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Operational Dynamic Configuration Analysis

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Abstract

Sectors may combine or split within areas of specialization in response to changing traffic patterns. This method of managing capacity and controller workload could be made more flexible by dynamically modifying sector boundaries. Much work has been done on methods for dynamically creating new sector boundaries [1-5]. Many assessments of dynamic configuration methods assume the current day baseline configuration remains fixed [6-7]. A challenging question is how to select a dynamic configuration baseline to assess potential benefits of proposed dynamic configuration concepts.

Bloem used operational sector reconfigurations as a baseline [8]. The main difficulty is that operational reconfiguration data is noisy. Reconfigurations often occur frequently to accommodate staff training or breaks, or to complete a more complicated reconfiguration through a rapid sequence of simpler reconfigurations. Gupta quantified a few aspects of airspace boundary changes from this data [9]. Most of these metrics are unique to sector combining operations and not applicable to more flexible dynamic configuration concepts. To better understand what sort of reconfigurations are acceptable or beneficial, more configuration change metrics should be developed and their distribution in current practice should be computed.

This paper proposes a method to select a simple sequence of configurations among operational configurations to serve as a dynamic configuration baseline for future dynamic configuration concept assessments. New configuration change metrics are applied to the operational data to establish current day thresholds for these metrics. These thresholds are then corroborated, refined, or dismissed based on airspace practitioner feedback.

The dynamic configuration baseline selection method uses a k-means clustering algorithm to select the sequence of configurations and trigger times from a given day of operational sector combination data. The clustering algorithm selects a simplified schedule containing k configurations based on stability score of the sector combinations among the raw operational configurations. In addition, the number of the selected configurations is determined based on balance between accuracy and assessment complexity.

This method was used to select a dynamic configuration baseline for Kansas City Center (ZKC) for a good weather, high volume day. A total of 78 configurations were used at some time in Kansas City Center on February 8, 2007. The clustering algorithm was applied to the 78 configuration schedule with k ranging from one to six. Preliminary results show that the overall stability score improves rapidly until the three-configuration schedule. For this day, the three-configuration schedule yields the best accuracy for the increased scenario complexity, and the two configuration triggering times are 2007/02/08 12:19:21 UTC and 2007/02/09 00:58:07 UTC.

The final version of this paper will include an analysis of reconfiguration metrics applied to operational configurations. These metrics include quantities of airspace volume and aircraft changing ownership during the change, number of sector pairs affected by the change, and resulting change in airspace complexity metrics.

It is impractical to assume a single sector configuration can balance controller workload and accommodate dynamic air traffic demand. By providing the most representative set of configurations and allowing multiple configurations to be triggered during a simulation, it has the potential to improve benefit assessment accuracy for new dynamic airspace designs.

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OPERATIONAL DYNAMIC CONFIGURATION ANALYSIS

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Abstract

Seventy-eight air traffic sector configurations, recorded in operational data for Kansas City Air Route Traffic Control Center on February 8, 2007, were analyzed. A method is used to select a sequence of configurations and trigger times from the operational sector combination data. The selection process considers two key characteristics of sector combining and splitting operations: controller familiarity and sector continuity. Based on a distance score, the method selects three representative configurations. Configurations selected from the clustering algorithm were compared with the actual operational configurations. The main findings of the study were: 1) on average 2.8 sectors were changed at each reconfiguration event, 2) on average, after a reconfiguration about two aircraft were handed-off, two aircraft were received, and five aircraft remained in the sector, and 3) aircraft density change is the best sector change metric to access new dynamic airspace designs using a simplified reconfiguration.

I. Introduction

Air traffic managers and controllers combine or split air traffic sectors in response to changing traffic patterns. This method of managing capacity and controller workload could be made more flexible by dynamically modifying sector boundaries. Prior work has developed methods for dynamically creating new sector boundaries [1-5]. Many assessments of dynamic configuration methods assume the current-day baseline configuration remains fixed [6-7], even though in actual operations it changes. To improve benefit assessment accuracy, baseline simulations should use multiple configurations triggered at realistic reconfiguration times. However, the large number of daily operational reconfigurations creates a complicated baseline for the current stage of dynamic airspace research. A challenging research question is how to select a representative, simplified set of configurations to assess potential benefits of proposed dynamic configuration concepts.

Bloem used operational sector reconfigurations as a baseline for evaluating benefits of combining and splitting sectors [8]. However, a difficulty with this approach is that operational reconfiguration data is noisy. Reconfigurations often occur frequently to accommodate staff training or breaks, or to complete a more complicated reconfiguration through a rapid sequence of simpler reconfigurations. Gupta quantified a few features of airspace boundary changes from this data [9]. Most of the metrics being used in the above literature are unique to sector combining operations and not applicable to more flexible dynamic configuration concepts. To better understand what sort of reconfigurations are acceptable or beneficial, configuration metrics more suitable for flexible boundaries should be developed, and their distribution in current practice should be computed.

This paper applies new configuration change metrics to operational data to establish current day thresholds for these metrics. A method is developed to select a simple sequence of configurations among operational configurations to serve as a dynamic configuration baseline for future dynamic configuration concept assessments. Configuration change metrics are compared between the operational and simplified configuration sets to determine which metrics are relevant to assess proposed dynamic configuration concepts.

Current-day sector combining practices and the operational data analysis are presented in Section II. Section III describes the clustering algorithm. An analysis of clustered vs. operational reconfiguration metrics is discussed in Section IV. Finally, conclusions are presented in Section V.

II. Operational Data Analysis

Today's operational dynamic airspace configurations are accomplished by combining and splitting sectors. In Bloem et al [8], feedback from subject matter experts indicated that there are multiple considerations when making decisions to combine or split sectors such as sector workload and

staff availability. Sectors are split to reduce the workload in the resulting sectors, thereby increasing safety. Sectors are combined when traffic volumes are low.

The following subsections analyze configurations, stored sector combinations, recorded in operational data for Kansas City Air Route Traffic Control Center (ZKC) on February 8, 2007.

1. Reconfiguration Patterns

This subsection analyzes patterns within the reconfiguration schedule. This includes analysis of reconfiguration frequency and the relationship between number of sectors and traffic volume.

A. Reconfiguration Frequency

Reconfiguration events occur frequently, with few sectors affected in any one reconfiguration. For example, there were 78 reconfiguration events between 74 unique configurations recorded in operational data for ZKC on the test day.

Operational reconfigurations often occur frequently to accommodate staff training or breaks, or to complete a more complicated reconfiguration through a rapid sequence of simpler reconfigurations. The following assumptions are used to filter noisy operational data:

- Do not consider any configuration lasting less than two minutes, as it is considered an intermediate configuration.
- After performing the above step, when consecutive reconfigurations are the same, retain only the last reconfiguration.

By removing the noisy data described above, the test data was reduced to 55 configuration events between 53 unique configurations. All remaining analysis within this section used this filtered configuration schedule.

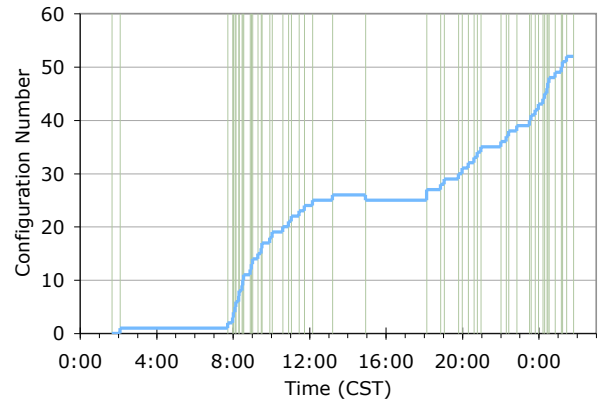

Figure 1. Reconfiguration Schedule

Figure 1 shows the filtered reconfiguration schedule throughout the day. The vertical green lines are reconfiguration trigger times. Most configurations were unique; however, the same configuration may be used more than once. For example, configuration 25 was used in two periods on the test day: (a) from 12:09 CST to 13:12 CST, and (b) from 14:56 CST to 18:08 CST.

Figure 1 also shows that the reconfiguration trigger times are not uniformly distributed throughout the day. There are four observed periods.

1. Few reconfigurations happened between nighttime (02:00 CST) and the morning (08:00 CST).
2. A series of reconfigurations happened rapidly from the morning (08:00 CST) to the afternoon (13:00 CST).
3. Few reconfigurations happened from the afternoon (13:00 CST) to the evening (19:00 CST).
4. A series of reconfigurations happened gradually from the evening (19:00 CST) to nighttime (02:00 CST).

An area of specialization (AOS) is a group of sectors on which all controllers working those sectors must be trained. Reconfiguration may occur only within an AOS, ensuring that an AOS controller will be familiar with the resulting airspace. There are six AOSs, or Areas, in Kansas City Center, namely, Flint Hills, Gateway, Ozark, Prairie, Rivers, and Trails. Figure 2 shows the reconfiguration schedule of individual AOSs. The number of reconfigurations in each AOS is between 9 and 16 on that day. Reconfigurations are less frequent within AOSs than

within the Center as a whole because reconfiguration events are not coordinated across AOSs.

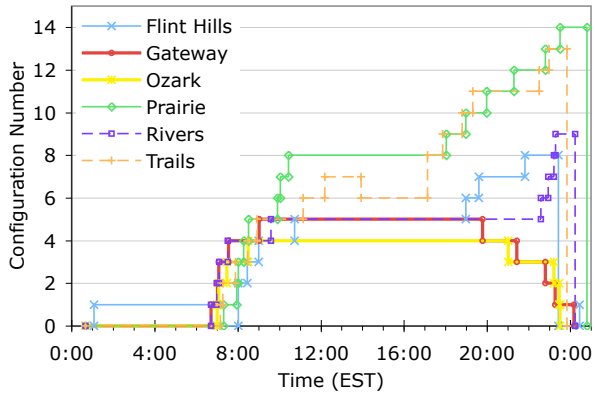

Figure 2. Reconfiguration Schedule for Areas of Specialization

B. Traffic Volume and Sector Count

Airspace configurations are directly related to traffic volume and staff availability. The number of sectors is increased and decreased to accommodate the fluctuating traffic load. Moreover, each controller can handle only a certain number of aircraft at the same time, and thus the overall traffic volume in a center depends on the number of staff available.

Figure 3 shows aircraft and sector counts in Kansas City Center on February 8, 2007. The number of sectors on that day was between 7 and 35. The correlation between aircraft count and sector count is over 0.95, indicating a strong relationship between traffic volume and number of sectors, as expected.

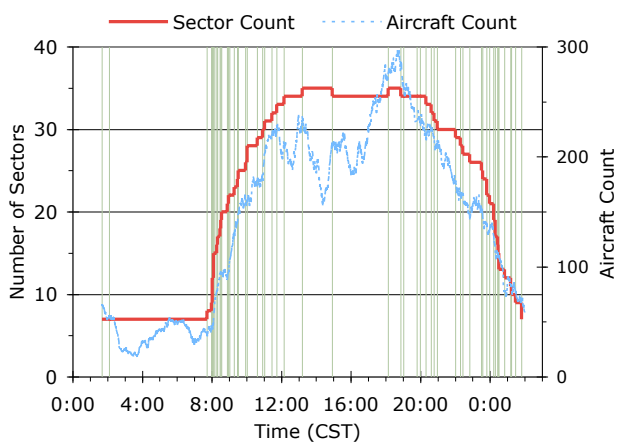

Figure 3. Number of Sectors and Aircraft Count

The green lines represent, same as in Figure 1, the reconfiguration trigger times. Trend changes in the curves occurred over the same four periods of reconfiguration frequency noted in the previous subsection with periods of rapid increase or decrease in traffic volume corresponding to periods of high reconfiguration frequency.

2. Familiarity and Continuity

In Gupta et al [9], feedback from air traffic experts indicates that two desirable characteristics of sector combining and splitting operations are 1) controller familiarity with sector combinations and 2) continuity in the sector combinations. The metrics analyzed in this subsection were designed to quantify these key characteristics. The hours of operation metric was used to quantify familiarity and the sector change metric was used to quantify continuity.

A. Hours of Operation

Figure 4 shows the distribution of operational sector hours on the test day. A total of 36 sectors were defined in the operational data. These sectors were active for some duration throughout the day. Seven sectors were active for the entire 24 hours, 9 (25%) were operating for 16 to 18 hours, and 33 (91.7%) were active for at least 10 hours. On average, sectors were active for 15 hours and 33 minutes.

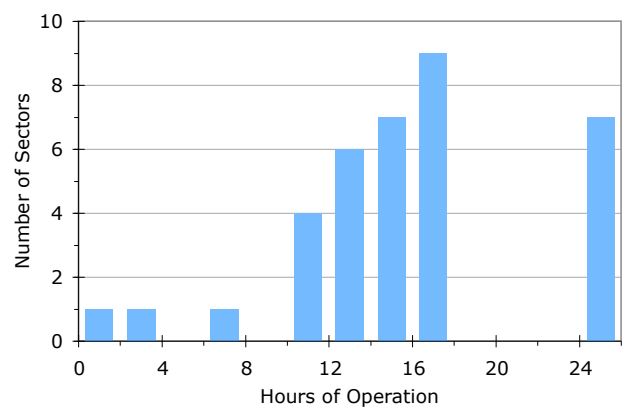

Figure 4. Sector Hours

B. Sector Change

Figure 5 depicts a breakdown of the numbers of sectors into two categories, sectors that changed and stayed the same, after each reconfiguration. A sector is changed when part of its associated airspace is reassigned during a reconfiguration. As illustrated in the figure, most sectors remained the same, while few sectors change at each reconfiguration.

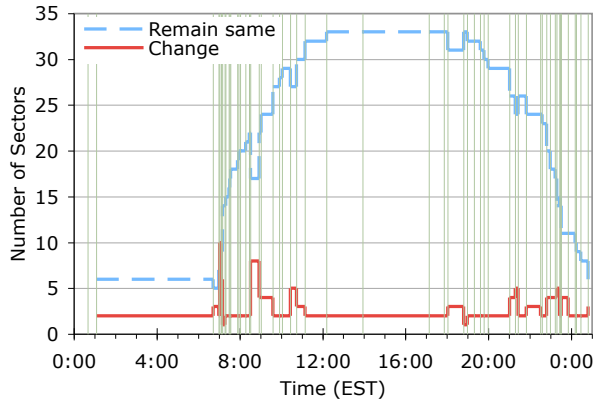

Figure 5. Sectors Changed in Reconfiguration

Figure 6 shows the histogram of the number of sectors changed in each reconfiguration on the test day. The majority (34 of 54, or 63%) of the reconfigurations involve two sectors changing. On average, 2.8 sectors are changed at each reconfiguration event. The few sectors affected at each reconfiguration suggest that current operations prefer to incrementally combine or split sectors, and thus, sector configuration continuity is preserved.

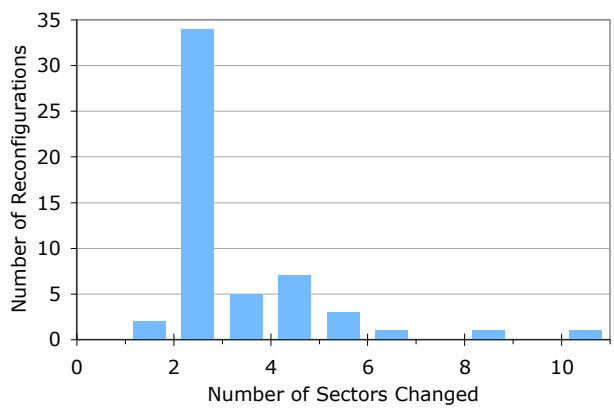

Figure 6. Histogram of Number of Sectors Changed in Reconfiguration

3. Detailed Sector Change Metrics

The airspace change metrics in the previous subsection counted total numbers of sectors that changed. Metrics analyzed in this subsection quantify the sector change in more detail. In addition to being applicable to sector combinations, these metrics may be applied to the finer boundary adjustments proposed in future airspace concepts. Jung et al [10] identified changes in aircraft ownership, sector volume, and sector shape to be significant contributors to increased controller workload during unplanned sector boundary changes. Metrics for these types of changes are discussed below.

A. Aircraft Ownership Change

For simplicity, this study assumed a controller owned all aircraft that were in the sector. This assumes that aircraft were transferred at the sector boundary during stable configuration periods or when the airspace they occupied transferred to another sector during a reconfiguration.

During a reconfiguration, sector controllers handle aircraft from one of the three categories – aircraft remaining within their current sectors, aircraft transferring from adjacent sectors, and aircraft transferring to adjacent sectors. Hereafter, these are referred to as remaining, inbound, and outbound aircraft. A hand-off action is required for inbound and outbound aircraft, but not for remaining aircraft.

Figure 7 shows the average number of aircraft ownership changes per sector, which is defined by dividing the total number of aircraft ownership changes by the number of sectors after a reconfiguration. The figure shows that in Kansas City Center, on average, 1.8 aircraft were handed-off to a sector, as well as 1.8 from a sector. Five aircraft, on average, remained in the same sector after a reconfiguration.

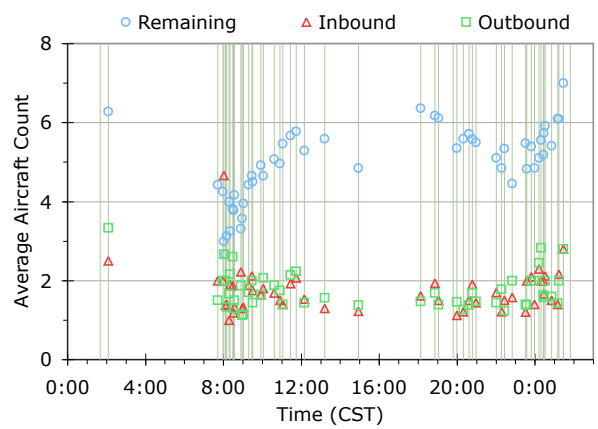

Figure 7. Average Aircraft Ownership Change

The maximum number of remaining, inbound, and outbound aircraft ownership changes share similar trends as those shown in Figure 7. The largest maximum aircraft ownership changes (no more than 15 inbound and 10 outbound) are found in the early morning and late evening hours. Maximum aircraft ownership changes remained low (no more than 5

inbound or outbound) between 12:00 CST and 19:00 CST, the peak traffic volume period.

B. Airspace Volume Change

The total airspace volume change metric captures the amount of change in sector volume during a reconfiguration event. Assume there are w sectors changed after a reconfiguration. The total airspace volume change is the sum of the absolute change in volume of all of the sectors,

$$\sum_{i=1}^{w} \left| V(i,t) - V(i,t-1) \right|,$$

where $V(i, t)$ is the volume of sector i at time t. If a new sector is created after a reconfiguration, its volume is considered zero before the reconfiguration. Similarly, when an existing sector is deleted after a reconfiguration, its volume is considered zero after the reconfiguration.

Figure 8 shows the total airspace volume change and sector count at each reconfiguration. A majority (35 of 54, or 64.8%) of the reconfigurations had total airspace volume change less than 3×10^5 nmi^3. On average, 2.9×10^5 nmi^3 total airspace volume was affected after a reconfiguration.

The total airspace volume change has an inverse relationship to the number of sectors. The more sectors in the center, the less airspace volume changed after a reconfiguration. This follows from the fact that for a fixed airspace volume, increasing the number of sectors decreases the volume of each sector. Therefore, when the number of sectors is high and a sector is combined with another one, or a sector is split, the affected airspace volume is limited.

Additionally, current practice prefers incrementally combining and splitting sectors. A large sector during a low traffic period results from merging small sectors progressively, and small sectors during a high traffic period result from splitting sectors progressively.

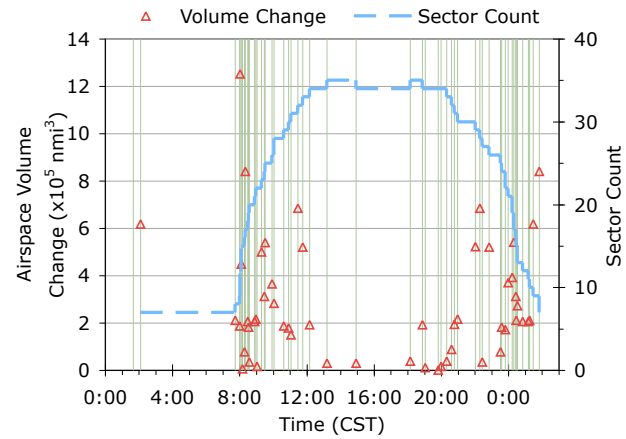

Figure 8. Total Airspace Volume Change and Number of Sectors

Figure 9 shows the cumulative frequency of average airspace volume change per sector as a percentage. The average percentage change is defined as

$$\frac{1}{w} \cdot \frac{\sum_{i=1}^{w} \left| V(i,t) - V(i,t-1) \right|}{\sum_{i=1}^{w} V(i,t-1)} \cdot 100\%,$$

where $V(i, t)$ is the volume of sector i at time t.

The figure shows that the 25th percentile of the reconfigurations had 26.5% average airspace volume change. The median of the average airspace volume change was 38%. The 75th percentile of the reconfigurations had 48.9% average airspace volume change.

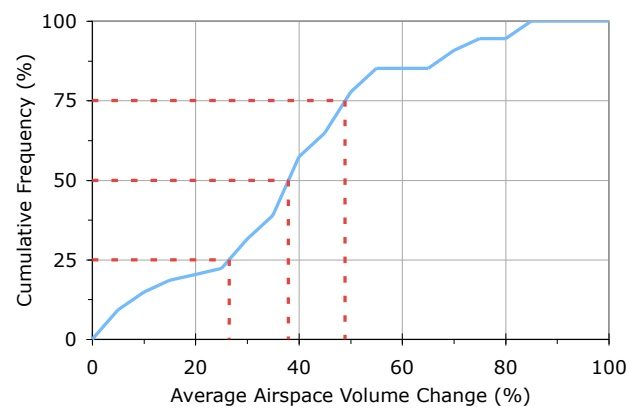

Figure 9. Cumulative Frequency of Average Airspace Volume Change (Percentage)

Figure 10 shows the average aircraft density change over time. The aircraft density change at a reconfiguration is computed by dividing the aircraft

ownership count by the affected sector volume. The figure illustrates that the average density change of inbound aircraft matched that of the outbound aircraft during reconfigurations. Overall, the average density change of remaining aircraft was about two times that of inbound and outbound aircraft.

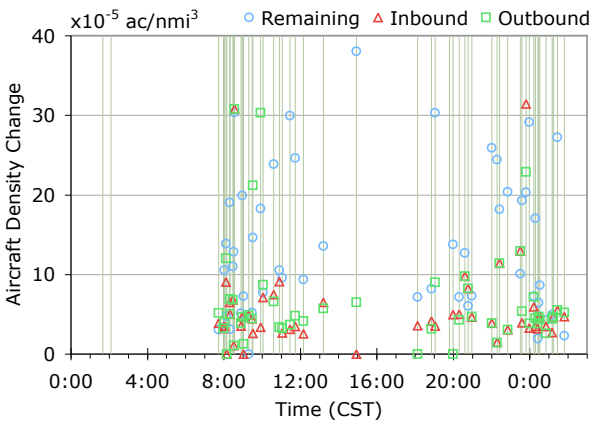

Figure 10. Average Aircraft Density Change

C. Hausdorff Distance Metric

The last metric being analyzed is the Hausdorff distance metric [11]. The Hausdorff distance measures how much similarity two shapes have, considering that each shape can be described by a set of vertex points. Because the Hausdorff distance between two identical point sets is zero, two identical configurations will always have zero metric value. Less similar sectorization pairs have larger metric value.

Figure 11 shows the Hausdorff distance metric between configurations before and after reconfiguration trigger times. The majority (30 of 54, or 55.6%) of the reconfigurations had metric values between 100 and 200 nmi. On average, the metric value was 156.9 nmi.

Table 1 lists the average and maximum measurements, in nautical miles, of changed sectors before reconfigurations. This indicates that the majority of the reconfigurations had Hausdorff distance metric values between the average width and the average length of changed sectors.

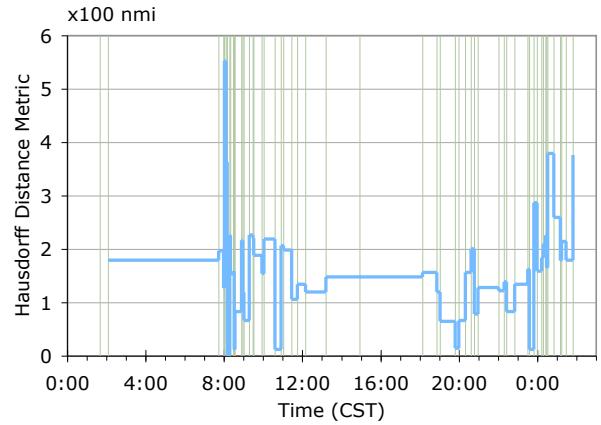

Figure 11. Hausdorff Distance Metric

Table 1. Average and Maximum Measurements of Changed Sectors (nmi)

	Length	Width	Diagonal
Average	215.8	121.6	191.8
Maximum	390.1	217.5	440.0

III. Clustering Configurations

Future airspace reconfiguration concepts should be evaluated against a current-day baseline to assess potential benefits. Many assessments assume the current-day baseline configuration remains fixed, even though in practice, it changes. By providing a representative, simplified set of configurations and allowing multiple configurations to be triggered during a baseline simulation, there is the potential to improve benefit assessment accuracy for new concepts.

In this section, a method is proposed using k-means clustering to select a sequence of configurations and trigger times from operational sector combination data. The selection process considers controller familiarity and sector continuity.

K-means is a process for partitioning multi-dimensional observations into k sets such that each observation is closest to its assigned cluster [12]. The process has four steps:

(1) Guess initial means of the clusters,

(2) Calculate distance score between each observation and the means of the clusters,

(3) Assign each observation to the cluster with the nearest mean based on the distance score, and

(4) Recalculate the means of individual clusters based on the assignments in (3).

After performing step (4), the process repeats until all the recalculated means of the clusters remain unchanged.

Configurations are stored assignments of different Fix Posting Areas (FPAs) to sectors. An FPA is a region containing at least one fix, a three-dimensional location for guidance. For a single configuration, each FPA may be assigned to only one sector. In operational data, each FPA is a right prism, in which vertical rectangular sides connect the top and bottom polygons. This is described by two-dimensional coordinates of vertices of the base polygon, and a pair of minimum and maximum altitudes.

Given a sequence of configurations in a center, the goal is to cluster all configurations into k clusters such that the sectors have the most stability with respect to duration of combination.

A matrix representation to detect FPA-pairwise combinations in a single configuration is presented in Subsection 1. Subsection 2 presents a matrix representation that describes FPA-pairwise stability in a sequence of configurations. Subsection 3 explains how to guess initial means of the clusters. Similarity scores between each observation and the means of the clusters are explained in Subsection 4. Cluster assignment and the final configuration selection process are detailed in Subsection 5. Finally, Subsection 6 presents the clustering results.

1. FPA-Pairwise Combination

In a given configuration, two distinct FPAs are pairwise combined when they are assigned to the same sector. It is not necessary that the two FPAs are adjacent. For example, when three FPAs are combined from left to right horizontally, the leftmost and rightmost FPAs are considered pairwise combined.

Assume a total of n FPAs are available for the sector assignment in a configuration. An FPA-pairwise combination matrix $\mathbf{F}$, an n-by-n binary square matrix, is constructed such that

$$\mathbf{F}_{i,j} = \begin{cases} 1 & \textit{if FPAs i and j } (i \neq j) \textit{ are combined,} \\ 0 & \textit{otherwise,} \end{cases}$$

where subscripts i and j denote the i-th row and j-th column, respectively, of the matrix. The matrix $\mathbf{F}$ has two properties:

i. Its elements on the main diagonal are zeros, as an FPA may not combine with itself. It follows that $\mathbf{F}_{1,1}=\mathbf{F}_{2,2}=\ldots=\mathbf{F}_{n,n}=0$.

ii. It is symmetric. That means $\mathbf{F}$ equals its transpose ($\mathbf{F}=\mathbf{F}^T$). When FPAs i and j are combined, so are the FPAs j and i; when FPAs i and j are not combined, neither are the FPAs j and i. Thus, $\mathbf{F}_{i,j}=\mathbf{F}_{j,i}$.

2. FPA-Pairwise Stability

Operational sector combination data consists of a sequence of triggered configurations of varying duration. Configuration duration relates directly to controller familiarity with sector combinations. The longer the configuration duration, the greater familiarity a controller has with it. The duration of a configuration can be calculated by subtracting the trigger time of the configuration from the trigger time of the next configuration.

The stability of a pair of FPAs relates directly to its combination duration. To measure stability of a pair of FPAs in the sequence of configurations, an FPA-pairwise stability matrix $\mathbf{M}$, an n-by-n square matrix, is defined such that the (i, j)-th element is a time-weighted sum of all (i, j)-th elements of individual FPA-pairwise combination matrices. Thus,

$$\mathbf{M}_{i,j} = \frac{\sum_{c=1}^{m} t_c \cdot [\mathbf{F_c}]_{i,j}}{\sum_{c=1}^{m} t_c},$$

where subscript c represents the m configurations in the sequence, t_c is the duration of configuration c, and $\mathbf{F_c}$ is the FPA-pairwise combination matrix for configuration c. The time-weighted function scales the total duration of an FPA-pairwise combination in the sequence of configurations to a value between zero and one. A value of zero in $\mathbf{M}$ indicates that the two corresponding FPAs are never combined among all the configurations. A value of one in $\mathbf{M}$ indicates that the two FPAs are always combined. Note that the matrix $\mathbf{M}$ has the same properties mentioned above for $\mathbf{F}$: all its elements on the main diagonal are zeros, and it is symmetric.

Elements in the FPA-pairwise stability matrix determine the fraction of time that two FPAs are

combined in a sequence of configurations. For example, an (i, j)-th element with a value of 0.8 means the FPAs at the i-th row and j-th column are combined 80% of the time in the sequence of configurations. This matrix can be used to represent the controller familiarity with sector combinations.

3. Initial Means of Clusters

A cluster contains a sequence of configurations, and its mean can be determined by selecting a configuration that has the most FPA-pairwise stability. The stability is computed as follows:

(1) For each configuration c in the sequence, construct the FPA-pairwise combination matrix, $\mathbf{F_c}$.

(2) Given a sequence of configurations, construct the FPA-pairwise stability matrix, $\mathbf{M}$, which defines the time-weighted stability among all the pairwise FPAs.

(3) Compute the matrix difference between $\mathbf{F_c}$ and $\mathbf{M}$. The difference score is obtained by summing absolute values of all the elements in the difference matrix. The absolute values are used because stability comparison is considered a symmetric operation, which means two configurations have the same level of stability regardless of their comparison order.

(4) Select the configuration that has the least difference score.

Step (4) repeats until k configurations are selected. Thus, the initial cluster means are the configurations that minimize the scoring function

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\left|\left[\mathbf{F_c}-\mathbf{M}\right]_{i,j}\right|,$$

where subscript c represents the sequence of configurations. Recall that the elements of $\mathbf{F_c}$ are either zero or one, and the elements of $\mathbf{M}$ are between zero and one. Therefore, the mean of the cluster is selected based on the FPA-pairwise duration.

4. Similarity Score

After defining the initial means of the clusters, the next step is to calculate a similarity score between each configuration and the means of the clusters. The scoring function in the previous subsection is applied to compute the similarity score between a configuration and the means of the clusters. Let r and c be the mean of a cluster and a configuration in the cluster, respectively. The similarity score between r and c is defined as

$$dist(r,c)=\sum_{i=1}^{n}\sum_{j=1}^{n}\left|\left[\mathbf{M_r}-\mathbf{F_c}\right]_{i,j}\right|,$$

where $\mathbf{M_r}$ is the FPA-pairwise stability matrix of the configurations in the cluster, and $\mathbf{F_c}$ is the FPA-pairwise combination matrix for configuration c. Configuration c will be assigned to the cluster that has the minimum similarity score.

The above similarity score is a distance metric between a mean of the cluster and a configuration. The distance metric measures the similarity and stability. The lower the score, the more similarity the two configurations have.

5. Configuration Selection

Given a sequence of configurations, the objective is to produce k clusters and a representative configuration for each cluster such that the total similarity score between this configuration and the others is minimal. The combination of the FPAs in the representative configuration will have both stability and similarity to the other configurations in the same cluster.

Mathematically, for m configurations, the k-means algorithm divides them into k clusters ($k < m$) such that the sum of the clusters' similarity scores is minimal, thus,

$$\underset{S}{arg\,min}\sum_{x=1}^{k}\sum_{c_y\in S_x}dist(r_x,c_y)$$

where "arg min" stands for the argument of the minimum operator, S is the set of k clusters, r_x is the representative configurations in S_x, c_y is the configuration in S_x, and $dist(r_x, c_y)$ is a function of similarity score between two specified configurations r_x and c_y. When the k-means algorithm halts, the means of the clusters indicate the most similar and stable configuration among other configurations in the same cluster. Thus, the means are the representative configurations in the dynamic configuration baseline. The cluster boundaries define the trigger times for configuration change.

6. Clustering Results

The k-means algorithm is applied to both the raw and processed data sets of operational sector combinations in Kansas City Center on February 8, 2007. The raw set contains all the 78 operational configurations; the processed set contains the 55 operational configurations without noise. Figure 12 shows the total similarity scores for k equals one through seven applied to the 55 operational configurations. The score improves (decreases) rapidly until the three-configuration schedule. For this day, the three-configuration schedule yields the best accuracy for the increased scenario complexity. This is consistent with Chatterji's conclusion that two to three sector configurations are adequate for a good weather day from safety and resource utilization perspectives [13].

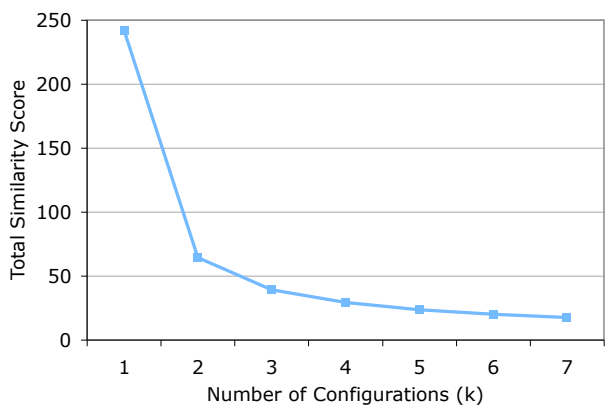

Figure 12. Total Similarity Scores

The three-configuration clustering results (selected configurations and reconfiguration trigger times) were identical between raw and processed data sets. The clustering results indicate that by using the similarity score, the algorithm is capable of filtering out operational noise.

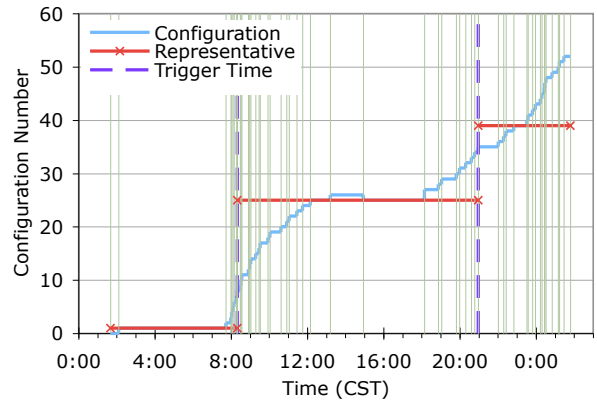

Figure 13. Three Representative Reconfigurations

Figure 13 shows the three-configuration clustering results. The blue line is the operational reconfigurations from Figure 1, the horizontal red lines are the three representative configurations, and the vertical dashed purple lines are the reconfiguration trigger times.

IV. Clustered Reconfiguration Analysis

In this section, the metrics used to analyze the operational data are modified to analyze the three-configuration cluster result presented in the previous section. Metrics that are directly related to frequency or expressed as a total or sum per reconfiguration would be significantly affected by representing multiple instances with a single reconfiguration. Instead, metrics were modified to be sector-centric rather than reconfiguration-centric so that metrics could be expressed as averages per sector for each reconfiguration.

1. Reconfiguration Patterns

A. Reconfiguration Frequency

The three representative reconfigurations had only two reconfiguration trigger times indicated by the vertical dashed purple lines in Figure 13. The first reconfiguration event occurred in the morning (8:19 CST), at the beginning of a rapid series of operational sector splitting. The second reconfiguration event occurred in the evening (20:58 CST), about two hours after a gradual series of operational sector combining. The two trigger times divided the day into two periods, daytime and nighttime. One configuration was assigned to the daytime, while two configurations were assigned to the nighttime.

B. Traffic Volume and Sector Count

Figure 14 shows the numbers of sectors in the actual and clustered reconfigurations, as well as the aircraft count in Kansas City Center. The numbers of sectors among the three representative reconfigurations are 7, 34, and 26, respectively. The correlation between traffic volume and the number of sectors in the clustered reconfigurations is over 0.86. The high correlation indicates that the sector count correlates with the trend of the traffic volume almost as well as the operational reconfigurations.

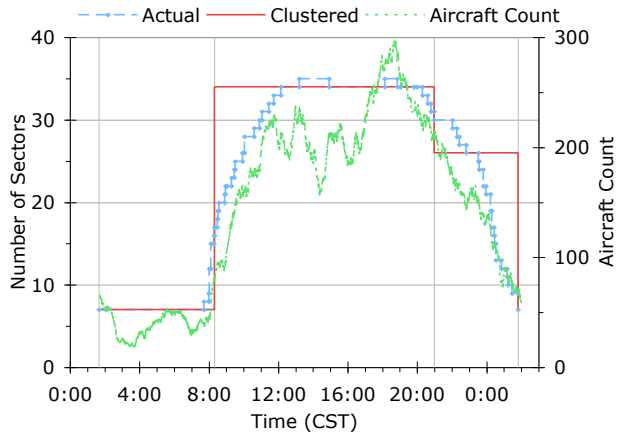

Figure 14. Number of Sectors and Aircraft Count

2. Familiarity and Continuity

A. Hours of Operation

The durations of the three representative reconfigurations are approximately 7, 13, and 4 hours. Figure 15 shows the distribution of sector hours of operation based on the actual and clustered reconfigurations.

Of the 36 sectors defined in the operational data, the same seven sectors were active for the entire 24 hours in both data sets. Two sectors having less than four sector hours in the actual operation were inactive in the clustered data.

Of the 34 sectors in the clustered data, all were operating for over 12 hours and the majority (19, or 55.9%) of them were operating for 16 to 18 hours. On average, the sectors were active for 17 hours and 43 minutes. This is roughly two hours longer than the actual operational average.

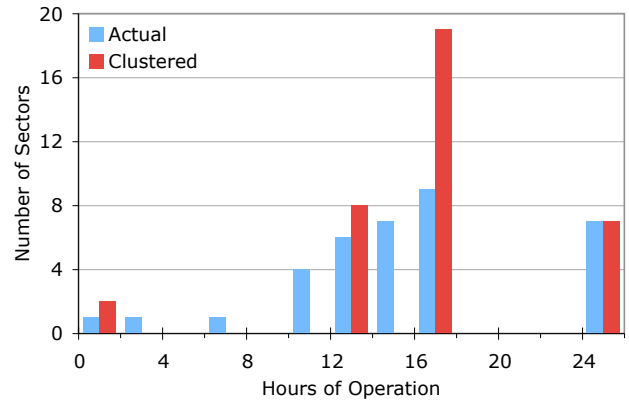

Figure 15. Sector Hours

B. Sector Change

Table 2 lists the number of sector changes based on the actual and clustered reconfigurations. The average and cumulative number of sector changes in the actual operation is calculated between two adjacent cluster means in the clustered operation. The cumulative number of sector changes in the actual operation was 74+36=110, while the number of sector changes in the clustered operation was 34+23=57, about half of the cumulative number of sector changes in actual operation. The number of sector changes in the clustered operation was about ten times the average number of sector changes in actual operation. This comparison indicates that the number of sector changes is not a good metric to access new dynamic airspace designs using a simplified reconfiguration.

Table 2. Number of Sectors Changed in Reconfiguration

Trigger	Actual Average	Actual Cumulative	Clustered
8:19 CST	3.01	74	34
20:58 CST	2.40	36	23

3. Detailed Sector Change Metrics

A. Aircraft Ownership Change

Figure 16 shows the average numbers (dark colors) and maximum numbers (light colors) of remaining, inbound, and outbound aircraft in Kansas City Center at the two clustered trigger times, 8:19 CST and 20:58 CST on February 8, 2007. The numbers of ownership change in the actual operation were computed based on data between two adjacent cluster means in the clustered operation.

In the actual operation between two adjacent cluster means, on average, most (54.4% and 64.6%) of the aircraft remained in the same sector after reconfiguration. In addition, the number of inbound aircraft matched the number of outbound aircraft. More aircraft remained in the same sector, while the hand-off actions were distributed equally among the inbound and outbound aircraft.

On the other hand, in the clustered operation, the average number of outbound aircraft was about triple of that of remaining and inbound aircraft during the first reconfiguration at 8:19 CST, while the numbers of remaining, inbound, and outbound aircraft were distributed fairly evenly during the second reconfiguration at 20:58 CST.

Regarding the maximum aircraft ownership change, most aircraft remained in the same sector after reconfiguration in the actual operation, while most aircraft were transferring to adjacent sectors in the clustered operation.

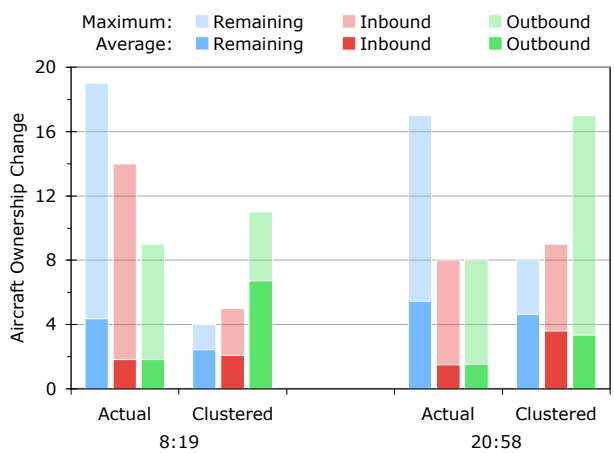

Figure 16. Aircraft Ownership Change

B. Airspace Volume Change

Table 3 lists total airspace volume change based on actual and clustered operations. During the first reconfiguration at 8:19 CST, the airspace volume change in the clustered operation was about half of the cumulative total airspace volume change in the actual operation between the first and second cluster means.

During the second reconfiguration at 20:58 CST, the airspace volume change in the clustered operation matched the cumulative total airspace volume change in the actual operation between the second and third cluster means.

The total airspace volume change in the clustered operation is more than ten times the average total airspace volume change in the actual operation.

This comparison indicates that the aircraft ownership change is not a good metric to access new dynamic airspace designs using a simplified reconfiguration.

Table 3. Total Airspace Volume Change ($\times 10^5$ nmi^3)

Trigger	Actual Average	Actual Cumulative	Clustered
8:19 CST	3.25	78.12	38.03
20:58 CST	1.75	26.30	24.67

Figure 17 shows the aircraft density change based on the actual and clustered operational data. The actual operational data values were the average of the data between two adjacent cluster means. The figure indicates that the average remaining, inbound, and outbound aircraft density change in the actual operation matched the density change of the remaining, inbound, and outbound aircraft in the clustered operation.

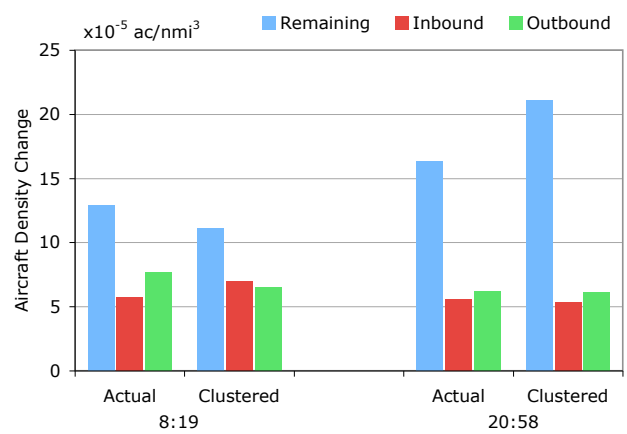

Figure 17. Aircraft Density Change

C. Hausdorff Distance Metric

Table 4 lists the Hausdorff distance metric values based on the actual and clustered operational data. When reconfiguration occurred progressively in the actual operation, the average metric values were 154.3 nmi and 128 nmi at the two trigger times respectively. However, in the clustered operation, the metric values increased to 4,328.55 nmi and 994.73 nmi respectively.

The large difference of the Hausdorff distance metric values is due to progressively evolved sectorizations in the actual operation. Actual reconfiguration events changed few pairs of sectors, and thus, many sectors remained the same. Recall that the metric is a sum of Hausdorff distances of sectors between two sectorizations, since the Hausdorff distance of unchanged sectors is zero, the metric value is relatively small for progressively evolved sectors. On the other hand, when sectors are completely changed from one sectorization to another sectorization, as in the clustered operation, the metric value becomes large because the Hausdorff distance of changed sectors is great than zero.

Table 4. Hausdorff Distance Metric Value (nmi)

Trigger	Actual Average	Actual Cumulative	Clustered
8:19 CST	154.30	3,982.89	4,328.55
20:58 CST	128.00	1,622.29	994.73

The metric value during the first reconfiguration in the clustered operation was within 8.7% of the cumulative metric value between the first and second means of the clusters in the actual operation. On the other hand, the metric value during the second reconfiguration in the clustered operation was about 61% of the cumulative metric value between the second and third means of the clusters in the actual operation.

V. Conclusions

Data from 78 sector configurations recorded from Kansas City Air Route Traffic Control Center operational data on February 8, 2007 were analyzed using seven metrics in three categories: (1) pattern within reconfiguration schedule, (2) metrics specific to controller familiarity and sector combination continuity, and (3) detailed sector change metrics.

Operational reconfigurations happened rapidly in the morning and happened gradually in the evening. Current practice prefers incrementally combining and splitting sectors, and there were 9 to 16 reconfigurations in each of six areas of specialization. Center-wide reconfigurations were uncoordinated. There is a strong relationship between traffic volume and number of sectors. On average, sectors were active for 15 hours and 33 minutes and 2.8 sectors were changed at each reconfiguration event. During reconfiguration, the number of aircraft transferred from adjacent sectors matched the number of aircraft transferred to adjacent sectors. On average, after a reconfiguration about five aircraft remained in the same sector, and two aircraft were handed-off to a sector, and two were received from a sector.

A method using k-means clustering was proposed to select a simplified sequence of configurations and trigger times from operational sector combination data. The selection process considered the two key characteristics of sector combining and splitting operations: controller familiarity with sector combination and continuity in sector combination. Based on the similarity score, the method selected three representative configurations. The clustered configurations were compared with the actual operational configurations. On average, clustered sectors were active for about two hours longer than actual operations. There were significant differences in most detailed sector change metrics between actual and clustered operations. However, the average remaining, inbound, and outbound aircraft density change from the actual operation matched that of the clustered operation. Therefore, of the sector change metrics presented in this paper, aircraft density change is the best sector change metric to assess new dynamic airspace designs using a simplified reconfiguration schedule.

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