# Classification of Days in the National Airspace System Using Cluster Analysis

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**ABSTRACT**

Scientific methods can describe the National Airspace System (NAS) in ways that provide intuitive insights into its operation and performance. One such method is classification and analysis of historical data. In this study we identify key metrics representing the NAS as a whole, and use cluster analysis techniques to classify days in the NAS spanning a four-year time period. Data are analyzed and compared before and after the September 11, 2001 national tragedy. Through classification, we reduce this data into manageable and meaningful subsets. Each subset has dominant characteristics that exemplify typical behaviors in the NAS, primarily based on traffic volume and weather. The data are then analyzed within and between subsets in order to gain information and knowledge from an otherwise unwieldy superset. The results of such an analysis can be utilized for efforts such as the testing and validation of NAS simulations, NAS trend analysis, cost/benefit annualization, and quality assurance.

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## INTRODUCTION

There has been considerable work of late in large-scale simulation models whose domain is the entire National Airspace System (NAS), or some large portion of it. For example, NASA's Future ATM Concepts Evaluation Tool (FACET) [Bilimoria, et al, 2001] and NASA's Airspace Concept Evaluation System (ACES) [Sweet, et al, 2002] help to evaluate NAS-wide impacts of operational concepts. Such operational concepts may include new Air Traffic Management (ATM) actions or traffic flow management policy changes.

The development and use of these NAS-wide simulation models poses two dilemmas. First, some form of validation must take place when the models are initially constructed. For validation, simulation results based on the filed flight plans are compared to actual NAS data for a given test day to determine whether the NAS components modeled in the simulation result in comparable NAS-wide performance metrics. Second, the quality of the validation results can vary with the operational behavior of the NAS on the day from which historical flight data is drawn. Some days are known to have abnormal events that created anomalous traffic flow patterns or other unusual conditions for some period of time afterward (September 11, 2001 being the most notable). Other days, known as 'blue sky' days, are known to have few disruptions in the system. Often, researchers would like to know which days they may consider 'normal' or 'typical' to use as a baseline for NAS behavior with some degree of objectivity. More generally, there is a need to classify days by similar behavior to provide a spectrum of validation data, thus ensuring tests of significantly different types of days and avoiding repetitive testing of similar types of days. As of yet, there is no objective method for pursuing this.

In this paper, we pursue two coupled interests. First, we design a daily NAS feature vector that can be used to characterize NAS-wide behavior for comparing days in the NAS. The feature vector comprises a set of post-analytic aggregate statistics of NAS behavior. This is analogous to economic indicators used for performance evaluation of the United States economy (e.g., unemployment rate, gross domestic product, and so on). A cluster analysis is performed to condense an initial collection of 97 aggregate, daily variables into a smaller and more manageable set of representative variables. This reduced set defines the NAS feature vector, characterizing each day of data ranging from January 1, 2000 through December 31, 2003. Each feature vector then represents the nature of NAS performance on its respective day, while each component of the vector represents a group of variables that provide virtually redundant information about the operation of the NAS on that day.

Second, another type of cluster analysis is used to classify and rank the daily NAS feature vectors (and therefore the days they represent) by levels of normality. We use the results to partition each day into a set of clusters grouped by their similarity in NAS operation and performance.

Finally, we discuss the categorization results and provide guidance in using these results for NAS simulation validation and cost/benefit analysis. In particular, the analysis shows that traffic volume, weather impacts and traffic management initiatives (e.g. Ground Stops (GSs) and Ground Delay Programs (GDPs)) play an important role in describing types of days in the NAS.

**Cluster Analysis**

Cluster analysis is a mature science [Gordon, 1999; Hartigan, 1975; Rand, 1971] that comprises a wide variety of clustering algorithms. Within a particular statistical endeavor, there can be many ways to cluster the data into meaningful groups. For instance, distance-based cluster algorithms map the variables into *n*-dimensional space, and then check for geometric proximity using any of a number of metrics. As clusters develop, the challenge is determining how to define distances between these clusters that contain multiple objects. Some reference point such as the concept of a cluster "center" must be applied. For the most part, clustering algorithms fall into one of the following categories:

1. Tree-based clustering, (data are broken into groups, by successive branching),
2. *K*-means clustering (forms a specified number *(K)* of clusters so that there is similar variance within each cluster but dissimilar variance between clusters),
3. Two-way joining (clusters formed for "cases" and variables at the same time), and
4. Clustering based on high-density contours, where clusters are formed based on high-probability regions.

In our analysis, we opted for a combination of tree-based clustering and *K*-means clustering. Our strategy thereby afforded us both robust control over and review of the clustering process.

The following analogy illustrates the value of cluster analysis. Suppose investigators surveying sleep habits ask a subject what time he rises on a "typical" day. Knowing that he rises early on weekdays (around 7 a.m.) and sleeps late on weekends (until 10 a.m.), the subject may be hesitant to give a single numerical response. An average for the week would be misleading, since there is never a day on which he rises at 7:51 a.m. A weighted average would be slightly more typical, but still fails to capture the essence of bimodality in rising times. If the investigators were to group the days by rising time, they would find two distinct clusters: one centered around 7 a.m., and another around 10 a.m. Within each group, the average rising time satisfies our intuitive concept of typical more than an average across the groups would. This clustering also gives some insight into the variance of the overall set of days, now explainable by the working schedule of the subject. Ideally, variance within each group is small, even though the overall variance may be large.

Likewise, we have used cluster analysis to group historical days in the NAS according to similar behavior in operational performance. For model validation, this provides a more objective basis for data selection than historical recollection can provide. We should note that even those clustering algorithms based on optimization are not entirely objective and require some guidance from the user. We will be careful to identify and justify any such interpositions.

**Related Research in Air Traffic Management**

Cluster analysis has seen limited use in ATM research. DeArman used cluster analysis to assess the dominant sources of demand in the NAS [DeArman, 1994] then again to identify the dominant traffic flows in certain sectors of the NAS [DeArman, 2000]. Finally, a clustering approach has been used to determine the contribution of weather on NAS performance [Callaham et al, 2001].

The latter investigation is most similar to the one presented in this paper. The primary difference is that the Callaham study subjectively pre-classifies the data into scheduled traffic demand, weather severity, and season, while our work uses a preliminary cluster analysis to scientifically identify the major factors influencing categorization of days. In part, our work serves as objective validation of the more subjective preconditioning of Callaham et al. Callaham et al conclude that weather explains the majority of the variation in NAS performance, followed by traffic demand; and season adds no additional explanatory power.

**Data Sources**

A total of 97 variables were considered in a cluster analysis over a period of four years (2000-2003). These were taken mainly from government databases that record NAS performance: the FAA's Operations Network Database (OPSNET) and the FAA's Aviation System Performance Metrics (ASPM). Additional descriptive statistics were gathered from the Bureau of

Transportation Statistics (BTS) and Air Traffic Control System Command Center (ATCSCC) quality assurance data sources. The variables captured delay statistics (e.g., en route, terminal), traffic counts, traffic management initiatives (e.g., GDPs, GSs, Miles-In-Trail (MIT) restrictions), and limited weather information (e.g., Instrument Flight Rule (IFR) vs. Visual Flight Rule (VFR) conditions). These data sources are discussed in further detail in [Krozel et al, 2002], including issues related to data cleansing. Additionally, many of these data sources and performance metrics are reviewed in [Parker et al, 2002].

Types of NAS performance data used in this study include (See Appendix for greater Detail):

- GDP / Expected Departure Clearance Time (EDCT) Delay
- Ground Stop Delay
- Overall Ground Delay
- Departure and Arrivals Counts
- Cancellations
- Schedule-based Delay
- Flight Plan-based Delay
- Flights delayed over 15 Minutes
- On-Time Performance
- Taxi Delay
- Airborne Delay
- Airport Performance Scores
- Airport Meteorological Conditions
- Total Operations
- Weather Delays

**Data Associated with September 11, 2001**

Clearly, September 11, 2001 (9/11) and a few days thereafter should be treated as a special event [Cherniavsky et al, 2003]. Because the cluster analysis procedure is sensitive to outliers, when the analysis was run with the full set of data (January 1, 2000 through December 31, 2003), many smaller outlier clusters were formed containing days that occurred during and immediately after the precipitous drop in operations on 9/11. These clusters obscured our search for types of days within the normal operational framework of the NAS. In order to avoid having this national tragedy obfuscate outlier events that occurred during ordinary NAS operations, 9/11 and the ensuing months were partitioned from the pre-9/11 and post-9/11 datasets (January 1, 2000 - September 10, 2001 and January 1, 2002 - December 31, 2003) and identified as a recovery period.

A basic one-way Analysis Of Variance (ANOVA) was performed on each of the clustered NAS variables to analyze the differences in the pre-9/11 and post-9/11 data sets. We found some statistically significant differences in the two datasets that require more detailed investigation. A complete understanding of the differences between these two datasets and the recovery period after 9/11 remains an open research question outside the scope of this study.

## APPROACH

We implemented a form of Principal Component Analysis (PCA) known as *oblique* PCA for the optimal feature vector analysis (Phase I), and *centroid-based clustering* for the 'types-of-days' analysis (Phase II) [Anderberg, 1973; Harman, 1976]. **Figure 1** depicts the process.

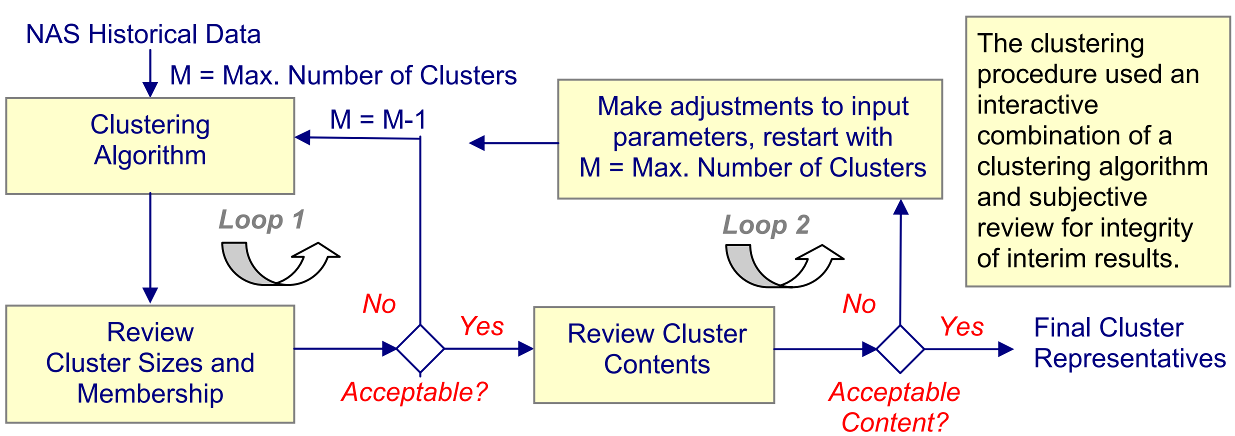



**Figure 1**: Cluster analysis flow chart – represents process used for both the optimal NAS feature vector analysis (Phase 1) and the types-of-day analysis (Phase 2).

In *Loop 1*, we first ran all data through the respective clustering procedure with a high number of allowable clusters. The overall number of clusters was evaluated, along with the number of objects per cluster. If the number of clusters was identified as too large, or the number of objects in a particular cluster was identified as too small, then the cluster result was rejected. The allowable number of clusters was then reduced by one and the process was repeated.

The iterative analysis process entered *Loop 2* if the configuration of objects making up each cluster was deemed acceptable. In this analysis loop, options were considered to change parameters of the clustering algorithm, force certain groupings based on subjective bias, or appeal to another type of clustering algorithm. During clustering for the optimal NAS feature vector some data that formed nonsensical clusters were analyzed in further detail, dropped from the analysis and the analysis was repeated until variable groupings were sound. Techniques such as variable weighting and parameter adjustments were experimented with in the types-of-day cluster analysis, but were not used for the final results. Tree-based and nonparametric techniques were experimented with as well, but did not prove useful for the final analysis. No groupings were forced in either phase.

**Phase I: Clustering to Determine an Optimal NAS Feature Vector**

In Phase I, we determined the optimal NAS feature vector. Based on scientific reasoning, certain variables were eliminated from the initial data set. These variables were identified during multiple trial runs of the clustering procedure. The criteria for potential elimination of a variable $x$ were:

- $x$ is redundant, i.e. there exists another variable $y$ with an unusually strong correlation with $x$ (hence there is no need for both $x$ and $y$) – e.g. Instrument Meteorological Conditions (IMC) hours are a complement of Visual Meteorological Condition (VMC) hours (i.e. Total Hours = IMC + VMC hours), therefore only one of the two is necessary;

- $x$ had an extremely weak association with all of the clusters and was identified as being of poor indicative quality – e.g. OPSNET count of Military Delays;
- $x$ is essentially constant over time.

The set of 97 candidate variables were clustered using a PCA clustering procedure. PCA is a statistical procedure that transforms a number of potentially correlated variables into a smaller number of uncorrelated variables called *principal components*. This technique calculates the variance of the original variables that is explained by each of the cluster components (a linear combination of variables within the cluster), and then attempts to maximize the sum of the variance explained across all clusters [Anderberg, 1973; Gordon, 1999].

We commenced by requesting 20 clusters of the NAS variables. This resulted in a number of clusters with a low membership of only one or two variables. We then iteratively examined 19, 18, etc. clusters, seeking to identify a condensed set of variables still having high within-cluster correlation. This examination focused on clusters with variables that had relatively high $R^2$ values (the squared correlation of the variable with its own cluster component), low $R^2$ values with the next-closest cluster component (indicating that the clusters are well separated), and low $1\text{-}R^2$ ratios (indicating sharper, well-defined clusters in the variable space). Statistically, the distribution of the $1\text{-}R^2$ ratio will be similar to an F-ratio in ANOVA. The $1\text{-}R^2$ ratio gives the within-cluster heterogeneity relative to between cluster heterogeneity and is expected to be small if the clusters are well separated.

Clusters were examined at each stage of the algorithm's iteration (as the algorithm started with 1 cluster and iteratively split clusters) with a subjective evaluation. At each stage, classifications were assigned to the clusters to describe their overall meanings (such as Cluster 1 is Volume, Cluster 2 is Delay, etc.). The intention was to converge to a number of clusters where the statistical measures matched intuition determining the merit of the clusters (predicated on domain knowledge of the NAS).

Based on the statistical indicators and the inferred qualities of the cluster meanings as they represented some measure of NAS operations, a clustering of 9 variables was accepted for the pre-9/11, post-9/11 and the combined pre-9/11 and post-9/11 data sets. The proportion of variance explained by the 9 clusters was above 85 % for all of the data sets.

For verification, the algorithm was run starting with one cluster, then splitting clusters until each cluster had only a single eigenvalue greater than one, thus satisfying the most popular criterion for determining the sufficiency of a single underlying factor dimension. This resulted in 9 clusters for each of the data sets, corroborating the earlier results.

A single variable was chosen from each cluster to represent the entire group. The choice of representative variable was based on rankings within each cluster by 1-$R^2$ ratios and $R^2$ values, assessment of the data integrity behind each variable, and further data analysis of the cluster constituents. The variable bundles and their representatives are listed in **Table 1**.

**Table 1:** Optimal variable cluster set used to create NAS Feature Vector.

| Cluster | Cluster Name | Representative Variable within Cluster | Members | | |
|---|---|---|---|---|---|
| | | | Pre 9/11* | Post 9/11 | Combined Data* |
| 1 | Delay from Schedule | Arrival Delay Min based on Schedule (v30) | 25 | 24 | 24 |
| 2 | Total Operations | Total Operations (v78) | 16 | 16 | 16 |
| 3 | GDP Delay | Minutes of GDP Delay (v2) | 8 | 14 | 8 |
| 4 | On-Time Performance | On-Time Arrivals based on Schedule (v51) | 6 | 6 | 7 |
| 5 | Average Ground Delay | Average Minutes of Ground Delay (v11) | 7 | 8 | 7 |
| 6 | Cancellations | Cancelled Departures (v20) | 4 | 4 | 4 |
| 7 | Weather Delay | Count of Weather Delays (v88) | 9 | 11 | 9 |
| 8 | Air Delay | Average Minutes of Air Delay (v68) | 3 | 4 | 3 |
| 9 | Ground Stop Delay | Minutes of Ground Stop Delay (v4) | 3 | 2 | 3 |

* Note: 8 variables related to EDCT delay were not included in the analysis due to missing values in the pre-9/11 ASPM data.

Each cluster was given a name to convey the major theme of the comprising variables. The 9 corresponding aggregate statistics were used to create 9-element feature vectors for each day in the study, with the intent of performing the Phase II cluster analysis to determine the different types of days in the NAS. For instance, the feature vector for May 17, 2002 is shown in **Table 2**.

**Table 2:** Feature vector for May 17, 2002.

| Total Operations | GDP Delay | GS Delay | Avg. Total Ground Delay | Cancellations | OAG-Based Arrival Delay | On-Time Counts | Avg. Total Air Delay | Weather Delay |
|---|---|---|---|---|---|---|---|---|
| 56,898 flights | 8,751 minutes | 10,743 minutes | 75.13 min/flt | 307 flights | 375,285 minutes | 15,379 flights | 8.37 min/flt | 877 flights |

**Phase II: Clustering to Determine the Types of Days in the NAS**

In Phase II, a cluster analysis was performed on the NAS feature vectors passed on from Phase I. The objective in Phase II was to classify the NAS feature vectors for each day from Jan. 1, 2000 through Sept. 10, 2001 (pre-9/11) and Jan. 1, 2002 through Dec. 31, 2003 (post-9/11) into groups that naturally described different types of days in the NAS. These two data sets were analyzed individually and also combined and analyzed as a whole. The period from Sept. 11, 2001 to Dec. 31, 2001 was labeled as a NAS recovery period. The data for this recovery period were examined, but were not used for the classification of days in the NAS. Each historical day that was represented by a feature vector will be referred to as an observation.

The types-of-days analysis used a centroid-based (*K*-means) cluster analysis. The *K*-means method performs a disjoint cluster analysis on the basis of distances computed using one or more variables. The algorithm first selects observations designated as cluster seeds. Temporary clusters are then formed around each seed observation. The cluster seeds are updated to be the means of the observations. The process is repeated until changes in the cluster seeds reach a minimal tolerance. In the final stage, the clusters are formed by assigning the observations to the nearest cluster seed.

Variables with larger variances have a larger influence when calculating the clusters using this method. Because the NAS variables are not measured in the same units and do not have equal variance, it was necessary to standardize the variables before performing the cluster analysis. This standardization gave equal weight to differences in all variables. There may be cases where equal changes in different variables warrant dissimilar weighting according to operational importance, however in the absence of validated operational justifications for doing so, we chose an equal weighting strategy.

The clustering algorithm was capable of breaking the feature vectors into any number of clusters, up to the number of total observations. Each cluster would represent a different type of day in the NAS, and within each cluster we could define typical and atypical days. It is certainly possible that there could be many types of days in the NAS, each grouped by subtle differences in the values and variances of the observations. This design is not very useful for our purposes, however, as a smaller number of clusters would better facilitate utilization of the final results for practical applications such as model validation and cost/benefit study annualization. For instance, a natural decomposition might be six clusters, resulting from two levels of traffic volume, each with three possible levels of weather conditions. This would allow researchers studying the NAS to choose from a small subset of representative days for analysis and experimentation, and identifies clearer factors to consider for decision-making by NAS users.

A relaxed cluster analysis was performed on the combined pre-9/11 and post-9/11 data set, meaning that we did not apply any subjective biases into the algorithm and allowed a generous upper bound on the maximum number of clusters (i.e. 20). As expected, this resulted in 20 clusters. However, only half of the clusters had significant membership (over 2% of the total observations). We executed the process again with the maximum number of clusters reduced to 10, thus driving the singletons back into the major clusters. This time, only 8 of the 10 resulting clusters had significant membership. We ran the process again with the maximum cluster value set at 8 and 7. The results of these two cases both had a single cluster below 2% membership, with the former case rounding down to 1%, and the latter case rounding up to 2%. As a smaller number of clusters is preferable, and the 7-cluster case had its lowest membership cluster closer to 2%, we chose 7 clusters as our final clustering number.

The resulting clusters had memberships of approximately 26%, 23%, 22%, 13%, 11%, 3%, and 2% (out of 1349 total observations). Each of the first six is considered significant with at least 2% of the number of data points. The low membership for Cluster 7 was due to statistical outliers, specifically observations with abnormally high Cancellations.

As a validation step, the algorithm was run with an additional parameter requiring that any initial seed with less than 2% of the observations assigned to it be eliminated. When run with a maximum of 20 clusters, the result was a final count of 7 clusters. This algorithmic result helped build confidence in the results derived through our iterative process.

We also used this process to identify properties of the pre-9/11 and post-9/11 data sets individually. Overall, the clusters created by these data showed similar properties to the complete data set when 7 clusters were specified. The memberships were below 2% for both clusters 6 and 7 in the pre-9/11 set, and for cluster 7 in the post-9/11 set. At the validation step, the pre-9/11 data resulted in 7 clusters, while the post-9/11 data resulted in 8 clusters.

**Analysis of the Phase II Clustering Results**

Satisfied with the resulting clusters and cluster membership counts, we proceeded to investigate which of the variables had been the primary determinants in dividing the data. (If there were no recognizable pattern, then it would be difficult to characterize the clusters as to which types of days they represent.) A software tool was used to examine many different representations of the data, including 2D, 3D, and higher dimensional displays of clustered data [Swayne et al, 2002].

Before proceeding to the cluster results, we present data that illustrates prevalent partitions we expected to see identified through cluster analysis. **Figure 2** shows the consistent bimodal nature of the total NAS operations for both the pre-9/11 and post-9/11 data on weekdays and weekends. Most low outlier weekdays are winter holidays, including: Thanksgiving, Christmas Eve, Christmas, New Years Eve and New Years. Weekends adjacent to holidays generally also have lower traffic volume. Weekdays with high cancellations (e.g. due to a severe winter snowstorm) often have unusually low operations.

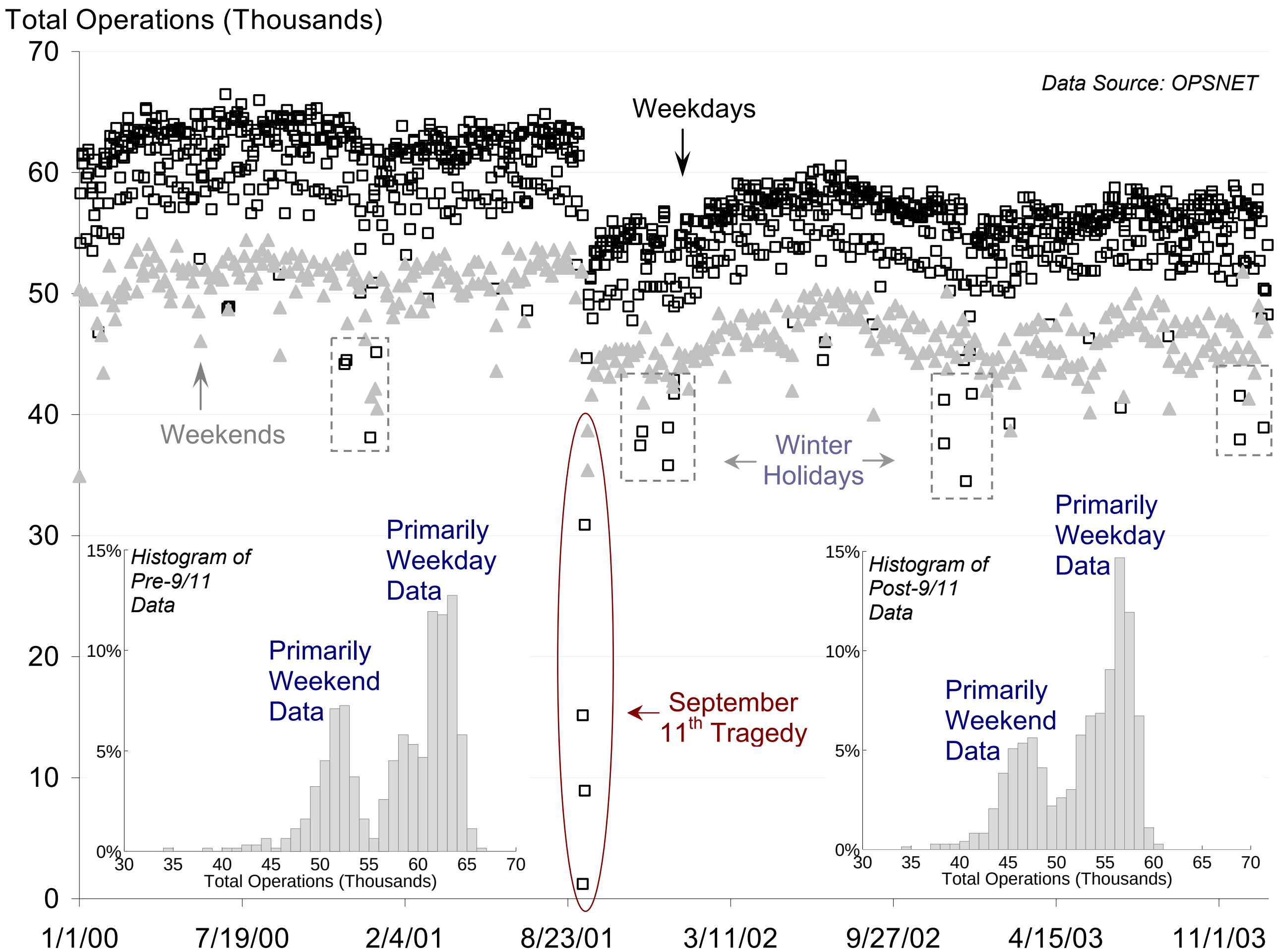



**Figure 2.** Comparison of traffic based on day of week for 2000 through 2003.

Further, we observed variations in data such as GS Delay Minutes and Weather Delays. These data tend to exhibit seasonal trends, peaking in the summers (during the height of the convective weather season) and subsiding in the winters (during the non-convective weather season). GSs are generally more reactionary, and used when weather cannot be anticipated and planned for using a GDP. The seasonal behavior of GSs is shown in **Figure 3.**

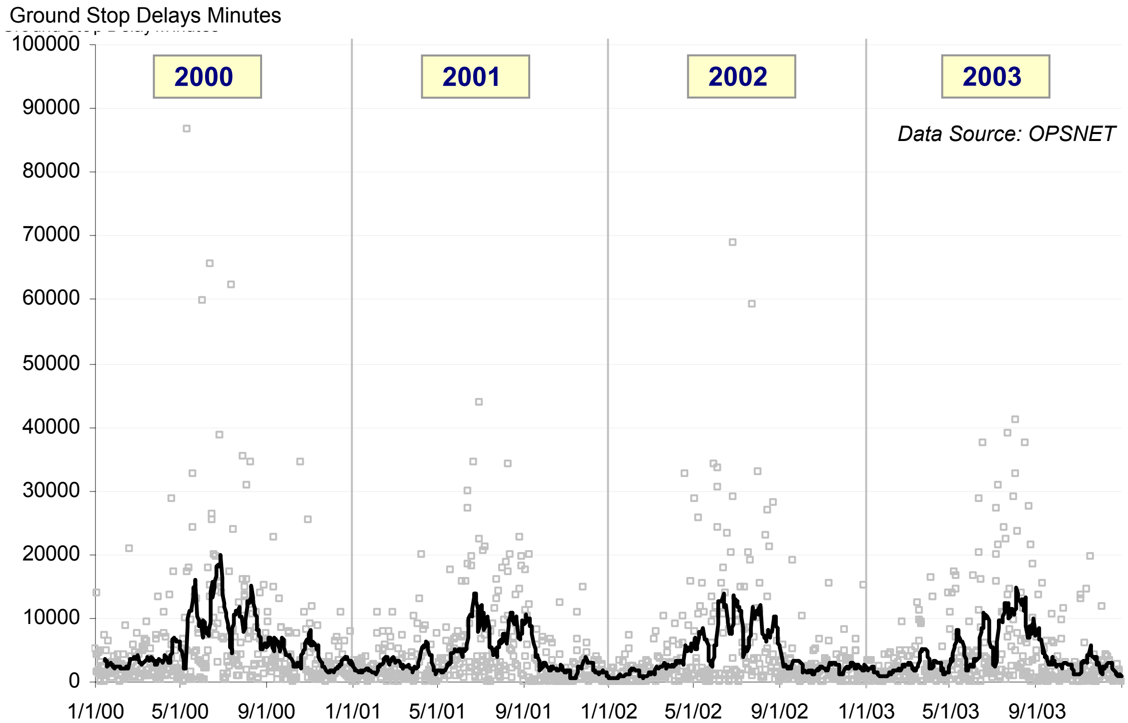
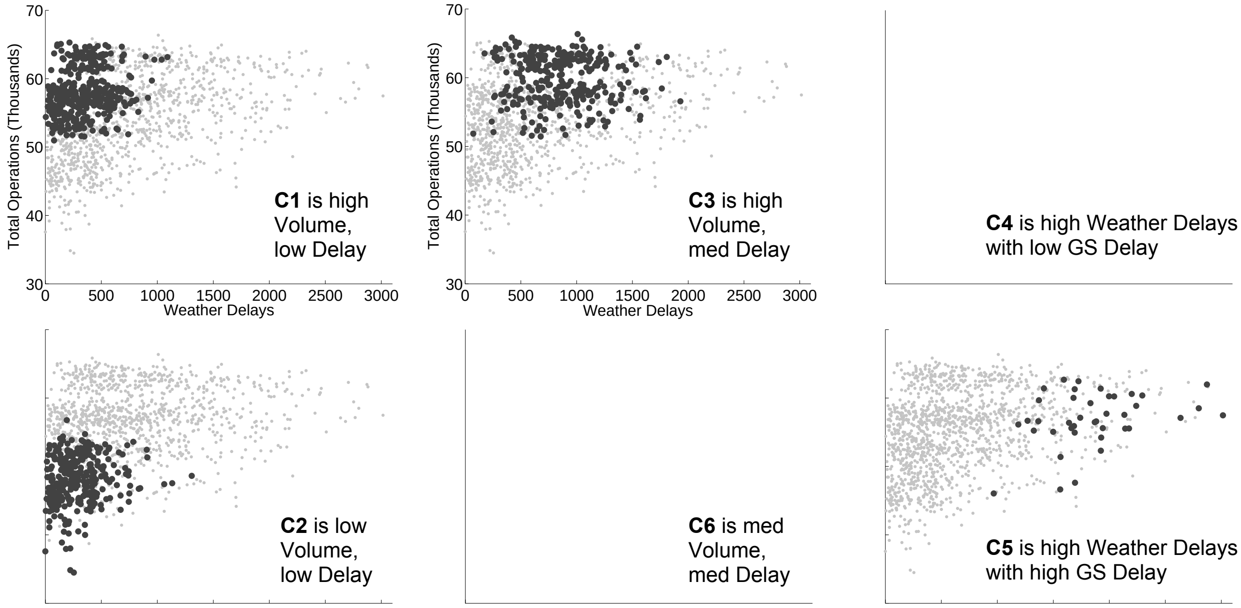



**Figure 3:** Ground Stop Delay peaks annually during the convective weather season, typically mid-April through mid-October (shown with a 2-week moving average).

The feature vectors used in the Phase II cluster analysis form a multidimensional space. The clustering results for the combined pre-9/11 and post-9/11 data are shown from multiple 2D perspectives in **Figure 4** through **Figure 6**. The primary dividing factors were related to volume and weather effects on the NAS (**Figure 4**). For days with low Weather Delays, Total Operations were the determining factor for discerning Cluster 1 from Cluster 2. This supported our original expectation that weekday versus weekend traffic volume would be a significant factor in the cluster analysis. The degree of GS Delay and GDP Delay were the determining factors for days with high Weather Delays (**Figure 5**). Cluster 3 and Cluster 6 represented moderate Weather Delays, separated respectively by high and low Total Operations. Finally, Cluster 7 was characterized by peak levels of Cancellations, and as a consequence had the associated low Total Operations, low On-Time Counts and generally had low delay (**Figure 6**).



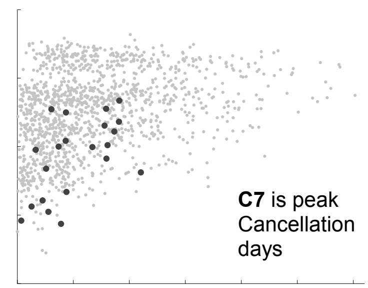




**Figure 4:** Seven clusters were formed in the Phase II Cluster Analysis. The clusters were primarily separated by Volume (as measured by Total Operations) and Weather Effects on the NAS (Weather Delays, GS Delay, GDP Delay, and Cancellations). Identical plots of Total Operations vs. Weather Delays are shown here, with each cluster individually highlighted.

The seasonal trends were captured through GS Delay minutes and Weather Delays. **Figure 5** displays the results of the clustering for these two variables. Peak Weather Delays formed Cluster 4 and Cluster 5. These clusters were further split by low and high GS Delay minutes.

Peak Cancellations were the defining characteristic of Cluster 7. Cancellations are shown versus On-Time Scheduled Arrivals in **Figure 6**. Cluster 7 had unusually high cancellations with low to medium on-time counts.

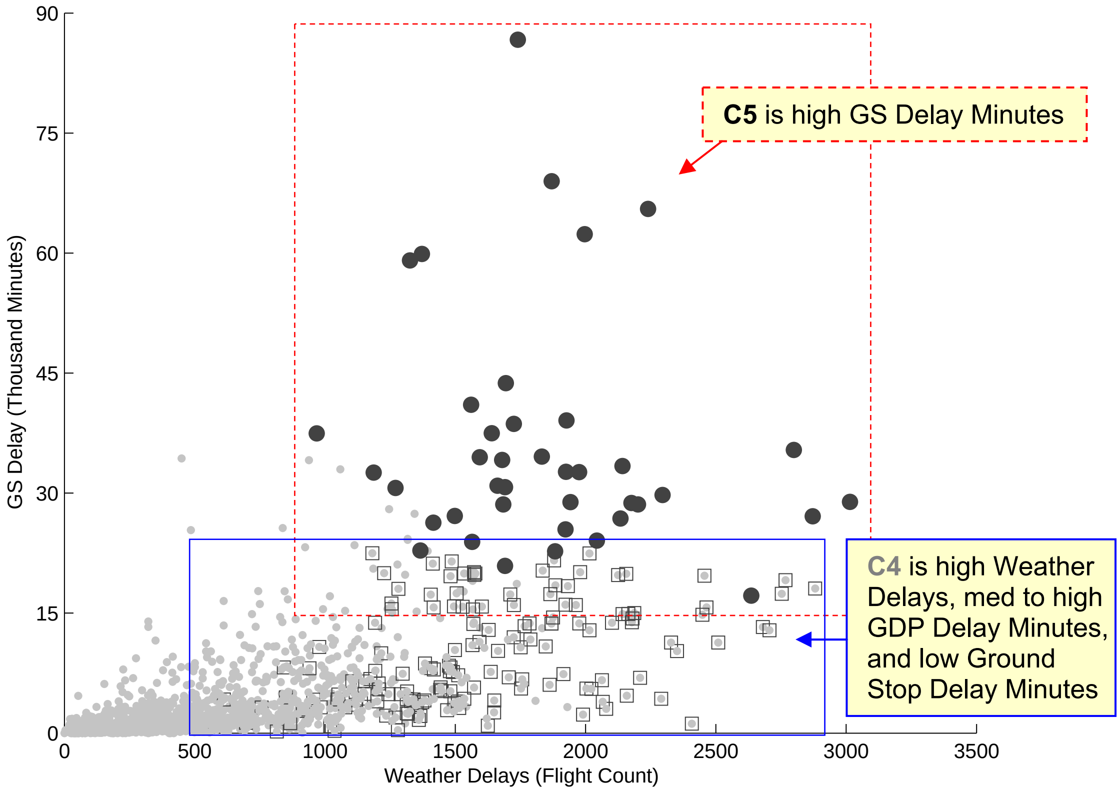



**Figure 5:** High Weather Delay clusters C4 and C5 are primarily separated by low vs. high GS Delay.

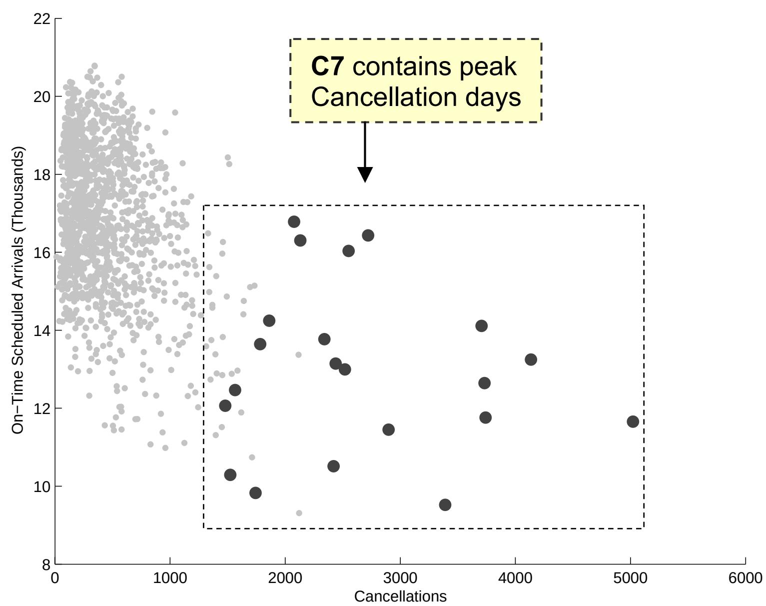



**Figure 6:** High Cancellation cluster C7 formed in Phase II Cluster Analysis.

Having established the seven type-of-day clusters, we were able to rank the days within each cluster according to how typical they were, using proximity to the center of the cluster as the criterion. That is, let $\mu = (\mu_1, \mu_2, \ldots, \mu_9)$ be the vector created by setting each element $\mu_k$ equal to the mean of the $k^{th}$ variable of the NAS feature vector, taken over the vectors in a fixed cluster. The mean vector $\mu$ is the center of the cluster mass. The vector closest to $\mu$ was considered to be the most typical day in the cluster. Proximity was defined using a Euclidean-based metric normalized for variance. Letting $v = (v_1, v_2, \ldots v_9)$ and $w = (w_1, w_2, \ldots w_9)$ be two 9-dimensional vectors, the weighted distance between them is defined as:

$$d(v, w) = \sqrt{\sum_{k=1}^{9} \frac{(v_k - w_k)^2}{\sigma_k^2}},$$

where $\sigma_k^2$ is the variance of the $k^{th}$ variable. Without this normalization, proximity would be skewed by the variables whose units resulted in larger absolute values.

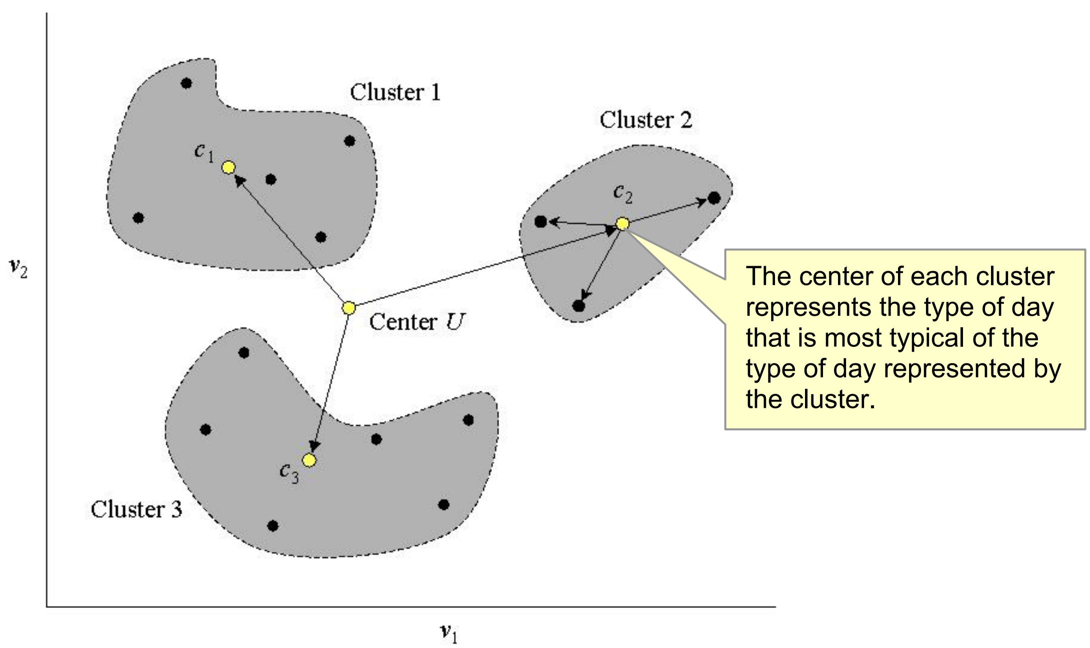



**Figure 7.** In this notional 2D plot, the Euclidean metric is used to measure the distance from a day's feature vector (point) to the center of its cluster (e.g., Cluster 2) and to measure the distance from a cluster's center (e.g., $c_2$) to the center of all clusters (*U*).

**Table 3** presents the mean vector for each type-of-day cluster (based on normalized data). The center of Cluster 1 is given by row 1. Within each cluster, days can then be ranked according to their proximity to the center. The day whose vector is closest to the center of the cluster is considered the most "typical" day in that cluster. **Table 4** presents the three closest days for each type-of-day cluster to their respective cluster means.

**Table 3:** Data for the Mean Vector for each Cluster, based on normalized values having the mean = 0 and standard deviation = 1. Maximum values are highlighted in bold.

| | | Variable | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | Count | Total Ops | GDP Delay | GS Delay | Average Total Ground Delay | Departure Cancellations | OAG-Based Arrival Delay | On-Time Counts | Average Total Air Delay | Weather Delay |
| 1 | 356 | 0.482 | -0.622 | -0.408 | -0.593 | -0.383 | -0.661 | **1.059** | -0.150 | -0.630 |
| 2 | 311 | -1.180 | -0.620 | -0.440 | -0.433 | -0.444 | -0.725 | -0.517 | -0.858 | -0.730 |
| 3 | 295 | **0.781** | 0.191 | 0.129 | 0.355 | 0.053 | 0.284 | 0.389 | 0.033 | 0.312 |
| 4 | 154 | 0.477 | **1.729** | 0.598 | 0.752 | 0.650 | 1.517 | -0.815 | 0.592 | 1.640 |
| 5 | 40 | 0.321 | 1.419 | **4.011** | **2.187** | 1.290 | **2.033** | -1.014 | 0.404 | **2.138** |
| 6 | 172 | -0.573 | 0.174 | -0.024 | 0.177 | 0.003 | 0.239 | -0.716 | **1.169** | 0.157 |
| 7 | 21 | -1.097 | 0.240 | -0.201 | 0.352 | **5.074** | 1.006 | -1.994 | 0.111 | -0.294 |

**Table 4.** Days closest to Cluster Means.

| Type of Day Cluster | Dates | | | Distances | | |
|---|---|---|---|---|---|---|
| | $1^{st}$ | $2^{nd}$ | $3^{rd}$ | $1^{st}$ | $2^{nd}$ | $3^{rd}$ |
| 1 | 4-26-2002 | 5-16-2002 | 6-25-2001 | 0.478 | 0.592 | 0.612 |
| 2 | 7-27-2002 | 4-13-2002 | 1-16-2000 | 0.501 | 0.614 | 0.654 |
| 3 | 8-28-2000 | 7-03-2001 | 4-11-2000 | 0.543 | 0.682 | 0.689 |
| 4 | 1-13-2000 | 6-21-2000 | 2-25-2000 | 0.975 | 1.082 | 1.144 |
| 5 | 8-04-2003 | 6-27-2000 | 8-01-2003 | 1.155 | 1.536 | 1.932 |
| 6 | 4-08-2002 | 4-22-2001 | 1-30-2002 | 1.013 | 1.025 | 1.027 |
| 7 | 2-18-2003 | 12-12-2000 | 9-18-2003 | 1.990 | 2.037 | 2.215 |

While the exact partitioning of days between different clusters was sensitive to parameter adjustments, the classifications (**Figure 8**) remained relatively stable. Clusters grouped consistently by volume and weather-related effects. Days with low and moderate delay were split into high and low volume clusters. Days with higher weather delays were split between GS and GDP delay. From examination of a random subset of high cancellation days, all were observed to have a high degree of measured reflectivity. Therefore we suggest these constitute another type of weather day – one in which overall weather delays are reduced because the flights have instead been cancelled (e.g. a severe snowstorm).

With no weather present, volume was the dominant determining factor in the clustering. However, severe weather brought conditions such as high delays and cancellations. The degree of the outliers associated with severe weather events was high enough to supersede the effect of volume on the clustering for these cases.

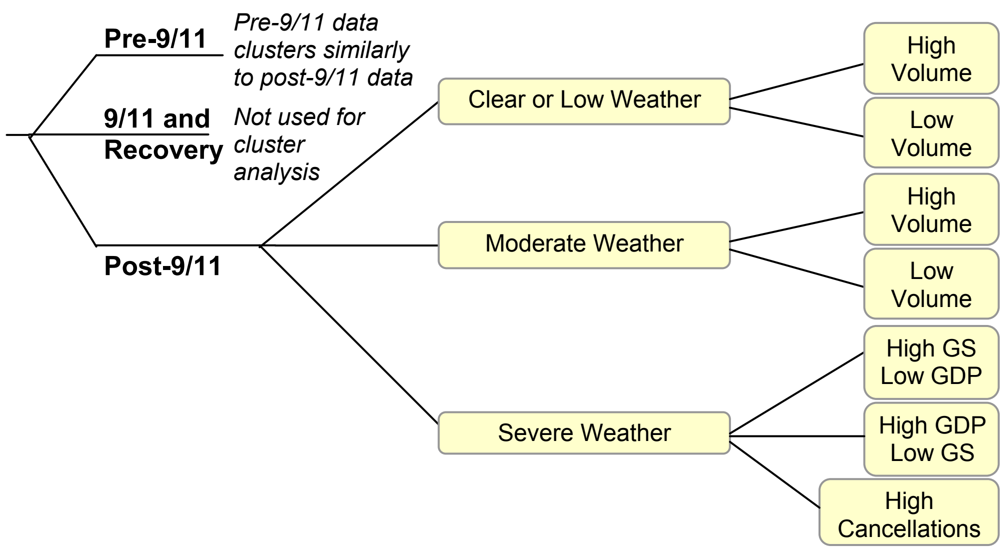



**Figure 8.** Dendrogram of conceptual classifications based on cluster analysis results.

## APPLICATION

These results indicate that simulation validation sets should consider traffic volume, weather and traffic management initiatives as a basis for validation data sets. If neither weather nor traffic management initiatives like GDPs and GSs are modeled in the NAS simulation, then the results of our study indicate there are two types of days that are useful for validating such simulations (Clusters 1 and 2). If weather, GDPs and GSs are included in the NAS simulation – and indeed, if weather is included then GDPs and GSs must almost necessarily be included – then there are several choices to be made. Depending on the degree of simulation validation that is desired, one can validate a NAS simulation with modeled weather and GDPs using Clusters 3 through 7 (with special attention to the lower membership size of Cluster 7). For a complete validation of a NAS simulation, simulation developers should validate their NAS simulations with at least one validation run from each type of day in the NAS.

These results are also useful in NAS-wide cost/benefit studies. Many cost benefit studies require that results be baselined to a typical day or annualized over a year. The types of days are pertinent to choosing one or more appropriate days for a study. The overall types of days can further be used to annualize results over a year. Given a single day within each type of day (it may or may not be the cluster center), an investigation may be performed to understand the cost/benefit tradeoffs of a concept for that type of day. Generalizing the results to a year would involve a weighted sum across the individual studies for each type of day, where the weighted sum considers the frequency of each type of day in the year. For instance, from our investigation into post-9/11 data, the proportions shown in **Table 5** would be used.

**Table 5:** Percent of types of days annualized over a post-9/11 type year.

| Cluster | Cluster Name | Number of Days | | | Frequency (%) | | |
|---|---|---|---|---|---|---|---|
| | | 2002 | 2003 | Total | 2002 | 2003 | Total |
| 1 | Clear Weather High Volume Type Day | 125 | 122 | 247 | 34.2 | 33.4 | 33.8 |
| 2 | Clear Weather Low Volume Type Day | 113 | 83 | 196 | 31.0 | 22.7 | 26.8 |
| 6 | Moderate Weather Low Volume Type Day | 45 | 76 | 121 | 12.3 | 20.8 | 16.6 |
| 3 | Moderate Weather High Volume Type Day | 58 | 37 | 95 | 15.9 | 10.1 | 13.0 |
| 4 | Severe Weather with Low GSs; High GDPs | 14 | 32 | 46 | 3.8 | 8.8 | 6.3 |
| 5 | Severe Weather with High GSs; Low GDPs | 9 | 9 | 18 | 2.5 | 2.5 | 2.5 |
| 7 | Severe Weather with High Cancellations | 1 | 6 | 7 | 0.3 | 1.6 | 1.0 |

## CONCLUSIONS

Our original objective was to determine a set of criteria that identify a day in the NAS as 'typical'. We have identified that several of the key variables measuring NAS performance exhibit wide variance or bi-modal properties, which confound our intuitive notions of central tendency. This motivated the use of cluster analysis techniques to break distributions into clusters such that, within each cluster, the notion of a typical day is preserved. Researchers can then apply standard Euclidean measures of proximity in the vector space to determine how typical or atypical a given day is by measuring its proximity to the center of the cluster from which it came. The clustering procedure showed a clear demarcation of data based on air traffic volume and delay (particularly delay caused by weather impacts). This leads us to believe that air traffic volume and NAS-impacting weather are the key factors in classifying days in the NAS.

While many NAS performance measures were available for this study, we found that only a small subset was necessary to represent some of the key driving factors of the NAS as a whole. We have described each day in the NAS by a set of nine key variables constituting an optimal NAS feature vector. This conclusion was reached by considering 97 NAS variables that statistically clustered into nine primary bundles. A single variable from each cluster was chosen to represent the nine variables that constitute the "optimal" feature vector for the NAS, including: volume, schedule delay, GDP delay, GS delay, weather delays, cancellations, on-time performance, average total ground delay, and average total airborne delay.

As with any applied statistical technique, the clustering methods naturally required some degree of subjective oversight. We attempted to minimize such interpositions and justified them based on operational domain knowledge when necessary.

**RECOMMENDATIONS**

Our analysis suggests that validations of low fidelity NAS-wide simulations should focus primarily on the nine variable classifications of the optimal NAS feature vector. This recommendation will potentially reduce the total quantity of data analyzed in validating a low fidelity NAS simulation. We did not investigate this issue with respect to medium and high fidelity simulations, so we refrain from making a recommendation for validating those types of simulations. When higher fidelity is added to a NAS simulation, more than just the aggregate statistics should be considered for validation. Additionally, note that our recommendation assumes that there is no other variable independent of the nine variables in the optimal NAS feature vector important to a NAS simulation validation. Our recommendation is that NAS simulation validations should consider at least those elements that constitute the optimal NAS feature vector, and if not possible, to attempt to select a variable from the same cluster set as a substitute.

The NAS is a very complex system with many variables that describe it. A small subset of these variables was studied in our analysis, and of those the minimal set of variables was determined to define an optimal NAS feature vector. The results are open to speculation when a new variable is introduced. While engineering judgment was used to select a set of nine variables that most likely characterize the NAS behavior, we were limited to variables that are available in historical datasets. Thus, our conclusions are limited to what can be said about how the 97 variables relate to the nine variables of the optimal NAS feature vector. Caution must be taken when considering new variables outside the set of 97 variables in this study. If the new variable is dependent on one or more of the dominant variables in the optimal NAS feature vector, then it is not recommended to add the new variable to the validation dataset. If the new variable is independent, then engineering judgment should be used to determine whether it should be included in a NAS simulation validation.

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**ACRONYMS AND SYMBOLS**

| | |
|---|---|
| 9/11 | September 11, 2001 |
| ADL | Aggregate Demand List |
| ANOVA | Analysis of Variance |
| ASPM | FAA's Aviation System Performance Metrics |
| ATCSCC | Air Traffic Control System Command Center |
| ATM | Air Traffic Management |
| BTS | Bureau of Transportation Statistics |
| EDCT | Expected Departure Clearance Time |
| FAA | Federal Aviation Administration |
| GDP | Ground Delay Program |
| GS | Ground Stop |
| IFR | Instrument Flight Rule |
| IMC | Instrument Meteorological Conditions |
| MIT | Miles In Trail |
| NAS | National Airspace System |
| NASA | National Aeronautics and Space Administration |
| OPSNET | FAA's Operations Network Database |
| PCA | Principal Component Analysis |
| VAMS | Virtual Airspace Modeling and Simulation |
| VFR | Visual Flight Rule |
| VMC | Visual Meteorological Conditions |

| | |
|---|---|
| C | Cluster |
| $c_i$ | Center point of the $i^{th}$ cluster |
| $d()$ | Distance function |
| $M$ | Mean |
| $R^2$ | Squared multiple correlation of a variable with its cluster component |
| $U$ | Center point of all clusters |
| $\mu$ | Feature vector corresponding to the cluster center |
| $v$, $w$ | Feature vectors |
| $x$, $y$ | Variables |
| $\sigma$ | Standard Deviation |

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## APPENDIX

**Table 6:** NAS metric and characteristic variables used in Cluster Analysis.

| Index | Variable Name | Description | Units | Source |
|---|---|---|---|---|
| 1 | GDP Length | Total Ground Delay Program (GDP) Length, Summed over Airports with GDPs each day (calculated as Cancel Time – Start Time) | Min | ADL |

| | | | | |
|---|---|---|---|---|
| 2 | GDP Delay | Total minutes of delay due to GDP (calculated on a per-flight basis as depart CTD – OETD) | Min | ADL |
| 3 | GS Delays | Number of delays due to ground stops (GS) at all domestic airports | Flts | OPSNET |
| 4 | GS Delay | Minutes of delay for all AC delayed due to GSs at all domestic airports | Min | OPSNET |
| 5 | GS Average | GS Delay / GS Delays | Min/Flt | OPSNET |
| 6 | EDCT Delays | Number of delays due to GDPs at all domestic airports | Flts | OPSNET |
| 7 | EDCT Delay | Minutes of delay for all AC delayed due to GSs at all domestic airports | Min | OPSNET |
| 8 | EDCT Average | EDCT Delay / EDCT Delays | Min/Flt | OPSNET |
| 9 | Total Ground Delays | GS Delays + EDCT Delays | Flts | OPSNET |
| 10 | Total Ground Delay | GS Delay + EDCT Delay | Min | OPSNET |
| 11 | Total Ground Average | Total Ground Delay / Total Ground Delays | Min/Flt | OPSNET |
| 12 | Efficiency Departures | Departures for ASPM Efficiency Computation | Flts | ASPM |
| 13 | Efficiency Arrivals | Arrivals for ASPM Efficiency Computation | Flts | ASPM |
| 14 | Scheduled Departures | Official Airline Guide (OAG) Scheduled Departures | Flts | ASPM |
| 15 | Scheduled Arrivals | OAG Scheduled Arrivals | Flts | ASPM |
| 16 | ETMS Departures | ETMS Departures | Flts | ASPM |
| 17 | ETMS Arrivals | ETMS Arrivals | Flts | ASPM |
| 18 | Metric Departures | Departures used for ASPM metric computations | Flts | ASPM |
| 19 | Metric Arrivals | Arrivals used for ASPM metric computations | Flts | ASPM |
| 20 | Cancelled Departures | Departure Cancellations | Flts | ASPM |
| 21 | Cancelled Arrivals | Arrival Cancellations | Flts | ASPM |
| 22 | Schedule Delay (Out) | Total OAG-based gate delay for flights delayed 1 minute or more | Min | ASPM |
| 23 | Average Schedule Delay (Out) | (Schedule Delay Out) / (Metric Departures) | Min/Flt | ASPM |
| 24 | Flight Plan (FP) Delay (Out) | Total FP–based gate delay minutes for flights delayed 1 minute or more | Min | ASPM |
| 25 | Average FP Delay (Out) | (FP Delay Out) / (Metric Departures) | Min/Flt | ASPM |
| 26 | Schedule Delay (Off) | Total OAG-based departure delay | Min | ASPM |
| 27 | Average Schedule Delay (Off) | (Schedule Delay Off) / (Metric Departures) | Min/Flt | ASPM |
| 28 | FP Delay (Off) | Total FP-based departure delay | Min | ASPM |
| 29 | Average FP Delay (Off) | (FP Delay Off) / (Metric Departures) | Min/Flt | ASPM |
| 30 | Schedule Arrival Delay | Total OAG-based arrival delay | Min | ASPM |
| 31 | Average Schedule Arrival Delay | (Schedule Arrival Delay) / (Metric Arrivals) | Min/Flt | ASPM |
| 32 | Block Delay | Total block delay (Actual gate-to-gate minus scheduled gate-to-gate) | Min | ASPM |
| 33 | Average Block Delay | (Block Delay) / (Metric Arrivals) | Min/Flt | ASPM |
| 34 | Departure Delays (over 15 Min) | Count of OAG-based departure delays over 15 minutes | Flts | ASPM |
| 35 | Departure Delay (over 15 Min) | OAG-based gate departure delay over 15 minutes | Min | ASPM |
| 36 | Avg departure delay (over 15 Min) | (Departure delay over 15 Min) / (Count of departure delays over 15 Min) | Min/Flt | ASPM |
| 37 | Off Delays (over 15 Minutes) | Count of OAG-based airport departure delays over 15 minutes | Flts | ASPM |
| 38 | Off Delay (over 15 Minutes) | OAG-based airport departure delay over 15 minutes | Min | ASPM |
| 39 | Avg Off Delay (over 15 Minutes) | (Off Delay over 15 Minutes) / (Count of Off Delays over 15 Minutes) | Min/Flt | ASPM |
| 40 | Arrival Delays (over 15 Minutes) | Count of OAG-based arrival delays over 15 minutes | Flts | ASPM |
| 41 | Arrival Delay (over 15 Minutes) | OAG-based arrival delay over 15 minutes | Min | ASPM |
| 42 | Avg Arrival Delay (over 15 Min) | (Arrival Delay over 15 Minutes) / (Count of Arrival Delays over 15 Min) | Min/Flt | ASPM |
| 43 | On-Time Scheduled Departures | OAG-based on-time gate departures | Flts | ASPM |
| 44 | Prct On-Time Sch. Departures | (On-Time Scheduled Departures) / (Metric Departures) | Prct | ASPM |
| 45 | On-Time FP Departures | FP-based on-time gate departures | Flts | ASPM |
| 46 | Percent On-Time FP Departures | (On-Time FP Departures) / (Metric Departures) | Prct | ASPM |
| 47 | On-Time Scheduled Off | OAG-based on-time airport departures | Flts | ASPM |
| 48 | Percent On-Time Scheduled Off | (On-Time Scheduled Off) / (Metric Departures) | Prct | ASPM |

| | | | | |
|---|---|---|---|---|
| 49 | On-Time FP Off | FP-based on-time airport departures | Flts | ASPM |
| 50 | Percent On-Time FP Off | (On-Time FP Off) / (Metric Departures) | Prct | ASPM |
| 51 | On-Time Scheduled Arrivals | OAG-based on-time arrivals | Flts | ASPM |
| 52 | Prct On-Time Scheduled Arrivals | (On-Time Scheduled Arrivals) / (Metric Arrivals) | Prct | ASPM |
| 53 | On-Time FP Arrivals | FP-based on-time arrivals | Flts | ASPM |
| 54 | Percent On-Time FP Arrivals | (On-Time FP Arrivals) / (Metric Arrivals) | Prct | ASPM |
| 55 | EDCT Departure Delay | EDCT hold time for departures | Min | ASPM |
| 56 | EDCT Arrival Delay | EDCT hold time for arrivals | Min | ASPM |
| 57 | EDCT Departure Holds | Departures with EDCT Holds | Flts | ASPM |
| 58 | EDCT Arrival Holds | Arrivals with EDCT Holds | Flts | ASPM |
| 59 | Early EDCT Departures | Departures with EDCT Holds departing early | Flts | ASPM |
| 60 | Late EDCT Departures | Departures with EDCT Holds departing late | Flts | ASPM |
| 61 | Early EDCT Arrivals | Arrivals with EDCT Holds arriving early | Flts | ASPM |
| 62 | Late EDCT Arrivals | Arrivals with EDCT Holds arriving late | Flts | ASPM |
| 63 | Taxi-out Delay | Total taxi-out delay time | Min | ASPM |
| 64 | Taxi-out Delays | Taxi-out delays | Flts | ASPM |
| 65 | Average Taxi-Out Delay | (Taxi-out Delay) / (Taxi-out Delays) | Min/Flt | ASPM |
| 66 | Airborne Delays | Total airborne delays | Flts | ASPM |
| 67 | Airborne Delay | Total airborne delay | Min | ASPM |
| 68 | Average Airborne Delay | (Airborne Delay) / (Airborne Delays) | Min/Flt | ASPM |
| 69 | Taxi-in Delay | Total taxi-in delay time | Min | ASPM |
| 70 | Taxi-in Delays | Total taxi-in delays | Flts | ASPM |
| 71 | Average Taxi-in Delay | (Taxi-in Delay) / (Taxi-in Delays) | Min/Flt | ASPM |
| 72 | IMC Hours | Total number of hours in IMC between 7:00-21:59 local time | Hours | ASPM |
| 73 | VMC Hours | Total number of hours in VMC between 7:00-21:59 local time | Hours | ASPM |
| 74 | Departure Demand | ASPM departure demand for 7:00-21:59 local time – the number of aircraft intending to take-off in the time period | Flts | ASPM |
| 75 | Arrival Demand | ASPM arrival demand for 7:00-21:59 local time – the number of aircraft intending to land in the time period | Flts | ASPM |
| 76 | Airport Score Mean | Average hourly airport score at ASPM airports between 7:00-21:59 local time | Prct | ASPM |
| 77 | Airport Score Variance | Variance of hourly airport score at ASPM airports between 7:00-21:59 local time | Prct | ASPM |
| 78 | Total Operations | Total number of operations at the 55 ASPM airports | Flts | OPSNET |
| 79 | Total Delays | Total number of reportable delays to IFR traffic delayed 15 min or more | Flts | OPSNET |
| 80 | Departure Delays | Total Delays divided by category – Departure Delays | Flts | OPSNET |
| 81 | Arrival Delays | by category – Arrival Delays | Flts | OPSNET |
| 82 | En Route Delays | by category – En Route Delays | Flts | OPSNET |
| 83 | TMS Delays | by category – Traffic Management System Delays | Flts | OPSNET |
| 84 | Air Carrier Delays | Total Delays divided by class – Air Carrier Delays | Flts | OPSNET |
| 85 | Air Taxi Delays | by class – Air Taxi Delays | Flts | OPSNET |
| 86 | GA Delays | by class – General Aviation Delays | Flts | OPSNET |
| 87 | Military Delays | by class – Military Delays | Flts | OPSNET |
| 88 | Weather Delays | Total Delays divided by cause – Weather Delays | Flts | OPSNET |
| 89 | Terminal Volume Delays | by cause – Terminal Volume Delays | Flts | OPSNET |
| 90 | Center Volume Delays | by cause – Center Volume Delays | Flts | OPSNET |
| 91 | Equipment Delays | by cause – Equipment Delays (outage or failure) | Flts | OPSNET |
| 92 | Runway Delays | by cause – Runway Delays (e.g. disabled aircraft, obstruction, construction, maintenance, runway change/selection) | Flts | OPSNET |
| 93 | Other Delays | by cause – Other Delays (e.g. emergency conditions or other special non-recurring activities such as an air show, VIP movement, or radio interference. International delays are also included in this category.) | Flts | OPSNET |

| | | | | |
|---|---|---|---|---|
| 94 | Delays per 1000 Operations | Number of delays per 1000 operations | Prct | OPSNET |
| 95 | Average Delay Time | Average Amount of delay (Total Delay Time / Total Operations) | Min/Flt | OPSNET |
| 96 | Total Delay Time | Total amount of delay for 55 ASPM Airports | Min | OPSNET |
| 97 | Percent of Operations Delayed | Total Delays / Total Operations | Prct | OPSNET |