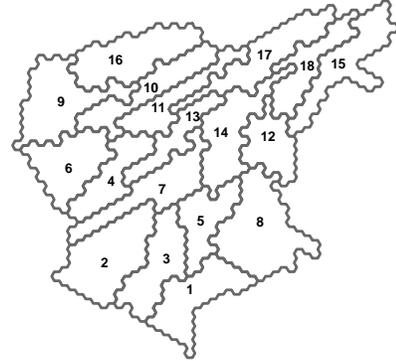


Figure 13. YMIP sector boundaries for low-demand variation

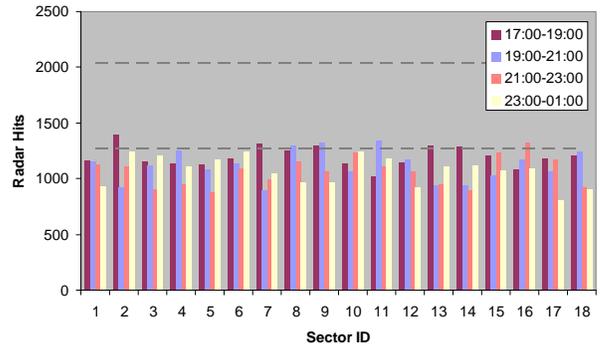


Figure 14. YMIP sector demand distribution for low-demand variation

Table 8: Summary of numerical results

Test Case	High Demand Variation		Low Demand Variation	
Planning Horizon	16 Hrs		8 Hrs	
Duration per Period	4 Hrs		2 Hrs	
Model (MIP)	MPVC	YMIP	MPVC	YMIP
Design Objective	Minimize no. of controller shifts and sectors; Minimize flow alignment cost	Balance workload among sectors; Minimize flow alignment cost	Minimize no. of controller shifts and sectors; Minimize flow alignment cost	Balance workload among sectors; Minimize flow alignment cost
Required Controller-hours	308	364	146	162
Avg. Flight Dwell Time	8.0	8.5	7.8	8.2
BalDev+	59.1%	5.0%	18.8%	5.0%
BalDev-	-23.7%	-5.0%	-13.4%	-5.0%

For the experiments above, we have shown that given the time-varying nature of traffic, the sectorizations from the proposed model not only accommodate the multi-period demand but also consider the overall efficiency of controller staffing requirements. An aggregated model, such as YMIP, is unaware of demand variation and might result in an inefficient design in terms of controller-hours. In the case of low-demand variation, when designing sectors from a clean sheet, one controller per sector is a more effective strategy than applying multiple controllers.

V. CONCLUSIONS

We have introduced a mixed integer program to design radar-controlled en route sectors so that multi-controller positions can address traffic demand variations. This extends workload-balancing sectorization techniques in the literature by capitalizing on the fact that sector capacity varies with the (discrete) number of controllers working that airspace. This minimizes controller costs, which will be of great interest to air navigation service providers.

Also, we have shown that we can avoid frequent and disruptive wholesale resectorization throughout the day, which is tacitly promoted by other sectorization techniques in the literature. Performance of our model (flow alignment and controller cost minimization) is confirmed on real traffic data from Washington Center. Specifically, we compared performance with a sectorization strategy that does not take demand variation into account. We will expand this study to other traffic regions, compare with current sectors and controller costs, and consider longer time periods (weeks, seasons, etc.) The principles at work are soundly demonstrated.

Quality sector design is a multi-objective problem; it should take into account many controller workload and sector geometric factors. In this paper, we have focused on flow alignment. We recognize that other design factors should be taken into account as well.

Run time for our integer program is an issue. As expected, we saw run times longer than its predecessor integer program (YMIP) because in addition to finding sectors that align with flows, which both models must do, our model must determine the number of sectors (these are input to YMIP). The problem size depends on the number of time periods and number of nodes. We will investigate heuristic approaches. Our informal observations of model behavior are that it intentionally creates sectors with high demand variation, within reason. (To be expected based on our motivational example.) This suggests a heuristic algorithm that isolates regions with high demand variation.

In concert with current FAA policy, our model assumes that 8-hour controller shifts can be staggered. A separate model would be required to map the controller-shifts output by our model to personnel. We introduced multiple sector capacity values to choose, but did not specify how the capacity values link to controller staffing. This requires further investigation. Also, there might be non-controller resources that impact sector capacity. Our model should be modified to reflect those resource constraints.

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AUTHOR BIOGRAPHIES

Shin-Lai (Alex) Tien is a Ph.D. candidate in the Department of Civil and Environmental Engineering at the University of Maryland. He received his M.S. degree in Civil Engineering from the National Taiwan University, Taipei, Taiwan in 2000.

Dr. Robert Hoffman is a principal analyst at Metron Aviation, a consulting firm specializing in researching and developing solutions for air traffic management, and a Visiting Research Scientist at the University of Maryland's Institute for Systems Research. Currently, he is involved in modeling and analysis of strategic ATM initiatives, specializing in resource allocation, optimization, and airspace design issues. He has published numerous journal and conference papers in the area of air traffic management and optimization, for which he has received multiple awards. He received his Ph.D. in applied Mathematics from the University of Maryland in 1997.