2007

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This study is an examination of the relationship between controller ratings of static and dynamic sector complexity factors and the occurrence of operational errors (OEs) at the Indianapolis air route traffic control center (ZID). Principal Components Analysis (PCA) of the complexity ratings produced four components that were used as predictors in a multiple regression analysis of the number of OEs in the ZID sectors. Only Component 1 (climbing and descending aircraft in the vicinity of major airports) and Component 2 (services provided to non-towered airports) contributed significantly to the total proportion of variance explained by the model (R = .78, R^2 = .61). Component 1 was positively associated with the number of OEs (i.e., higher scores were related to a higher number of OEs), whereas Component 2 had a negative relationship (higher scores were related to fewer OEs). These results will be used to guide the choice of objective measures for further analysis of the influence of static and dynamic sector characteristics in the occurrence of OEs.

Introduction

The Federal Aviation Administration (FAA) is currently implementing strategic safety initiatives aimed at reducing operational error rates (FAA, 2005). Toward that goal, a considerable amount of research has focused on behavioral and organizational aspects of operational error (OE) occurrence. While recognizing that the human component of OEs is extremely important, it is also important to remember that air traffic controllers do not operate in a void. Logic dictates that environmental and contextual factors contribute to the development of at least a portion of these errors. Otherwise, the frequency of OEs would be relatively equal in all sectors. This simply is not the case. Some sectors are more prone to OEs than others.

The idea that sector characteristics might contribute to the occurrence of OEs is not new. Environmental and contextual factors affecting controller workload and performance – often referred to as sector complexity – have been the focus of numerous studies (e.g., Arad, 1964; Buckley, O'Connor, & Beebe, 1969; Davis, Danaher, & Fischl, 1963; Grossberg, 1989; Hurst & Rose, 1978; Kirwan, Scaife, & Kennedy, 2001; Kopardekar & Magyarits, 2003; Laudeman, Shelden, Branstrom, & Brasil, 1998; Masalonis, Callaham, & Wanke, 2003; Mogford, Murphy & Guttman, 1994; Rodgers, Mogford, & Mogford, 1998; Schmidt, 1976; Stager, Hameluck, & Jubis, 1989; Stein, 1985). Even so, a single set of reliable general complexity factors has remained elusive. This may be partially due to the complicated interaction between static and dynamic sector characteristics. Static sector characteristics are usually related to airspace design and change infrequently or not at all. Dynamic sector characteristics are those that fluctuate, such as traffic volume or weather. Mogford, Guttman, Morrow, and Kopardekar (1995) observed that "a given level of traffic density and aircraft characteristics may create more or less complexity depending on the structure of the sector" (p. 3). Buckley, DeBarysche, Hitchner, and Kohn (1983) concluded that traffic characteristics and sector geometry were "important factors in determining the results which will occur in a given experiment, but they interact in a complex way. The nature and extent of this interaction depends upon the measures involved" (p. 73).

Perhaps one of the greatest challenges to the study of environmental factors in the development of OEs is that sectors are almost as unique as the people who work them. For example, Grossberg (1989) found that the highest-rated complexity factors in the Chicago air route traffic control center (ARTCC) were control adjustments involved in merging and spacing aircraft, climbing and descending aircraft, mix of aircraft types, frequent coordination, and amount of traffic. An index based on these factors was significantly correlated with the number of OEs. In the Jacksonville airspace, Mogford and coworkers (1994) found complex routings, spacing and sequencing for departures and arrivals, and frequency congestion to be most predictive of a subjective complexity index. Comparing their results with Grossberg's, they concluded that complexity factors that were salient in one facility might not be applicable to another. Although this observation may be valid, another interpretation is that different complexity factors were found to be predictive because the two studies used different criteria. In other words, numbers of OEs and the value of a subjective complexity index may not be comparable.

This brings us to an important point: It is extremely difficult to compare the results of the studies cited because of the variety of methods and measures used to assess complexity. Some of the studies compared sector complexity factors with OEs, some with subjective workload measures, and some with subjective complexity ratings. On the basis of a comprehensive review of the literature that spanned more than 40 years of research and identified in excess of 100 complexity factors, Hilburn (2004) concluded that "despite the breadth and depth of previous work done into identifying ATC complexity factors, a good deal of work remains. Nobody, it seems, has yet managed to construct a valid and reliable model of ATC complexity that [1] moves substantially beyond the predictive value of simple traffic density alone, and [2] is sufficiently context-free" (p. vi). The only drawback to this argument is that it fails to recognize that sometimes the context *is* the factor of interest. This is not to imply that Hilburn was ignoring the importance of context or the inevitability of contextual influences in airspace complexity. Rather, it emphasizes the fact that development of a context-free model is not always a desirable goal in research.

In spite of the "embarrassment of riches" represented by the literature, one precept is evident: It is extremely important to compare complexity factors in as many environments as possible. The Sector Characteristics and Operational Errors (SCOpE) project is an extension of a study conducted by Rodgers, Mogford, and Mogford (1998) that examined the relationship between sector complexity factors and the occurrence of OEs at the Atlanta ARTCC (ZTL). Specifically, the SCOpE project was initiated to compare and contrast the results of selected analyses from the 1998 study with similar analyses conducted using data from the Indianapolis ARTCC (ZID). The methodology of developing a regression model at one facility and applying the derived regression weights to another facility has met with limited success (e.g., Laudeman et al., 1998; Masalonis et al., 2003). The advantage of the SCOpE paradigm is that it employs discrete models, thus enabling us to collect a set of general factors (i.e., factors that may reliably predict OEs at more than one facility) while documenting differences between facilities. After all, facility differences often represent important environmental and contextual elements as well.

In the present study, subjective complexity ratings provided by ZID controllers will be examined to evaluate their relationship with OEs at ZID using linear multiple regression analysis. With 22 complexity factors and only 37 sectors in the ZID sample, the case-to-IV ratio would be unacceptable for multiple regression. As the number of predictors approaches the number of cases, "one can find a regression solution that completely predicts the DV for each case, but only as an artifact of the cases-to-IV ratio" (Tabachnick & Fidell, 2006, p. 123). Principal Components Analysis (PCA) is a statistical technique that consolidates complex variables into parsimonious groups. Component scores (computed by weighting variable scores using regression-like coefficients) can be substituted for individual complexity factor ratings, thereby reducing the number of predictors without losing information about their interrelationships. In addition to circumventing the case-to-IV ratio problem, the combination of PCA and linear regression analysis allows us to explore the underlying dimensions represented by the various complexity factors and the way in which these dimensions relate to the occurrence of OEs.

Method

Participants

Participants were 37 volunteers from ZID. Of these, 32 were Certified Professional Controllers (CPCs), 4 were operations supervisors, and 1 was a developmental controller who had completed Radar Associate training on all sectors in his area of specialization but was not yet certified on the corresponding radar positions. The mean age of the volunteer participants was 42 years (*SD* = 6 years). Participants had been certified to control traffic for an average of 15 years (*SD* = 7 years), had been working at an ARTCC facility for a mean of 17 years (*SD* = 7 years), and had been working at their current facility for an average of 16 years (*SD* = 8 years). Four had previous experience in the Terminal Radar Approach Control (TRACON) environment, and six had previously worked at an Airport Traffic Control Tower (ATCT). ZID is divided into seven areas of specialization, each comprising either five or six sectors. All areas were reasonably well represented by the sample of volunteer controllers and supervisors.

Materials

Complexity Factor Questionnaire (Complexity-Q). "Complexity-Q" refers to an automated experimental protocol software program and the questionnaire it was designed to administer. The Complexity Factor Questionnaire followed the same basic structure for each sector on which the participants were certified. They were asked to provide a general "Complexity Rating" for a sector using a slider object with an underlying scale ranging from 0 to 100. The end points of the slider were labeled “Low” and “High” with visual anchors set at 10-point intervals. Once the participants entered an overall complexity rating, they were presented sequentially with a series of 22 complexity factors and asked to indicate the level of influence each factor had on the complexity of the sector. The “Factor Rating” was made using the same slider and scale as the general complexity rating. The list of factors and their descriptions was initially derived from the 19 complexity factors identified by Mogford et al. (1994). Subject Matter Experts (SMEs) from the facility and the FAA Academy provided two additional factors prior to data collection. The Complexity-Q factors are provided in Table 1. The “mix of aircraft with different performance characteristics” and “VFR versus IFR traffic” factors were combined in the original list but were separated into two distinct factors for this study.

Table 1. Complexity-Q Factors

Complexity Factor
Climbing and descending traffic
Mix of aircraft with different performance characteristics
VFR versus IFR traffic
Number of intersecting aircraft flight paths
Number of multiple functions controller must perform
Traffic volume
Amount of military or other special traffic
Number of required procedures that must be performed (i.e., crossing restrictions in LOAs)
Amount of coordination/ interfacing required
Major airports (inside and outside sector boundaries) that might influence the number of procedures used, etc.
Extent operations are affected by weather
Relative frequency of complex routings
Special Use Areas (Restricted areas, warning areas, and military operating areas) and their associated activities
Size of sector airspace
Requirement for longitudinal spacing/ sequencing
Adequacy of radio/radar coverage
Amount of radio frequency congestion
Traffic Management Initiatives
Terrain/Obstructions
Shelves/Tunnels
◊ Foreign aircraft/pilots with English as a second language
◊ Non-towered airports

* Complexity factors and descriptions adapted from Rodgers, Mogford, and Mogford (1994) except where indicated (◊)

Procedure

Testing took place from 6/13/2005 to 6/17/2005 in a classroom at ZID. The Complexity-Q automated protocol was administered on laptop computers arranged around a large table to provide participants with as much privacy as possible. Participants were first given informed consent forms to read and sign. Once their written consent was obtained, they were shown the basic structure of the Complexity-Q interface, and the “Work Experience” section was brought up on the screen. Participants were requested to complete this section and then move through all subsequent sections in the order they appeared (i.e., Tutorial, Demonstration, and Questionnaire). They were encouraged to ask questions about the interface or content of the Complexity-Q at any time during the automated protocol. Most participants completed the protocol in 40 minutes.

Measures

Operational Errors. The OE database consisted of information extracted from electronic records of the Final Operational Error/Deviation Report (FAA Form 7210-3) for 247 OEs occurring in ZID airspace from 1/15/2001 through 5/28/2005. OEs were tallied for each sector in the ZID airspace.

Results and Discussion

Principal Components Analysis

A total of 181 complexity ratings provided by CPCs (n = 169) and operations supervisors (n = 12) were submitted to analysis. PCA with Varimax rotation converged in nine iterations and produced four components with eigenvalues > 1. These components accounted for approximately 62% of the variance in the dataset. As shown in the rotated component matrix in Table 2, all but one of the variables (*Relative frequency of complex routings*) had a loading of .50 or greater with at least one of the components.

Component 1 had an eigenvalue of 4.93 and accounted for approximately 22% of the variance in the dataset. As shown in Table 2, the variables with high loadings on this component seem to describe activity related to climbing and descending aircraft in the vicinity of major airports. When considering these kinds of flights, it is easy to see how the variables that describe this component relate to one another. For example, arrival and departure traffic associated with *Major airports* (.68) would tend to increase the *Number of climbing and descending aircraft* (.79). Airspace around major airports tends to

Table 2. Principal Components Analysis Rotated Component Matrix

	Component			
Variable	1	2	3	4
Climbing/ Descending	.79			
Mix of aircraft types	.69			
VFR versus IFR		.90		
Intersect. flight paths	.63			
Multiple functions	.73			
Traffic volume	.59			.51
Military/Special traffic			.76	
Required procedures	.66			
Coordination	.74			
Major airports	.68			
Weather				.74
Complex routings				
Special Use Areas			.72	
Size of sector airspace	.51		.56	
Spacing/ Sequencing				.54
Radio/ Radar coverage		.60		
Radio freq. congest.	.58			
TMI				.59
Terrain/Obstructions		.88		
Shelves/Tunnels			.53	
Foreign aircraft/pilots			.60	
Non-towered airports		.91		

* Component loadings < .50 not shown.

have more *Intersecting flight paths* (.63). *Traffic volume* (.59) also tends to be higher proximal to major airports. Increased traffic directly impacts the *Amount of radio frequency congestion* (.58), and in some sectors would increase the *Mix of aircraft types* (.69). The *Amount of coordination required* (.74), *Number of multiple functions* (.73), and *Number of required procedures* (.66) represent tasks the controller must perform in complex airspace that often surrounds larger airports and would become more exigent in conjunction with the other factors. Perhaps the association of the *Size of sector airspace* (.51) represents a relationship between the size of the sector and the impact of these activities. In other words, their effects may be mediated by the amount of time available for resolution or completion.

Component 2 had an eigenvalue of 3.67 and accounted for approximately 17% of the variance. This component comprises complexity issues associated with low-altitude sectors that provide approach services into *Non-towered airports* (.91), the variable with the highest loading on this component. In the Indianapolis airspace, 11 sectors provide approach services to airports without towers. Radar coverage does not always reach to the ground, so a loading of .60 for the *Adequacy of radio/radar coverage* may reflect difficulties associated with this factor. Aircraft flying VFR would also be present in these low-altitude sectors, thus increasing the ratio of *VFR versus IFR traffic* (.90), the second-highest loaded variable. The complexity factor *Terrain and other obstructions* (.88) is exclusively low-altitude and is relevant in sectors that provide approach services. In contrast, sectors with non-towered airports do not have a high mix of aircraft types (as most aircraft have lower performance characteristics), have low traffic volume, and limited frequency congestion. Moreover, these sectors have limited multiple functions, coordination, procedures, complex routings, spacing and sequencing, traffic management initiatives, and shelves/tunnels. Thus, it makes sense that complexity ratings for those factors did not load on Component 2.

Component 3 had an eigenvalue of 2.78 and accounted for approximately 13% of the variance in the dataset. Variables associated with this component are primarily related to *Military operations* (.76) and other *Special Use Area (SUA)* restrictions (.72). In the ZID airspace, tunnels are associated with military operations. This might account for the relationship of *Shelves/Tunnels* (.53) with this dimension. Restrictions due to military operations would reduce the amount of usable airspace. Thus, a .56 loading of *Size of sector airspace* on this dimension makes sense. However, it is unclear why *Foreign aircraft/pilots* would be associated with this component to such a high degree (.60). Perhaps the unifying theme of this dimension is that each of these factors warrants special consideration or attention, and *Foreign aircraft/pilots* fall into this category.

Component 4 had an eigenvalue of 2.35 and accounted for approximately 11% of the variance. The variables most strongly associated with this component relate to difficulties associated with inclement weather, as evidenced by the two highest-loaded variables, *Extent operations are affected by weather* (.74) and *Traffic Management Initiatives* (.59). *Requirements for longitudinal spacing/ sequencing* (.54) and problems associated with *Traffic volume* (.51) are also magnified by inclement weather.

Multiple Regression Analysis

The method used to compute component scores generally produces variables with normal distributions. Moreover, orthogonal rotation methods make it virtually impossible for the components, as a predictor set, to suffer from multicollinearity. Therefore, there is little question as to their appropriateness for multiple regression analysis. The distribution of the number of OEs per sector had a mean of 6.68, with a standard deviation of 4.23 (*Skewness* = .61, *SE Skewness* = .39; *Kurtosis* = -.67, *SE Kurtosis* = .76). This was less than two standard deviations from normal in skewness, and less than one standard deviation from normal in kurtosis. Consequently, both the predictors (the component scores) and the criterion (the number of OEs) met assumptions of normality. No univariate or multivariate outliers were detected. Studentized residuals plotted against predicted values were randomly distributed in a horizontal band around zero, indicating that the assumption of linearity and the assumption of equality of variance were met. Visual examinations of the cumulative probability plot of the observed distribution of residuals against a normal distribution demonstrated that the assumption of normally distributed errors was also met.

Standard multiple regression of the extracted complexity components on the number of OEs per sector produced a multiple $R = .78$ ($R^2 = .61$) that was significantly different from zero, $F(4,32) = 12.72$, $p < .01$. Note that in this analysis the number of ZID sectors has been reduced from 40 to 37 due to sector combinations that were recommended by ZID personnel to facilitate the administration of the Complexity-Q questionnaire. As shown in Table 3, Components 1 and 2 contributed a significant amount of unique information to the model, whereas Components 3 and 4 did not.

Table 3. Multiple Regression Analysis: Complexity Component Scores on Number of Operational Errors (N = 37)

Variable	***B***	***SE B***	***t***	***β***
Component 1	4.62	.69	6.67	.75 **
Component 2	-1.18	.51	-2.33	-.26 *
Component 3	1.54	.95	1.62	.19
Component 4	-.33	.73	-.45	-.05

** p = <.01; * p = <.05

Conclusions

Considering that the component scores were based on subjective ratings of sector complexity factors and did not include any variables explicitly describing individual behavioral or organizational aspects associated with OEs, 61% explained variance is impressive. However, components were constructed from “human-weighted” complexity factors, and so the human element was not entirely missing from the equation. The relationship between Component 2 (Non-towered Airports) and the incidence of OEs reminds us that sector complexity does not always produce a negative outcome. Indeed, a certain degree or type of complexity may be related to a reduction in OEs. The fact that Component 3 (Military Airspace/SUAs) failed to contribute significantly to the prediction of OEs in this analysis does not mean that military airspace or SUAs don’t make a sector more difficult to work or increase the likelihood of an OE. It simply means that subjective ratings of these factors failed to predict OEs. Similarly, the inability of Component 4 (Weather) to contribute significantly to the regression model may reflect the intermittent nature of this dynamic event, or it may simply be an artifact of the way the variable was measured. In other words, the presence of inclement weather might be highly correlated with the occurrence of OEs but the component scores based on subjective ratings of variables associated with inclement weather were not.

The next phase of the SCOpE project will involve analyzing objective measures that correspond to the subjective ratings of dynamic complexity factors examined in this study. Practical prediction models (linear or otherwise) must eventually be calculated from objective measures because the actual characteristics of the sectors must be addressed when developing strategies to reduce OEs. Nevertheless, information about the importance of complexity factors gained from this analysis can guide the choice of objective measures in future analyses and may also be used to weight their importance.

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