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Logistic Regression Analysis of Operational Errors and Routine Operations Using Sector Characteristics

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16. Abstract

Two separate logistic regression analyses were conducted for low- and high-altitude sectors to determine whether a set of dynamic sector characteristics variables could reliably discriminate between operational error (OE) and routine operation (RO) traffic samples. OE data were derived from SATORI re-creations of OEs occurring at the Indianapolis Air Route Traffic Control Center between 9/17/2001 and 12/10/2003. RO data were extracted from System Analysis Recordings (SARs) taped between 5/8/2003 and 5/10/2003. Dynamic sector characteristics submitted as potential predictors were: Average Control Duration, Number of Handoffs, Number of Heading Changes, Number of Intersecting Flight Paths, Number of Point Outs, and Number of Transitioning Aircraft. In the low-altitude sector model, backward stepwise elimination reduced the variables to the Number of Intersecting Flight Paths, the Number of Point Outs, and the Number of Handoffs with 75% overall classification accuracy. In the high-altitude sector model, backward stepwise elimination reduced the variables to the Number of Intersecting Flight Paths, the Number of Heading Changes, the Number of Transitioning Aircraft, and Average Control Duration with 79% overall classification accuracy. Classification rates achieved through the use of the selected sector characteristics support the assumption that elements of the sector environment contribute to the occurrence of OEs. Continued investigations along these lines may highlight complexity factors that should be addressed to ensure that separation is maintained.

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Executive Summary

Although a considerable amount of research has focused on the relationship between sector characteristics and controller workload or perceived complexity, relatively few studies have examined the relationship between sector characteristics and the occurrence of operational errors (OEs). In many early studies of OE causal factors, examinations of sector characteristics were limited to purely theoretical relationships or to traffic counts and altitude transitions of the involved aircraft. When sector characteristics were examined, they consisted primarily of ratings rather than objective measures. Most of this work has been conducted without reference to routine operations (ROs). Yet, for every OE that occurs in a sector, there are hundreds (possibly thousands) of hours in which an OE did not occur. To truly understand the environmental and contextual factors that contribute to OEs, it is necessary to identify what was different about the sector environment at the time the OE occurred.

In the present study, OE and RO traffic samples were compared using logistic regression analysis. Two separate logistic regression analyses were conducted for low- and high-altitude sectors. The OE sample was drawn from 119 OEs occurring in the Indianapolis en route airspace from 9/17/2001 through 12/10/2003. Of these, 40 occurred in the low-altitude sectors and 79 occurred in the high-altitude sectors. The RO traffic samples were recorded between 5/8/2003 and 5/10/2003. These data were processed in 5-minute intervals using custom software designed to calculate objective measures from routinely recorded National Airspace System (NAS) data. This produced a total of 2763 RO traffic samples. The 79 high-altitude OE traffic samples were combined with 79 randomly-selected high-altitude RO traffic samples to produce a total of 158 traffic samples for the high-altitude sector analysis

In logistic regression analysis of the low-altitude sector samples, Average Control Duration, the Number of Handoffs, the Number of Heading Changes, the Number of Intersecting Flight Paths, the Number of Point Outs, and the Number of Transitioning Aircraft were submitted as the initial set of predictors. Backward stepwise elimination reduced the variables in the final low-altitude sector model to the Number of Intersecting Flight Paths, the Number of Point Outs, and the Number of Handoffs. In the low-altitude sector model, each intersecting flight path increased the likelihood that the traffic sample was an OE by 189%, each point out increased the likelihood by 57%, and each handoff increased the likelihood that the traffic sample was an OE by 19%. Of the 40 ROs in the low-altitude sample, 32 (80%) were correctly classified and 8 (20%) were misclassified as OEs. Of the 40 OEs in the sample, 28 (70%) were correctly classified and 12 (30%) were misclassified as ROs. Overall, the low-altitude model had 75% classification accuracy.

In logistic regression analysis of the high-altitude sector samples, Average Control Duration, the Number of Handoffs, the Number of Heading Changes, the Number of Intersecting Flight Paths, the Number of Point Outs, and the Number of Transitioning Aircraft were submitted as the initial set of predictors. Backward stepwise elimination reduced the variables in the final high-altitude sector model to the Number of Intersecting Flight Paths, the Number of Heading Changes, the Number of Transitioning Aircraft, and Average Control Duration. In the high-altitude sector model, each one-unit increase in the Number of Intersecting Flight Paths increased the likelihood that a traffic sample was an OE by 100%, each one-unit increase in the Number of Heading Changes increased the likelihood by 36%, every Transitioning Aircraft increased the likelihood by 27%, and each one-second increase in Average Control Duration increased the likelihood by 1%. Of the 79 ROs in the high-altitude sample, 64 (81%) were correctly classified and 15 (19%) were misclassified as OEs. Of the 79 OEs in the sample, 60 (76%) were correctly classified and 19 (24%) were misclassified as ROs. Overall, the high-altitude model had 79% classification accuracy.

The results of the logistic regression analyses indicate that sufficient models may be constructed from sector characteristics variables. Overall classification accuracy between 75-79% is remarkable for models constructed solely of environmental and contextual factors. After all, other factors (e.g., human elements, organizational influences) also contribute to the occurrence of OEs. Unfortunately, all the logistic regression models were better at classifying ROs than OEs. Classification of OEs ranged from as low as 70% in the low-altitude sector sample to 76% in the high-altitude sample. Although this level of accuracy would be unacceptable for most automation tools, it is unrealistic to expect definitive results from one or two analyses. Moreover, the sector characteristic variables used in these analyses do not represent an exhaustive list of all the potential predictors of OEs.

Although logistic regression cannot be used to identify causal factors directly (i.e., prediction is not the same as causation), the logistic regression coefficients do provide information about the *likelihood* of an OE relative to the predictors in the model. Thus, the results have immediate heuristic value in that they invite questions about how the dynamic predictors interact with static sector characteristics. Dynamic elements lend themselves to automation applications, but static characteristics must be addressed for sector restructuring. The dynamic predictors that make up the logistic regression models are indicants of conditions that discriminate between OEs and ROs. These indicants may be used to reveal aspects of the sector environment that might be altered to reduce the number of OEs. For example, the combination of the Number of Point Outs and the Number of Handoffs in the low-altitude sector model may indicate that the location of sector boundaries increases coordination workload and complexity. On the other hand, the combination of the Number of Point Outs and the Number of Intersecting Flight Paths may point to problems with the orientation of traffic paths relative to those boundaries. The combination of the Number of Heading Changes and the Number of Transitioning Aircraft in the high-altitude sectors is suggestive of traffic complexity in high-altitude sectors adjacent to low-altitude arrival or departure sectors. Average Control Duration may be a function of the size of high-altitude sectors.

Given the sample size and consequent restriction of the predictor set, there is no guarantee that these results will generalize to other samples. Multiple studies, with samples sizes that allow for a more inclusive list of predictors, must be conducted at a number of facilities before such models might be reliable enough for practical applications. Nevertheless, the methodology of comparing OE and RO traffic samples is promising. Continued investigations along these lines may highlight complexity factors that must be addressed to ensure that separation is maintained.

Logistic Regression Analysis of Operational Errors and Routine Operations Using Dynamic Sector Characteristics

In the current Air Traffic Control (ATC) system, an Operational Error (OE) occurs when there is a violation of aircraft separation minima as defined by Federal Aviation Administration regulations (FAA, 2007). Although the FAA has called for a reinvention of the National Airspace System (NAS), it is reasonable to assume that future systems will also include some kind of aircraft separation standards. As changes to procedures and airspace structure are being considered, it becomes increasingly important to understand the environmental and contextual factors (often referred to as sector characteristics) that contribute to the loss of separation to ensure that safety is not compromised.

A considerable amount of research has focused on the relationship between sector characteristics and controller workload or perceived complexity (e.g., Buckley, DeBarysche, Hitchner, & Kohn, 1983; Chatterji & Sridhar, 2001; Christien & Benkouar, 2003; Kopardekar & Magyarits, 2003; Laudeman, Shelden, Branstrom, & Brasil, 1998; Mogford, Murphy, & Guttman, 1994; Robertson, Grossberg, & Richards, 1979). However, relatively few studies have examined the relationship between sector characteristics and the occurrence of OEs. In many early studies of OE causal factors, examinations of sector characteristics were limited to purely theoretical relationships (e.g., Arad, 1964; Schmidt, 1976) or to traffic counts and altitude transitions of the involved aircraft (e.g., Kershner, 1968; Schroeder, 1982; Spahn, 1977).

Grossberg (1989) expanded on this by collecting ratings from 97 controllers and supervisors regarding various aspects of the sector environment. He found that the highest-rated sector complexity factors in the Chicago Air Route Traffic Control Center (ARTCC) were control adjustments (e.g., merging, spacing, and speed changes), climbing and descending flight paths, and mix of aircraft types. An index based on these factors was significantly correlated ($r = .74$) with the number of OEs occurring in 27 Chicago sectors over 21 months in 1987 and 1988.

Rodgers, Mogford, and Mogford (1998) evaluated the relationship between sector characteristics and the incidence of OEs at the Atlanta ARTCC. OE data were extracted from Facility Operations and Administration reports for 85 OEs occurring over a three-year period from 1992 to 1995. Sector characteristics variables were derived from a number of sources and included static sector characteristics from the facility's Adaptation Control Environmental Systems (ACES), average complexity and density ratings drawn from the 1995 annual facility review, and complexity factor ratings provided by one Airspace and Procedures specialist from each area in the facility. Several statistical techniques were employed to predict OE occurrence in the Atlanta sectors. In a linear multiple regression analysis, ratings of radio frequency congestion and the effects of restricted airspace accounted for 31% of the variance in the number of OEs per sector. The same two predictors generated a function that classified OE frequency groups (i.e., sectors with no OEs, fewer than four OEs, and sectors with four or more OEs) with 58% accuracy in a discriminant function analysis. Ratings of weather influences, radio frequency congestion, and complexity were significantly different in a MANOVA of OE frequency groups. The authors stated that the overall Hotellings $F(16, 68) = 1.60$, $p = .094$ of the MANOVA was acceptable due to the exploratory nature of the study and emphasis on data exploration. Sector size failed to emerge as a significant contributor in any of these models, but a t-test between the combined no- and low-OE groups and the group consisting of sectors with four or more OEs was statistically significant ($p<.05$).

In both the Grossberg (1989) and Rodgers, Mogford, and Mogford (1998) studies, sector characteristics were evaluated against the number of OEs per sector. The risk of OE occurrence increases as a function of the number of hours a sector is in operation (i.e., exposure increases the risk of occurrence). If OE incidence is not adjusted for this, the internal validity of the analysis may be compromised. However, there is no evidence to suggest that these adjustments were made in either study.

Another disadvantage of OE incidence as a dependent variable is that it restricts the number of independent variables that may be analyzed without detriment to external validity. With most statistical analyses, the risk that results will fail to generalize increases as the number of independent variables approaches the number of cases. In spite of this, Rodgers, Mogford, and Mogford (1998) submitted 28 predictors for stepwise linear multiple regression analysis of OE incidence in 45 sectors at the Atlanta ARTCC (i.e., a ratio of 1.6 cases for each predictor). A correlation matrix of the predictors revealed 26 comparisons with $r \geq .60$. The authors relied on tests for tolerance in the stepwise procedure to eliminate redundancies and reduce the number of variables in the predictor set. However, in stepwise linear multiple regression, a minimum of 40 cases for each predictor is necessary to ensure the solution will generalize to other samples (Tabachnick & Fidell, 2006).

Perhaps the biggest drawback to OE frequency as a dependent measure is that it affords no comparison with routine operations (ROs). Yet, for every OE that occurs in a sector, there are hundreds (possibly thousands) of hours during which an OE did not occur. Variables that correlate with sector OE frequency do not describe what was different about the sector at the time of the OE. To truly understand the environmental and contextual factors that contribute to OEs, it is necessary to identify what was different about the sector environment at the time the OE occurred.

Pfleiderer and Manning (2007) conducted an investigation to determine whether logistic regression analysis of objective sector characteristics could discriminate between OE and RO traffic samples. Prior to this study, investigations of the contribution of sector characteristics to the occurrence of OEs relied heavily on attributed causal factors and subjective ratings. Although interviews and ratings about the importance of complexity factors are beneficial in the early stages of research, practical prediction models must eventually be calculated from objective measures. After all, it is the actual characteristics of the sectors that must be addressed when developing strategies to reduce OEs rather than opinions or beliefs about those characteristics. Two separate logistic regression analyses were performed for high- and low-altitude sector samples at the Indianapolis ARTCC (ZID). In the high-altitude sector sample, a logistic regression model comprising the Number of Heading Changes, the Number of Transitioning Aircraft, and Average Control Duration was able to accurately classify 80% of the OE and RO traffic samples. In the low-altitude sector sample, variables included in the final model were the Number of Point Outs, the Number of Handoffs, and the Number of Heading Changes. This model was able to accurately classify 79% of the low-altitude OE and RO traffic samples.

Unfortunately, the Pfleiderer and Manning (2007) study was flawed. Available traffic data consisted of OEs from 9/17/2001 to 12/10/2003 and ROs from 2/25/2005 to 3/3/2005. Clearly, the time differential between the OE and RO traffic samples was a confounding influence because it represented an uncontrolled, systematic difference between the two groups.

A second problem with the Pfleiderer and Manning (2007) design involved pairing OE and RO traffic samples (by sector, day of week, and time of day). Logistic regression analysis assumes that all cases are independent of one another. Violation of this assumption results in over-dispersion, which produces an inflated Type I error rate for tests of predictors (Tabachnick & Fidell, 2006). Although there is no reason to assume that errors would be correlated between the OE and RO traffic samples (particularly in light of the disparate time frames from which the samples were drawn), neither is there evidence to the contrary. Random selection of RO traffic samples would have guaranteed that the assumption of independence had been met.

Another possible source of inflation for tests of predictors involved the variables Number of Heading Changes and Number of Transitioning Aircraft. When controllers become aware that an OE is developing, they may issue clearances in an attempt to resolve the situation. Inclusion of altitude or heading changes made in response to such clearances would inflate the contributions of the Number of Transitioning Aircraft (based on the number of altitude changes) and the Number of Heading Changes as predictors of OEs. The choice of processing interval (four minutes prior to loss of separation and one minute after) may have magnified this effect.

In the present study, OE and RO traffic samples are again compared using logistic regression analysis, but some important modifications were made to the design. Both the OE and RO traffic samples used to build the logistic regression model were from 2003, thus eliminating the confound of the previous analysis. A randomly-selected sub-sample of the RO traffic data was designated for model building. The remaining RO cases and traffic samples from OEs occurring in the ZID airspace from 2001-2002 were set aside for cross validation. No attempt was made to match the RO traffic samples to the OE samples, thus meeting the assumption of independence and eliminating the potential for Type I errors for tests of predictors. The Number of Heading Changes and Number of Transitioning Aircraft were adjusted to eliminate changes made in response to control actions to avoid an imminent OE (described in detail in the Method section) to guard against inflated contributions by these two predictors. In addition, the processing interval for the OE traffic samples was changed to include only the five minutes prior to initial loss of separation.

Unfortunately, restricting the OE traffic samples to a single year reduces the sample size. This prohibits separation of low- and high-altitude sector samples for individual analyses, even though there is reason to suspect they constitute heterogeneous sub-samples. To begin with, OE incidence differs between strata. Of 119 OEs in the full sample, 40 occurred in low-altitude sectors, and 79 occurred in the high-altitude sectors. Inclusion of sector strata as a binary categorical variable would provide no information beyond this fact. Second, separate logistic regression analyses of the low- and high-altitude samples produced two very different models in the Pfleiderer and

Manning (2007) study. It is possible that combining low- and high-altitude sector samples would produce a model that fits the high-altitude sectors poorly and the low-altitude sectors not at all. Cross validation can be used to determine whether the 2003 data are similar enough to the 2001-2002 data to justify pooling the OE samples. If OE classification is similar in the model-building and cross-validation results, this suggests that the model works equally well for both samples and that they may be similar enough to be pooled. If that is the case, the OE data will be pooled, and separate logistic regression analyses will be conducted for the low- and high-altitude sector samples.

The sector characteristics used as independent variables in this study are based on measures that have previously demonstrated a relationship with workload, complexity, or the occurrence of OEs. These variables are described in detail in the following paragraphs.

Predictor Variables

Average Control Duration. Aircraft control duration is influenced by a number of factors, including aircraft performance characteristics, Traffic Management Initiatives (TMI), and sector size – all of which have been associated with sector workload or complexity (Grossberg, 1989; Mogford, Murphy, & Guttman, 1994; Pfleiderer, Manning, & Goldman, 2007). Average Control Duration is the mean of the durations (in seconds) of all aircraft controlled by the sector within a processing interval. Control time occurring before or after the interval was not included in the calculations.

Number of Handoffs. Although traffic count remains the best single predictor of the number of OEs on a national level, previous research suggests that it is not an effective predictor of OEs at the sector level (e.g. Schroeder, 1982; Schroeder, Bailey, Pounds, & Manning, 2006; Spahn, 1977). Aside from doubts about its effectiveness as a predictor, perhaps the biggest drawback to traffic count is that it tends to be highly correlated with other traffic-related measures. As a result, traffic counts create redundancies that may overshadow more effective predictors. Handoffs, however, are correlated with the number of aircraft in the sector, but they are not synonymous with it. In the ZID traffic samples used in this study (described in the Method section), the total number of aircraft and the total number of handoffs had a Spearman's correlation of $r_s = .66$ ($N = 2763$). Handoff counts capture elements of communication workload and required attention. Handoff initiates (i.e., outbound handoffs from the current sector to another sector or facility) are generally associated with the issuance of a frequency change clearance. Handoff accepts (i.e., inbound handoffs from another sector or facility to the current sector) are accompanied by an eventual (but not necessarily concurrent) verification that aircraft coming into the sector are tuned to the appropriate frequency. Handoff counts also provide information about coordination and required procedures. Although most handoffs are fairly automatic, some require coordination with other sectors. In some instances, aircraft must comply with altitude or other restrictions before they can be handed off or a handoff can be accepted. Handoffs may also reflect the impact of sector geography. According to Couluris and Schmidt (1973), the number of handoffs, coordination, and point outs "result from, or are influenced by, the existence and design (shape) of the sectors. The additional work created can be thought of as the cost of sectorization" (p. 657). The Number of Handoffs is the total number of handoff initiates and handoff accepts occurring within the 5-minute processing interval.

Number of Heading Changes. Heading changes have demonstrated a relationship with controller ratings of activity (e.g., Laudeman et al., 1998), workload (e.g., Stein, 1985), and complexity (e.g., Kopardekar & Magyarits, 2003). Heading changes are involved with a number of procedures such as merging and spacing, Standard Terminal Arrival Routes (STARs), Standard Instrument Departure Routes (SIDs), and holding. The Number of Heading Changes is a count of all turns in excess of 10 degrees per 12-second radar update that continue in the same direction for at least three updates. Heading changes made in an attempt to avoid an imminent OE were excluded from the counts for OE traffic samples. The criteria for these exclusions are described in the Method section.

Number of Intersecting Flight Paths. This factor was one of the highest rated complexity factors in the high-altitude and super high-altitude sectors in the Pfleiderer, Manning, and Goldman (2007) study, in which a sample of 32 controllers and 4 supervisors from ZID provided ratings for a set of 22 sector complexity factors. In addition, the Number of Intersecting Flight Paths was associated with a component (i.e., composite factor score) that demonstrated a reliable relationship with the number of OEs in the ZID sectors. A similar factor (several traffic flows converging at the same point) was among the top-rated complexity factors in an investigation of Maastricht airspace conducted by Eurocontrol (2006). The Number of Intersecting Flight Paths is the maximum number of flight paths that might be expected to intersect, irrespective of altitude, within a 10-minute projected time frame given the current speed and trajectory of the aircraft. Projections were calculated at each 12-second radar update within each minute of data. The length and slope of the projected paths were based on the distance and angle of the current and previous radar position coordinates.

Number of Point Outs. Coordination between controllers was one of the events selected by Schmidt (1976) for his Control Difficulty Index even though he considered it to be one of the most difficult to process – with good reason. Coordination is not often recorded. However, point out entries represent one of the few instances in which coordination between sectors is recorded. The Number of Point Outs is the total number of point out entries made by the Radar and Radar Associate controllers during the 5-minute processing interval.

Number of Transitioning Aircraft. The amount of climbing and descending traffic has long been recognized as a contributor to the difficulty of working a sector (e.g., Arad, 1964). Grossberg (1989) observed that one of the factors most often identified as being responsible for sector complexity in the Chicago ARTCC was climbing and descending flight paths. More recently, Kopardekar and Magyarits (2003) found that the number of descending aircraft and the number of altitude changes greater than 750 feet per minute both contributed significantly to the explanation of variance in a linear regression model of subjective complexity ratings collected at the Fort Worth, Atlanta, Cleveland, and Denver ARTCCs. The Number of Transitioning Aircraft represents the number of aircraft making one or more altitude changes during the 5-minute processing interval. To be counted as a change, altitude must increase or decrease by a minimum of 200 feet per 12-second radar update and must continue to change in the same direction for at least three updates. Altitude changes resulting from last-minute clearances made in an attempt to avoid the OE were excluded from counts for the OE sample. The criteria for these exclusions are described in the Method section.

Exclusion of Static Predictor Variables

Sector complexity factors are generally described in two ways: static and dynamic (Mogford, Guttman, Morrow, & Kopardekar, 1995). The predictor variables just described represent dynamic sector characteristics because they change over time. Static sector characteristics are those that change infrequently or not at all and are generally related to airspace design (e.g., size of the sector, number of shelves or tunnels). Static sector characteristics may vary between sectors, but they do not vary within sectors. Consequently, the variance of static variables would be seriously limited in the present study because multiple OEs occurred in many of the same sectors in the sample. Even if static sector characteristics were related to OEs, it is unlikely this relationship would be detected. For this reason, predictors were restricted to dynamic sector characteristics. These were submitted to logistic regression analysis to determine the degree to which they could discriminate between OE and RO traffic samples.

Method

Data Sources

Traffic Samples. All traffic samples were initially derived from System Analysis Recordings (SARs) generated by en route Host Computer Systems. The Host features data reduction programs that generate text reports of selected subsets of SAR data. The information used to calculate the predictor variables was extracted from Log and Track reports produced by one of these programs, the Data Analysis and Reduction Tool (DART). Log reports include controller entries and information sent to the radar display and the auxiliary text display (e.g., data blocks and list items). Track reports contain detailed information (e.g., altitude, heading, ground speed, and position) from the Host computer's internal radar track database.

OE traffic samples were derived from Systematic Air Traffic Operations Research Initiative (SATORI; Rodgers & Duke, 1993) files. SATORI files contain reconfigured DART information (i.e., log and track reports in a slightly different format). SAR data are difficult to obtain from facilities because they require a prohibitive amount of storage space. SATORI re-creations require less space and so these files are often the only traffic data saved after an OE. Therefore, the primary constraint on the size and range of the data set was the availability of SATORI re-creations. SATORI data meeting processing criteria (i.e., five minutes prior to the initial loss of separation) were only available for 119 OEs occurring in the ZID airspace from 9/17/2001 through 12/10/2003. OE traffic samples from 2003 (n = 48) were used for model building, and the remaining OE traffic samples (n = 71) were used for cross validation.

The RO traffic samples were derived from ZID SAR data recorded on 5/8/2003 (15:55 to 17:05, 18:55 to 20:10, and 20:50 to 22:15 ZULU), 5/9/2003 (0:00 to 1:10 ZULU), and 5/10/2003 (11:20 to 12:40 ZULU). DART log and track text reports were first encoded into database files and then processed in 5-minute intervals using custom software designed to calculate objective measures from routinely recorded NAS data. This produced a total of 2644 RO traffic samples. A randomly-selected set (n = 48) were used for model building, and the remaining samples (n = 2596) were set aside for cross validation. Random selection was accomplished by first sorting traffic samples by date, time, and sector number, then assigning each sample a random number (generated by the Microsoft Excel RAND function), and then resorting the samples according to this value. The first 48 cases (equal to the number of OE samples) were assigned to the model-building sample. A list of the ZID sectors and the number of associated traffic samples in the model-building and cross-validation samples is provided in Table A1 of Appendix A.

In the model-building sample, the number of samples in the RO and OE groups is equivalent. This is important because widely disparate group size produces logistic regression models that favor (i.e., over-represent) the largest group. Equal group size also ensures that classification accuracy in excess of 50% represents improvement over chance. On the other hand, group size does not matter in the cross-validation sample because these cases are not used to build the model. The existing model is simply being *applied* to the sample.

Transitioning Aircraft and Heading Change Adjustments

Altitude and heading changes made in an attempt to avoid an imminent OE were excluded from the analysis using summary incident narratives from the Operational Error Investigation form and lists of computer-detected changes. The summary incident narratives described events leading up to the loss of separation. The lists included the aircraft identifier, start time, stop time, and direction of all computer-detected altitude and heading changes used in the calculation of the Number of Transitioning Aircraft and Number of Heading Changes.

The time at which the controller became aware of a potential OE and any action taken to avoid loss of separation were usually described in the narrative. The time and content of the clearances obtained from the narrative were then compared with the list of computer-detected changes for the OE traffic sample. If the listed clearance matched one of the changes (i.e., matched by aircraft identifier, time, and direction), it was marked for exclusion. In the event that the controller was not aware that an OE was about to occur or the clearance information was not contained in the narrative, all altitude and heading changes occurring after the conflict alert warning (i.e., the alert just prior to the loss of separation) were marked for exclusion. The exclusions were then subtracted from the summary measures (i.e., Number of Transitioning Aircraft and Number of Heading Changes). Altitude changes were evaluated by aircraft rather than tabulated changes. The value of the Number of Transitioning Aircraft remained unaltered if an aircraft with one excluded altitude change had other changes not associated with an OE. If an aircraft made only one change or all altitude changes were associated with the OE, then the aircraft was subtracted from the total value of the Number of Transitioning Aircraft.

Results

Preliminary Logistic Regression Analysis

Stepwise elimination was employed because such methods are extremely valuable in the exploratory stages of research when the focus is on identifying predictors. Backward elimination was used for selection because it is less prone to omit useful variables, since all variables are in the model at the beginning of the process (Menard, 1995). The likelihood-ratio test, which compares the fit of the model with and without each predictor at every step, was the selection criterion used because it is more rigorous than other methods (Norušis, 1990; Pampel, 2000; Tabachnick & Fidell, 2006). Hosmer and Lemeshow (2000) recommend using criterion levels as high as .15 or .20 to ensure that all relevant variables are included in the logistic regression model. However, a more conservative criterion level of .10 was used in this analysis.

Descriptive statistics for the model-building sample are shown in Table 1. Descriptive statistics for the cross-validation sample are shown in Table 2. It is clear that several of the variables were not normally distributed. In the model-building sample, the distribution of the Number of Point Outs differed from normal by nearly 10 standard deviations in skewness and 14 standard deviations in kurtosis. The Number of Intersecting Flight Paths deviated by 14 standard deviations in skewness and by more than 40 standard deviations in kurtosis. In the cross-validation sample, departures from normality in skewness ranged from 13 (Average Control Duration) to more than 91 (Number of Point Outs) standard deviations. Departures from normality in kurtosis ranged from just under 4 (Number of Transitioning Aircraft)

Table 1. ***Descriptive Statistics: Model-building Sample (N* = 96*)***

Variable	Mean	*SD*	Skew.[1]	Kurtosis[2]
Average Control Duration (seconds)	182.05	50.91	-1.19	2.09
Number of Handoffs	4.54	3.05	.72	.02
Number of Heading Changes	2.19	2.19	1.27	1.28
Number of Intersecting Flight Paths	.56	.97	3.54	19.67
Number of Point Outs	1.13	1.76	2.44	6.67
Number of Transitioning Aircraft	3.54	2.29	.54	-.27

[1]*SE Skewness* = .246; [2]*SE Kurtosis* = .488

Table 2. ***Descriptive Statistics: Cross-validation Sample (N = 2667)***

Variable	Mean	*SD*	Skew.[1]	Kurtosis[2]
Average Control Duration (seconds)	173.13	53.60	-.63	.90
Number of Handoffs	3.75	2.70	1.01	1.82
Number of Heading Changes	1.45	1.57	1.58	3.77
Number of Intersecting Flight Paths	.26	.52	2.10	5.18
Number of Point Outs	.87	1.59	4.32	34.39
Number of Transitioning Aircraft	2.95	2.23	.80	.36

[1]*SE Skewness* = .047; [2]*SE Kurtosis* = .095

Table 3. ***Correlation* Matrix: Model-building Sample (N = 96)***

		1	2	3	4	5
1	Average Control Duration					
2	Number of Handoffs	-.29**				
3	Number of Heading Changes	.23*	.33**			
4	Number of Intersecting Flight Paths	.40**	.26*	.56**		
5	Number of Point Outs	.07	.08	.22	.17	
6	Number of Transitioning Aircraft	.03	.38**	.58**	.38**	.22*

* Spearman's rho; ***p* < .01; **p* < .05

Table 4. ***Correlation* Matrix: Cross-validation Sample (N = 2667)***

		1	2	3	4	5
1	Average Control Duration					
2	Number of Handoffs	-.10**				
3	Number of Heading Changes	.26**	.29**			
4	Number of Intersecting Flight Paths	.27**	.26**	.33**		
5	Number of Point Outs	.06**	.23**	.26**	.19**	
6	Number of Transitioning Aircraft	.13**	.42**	.45**	.33**	.23**

* Spearman's rho; ***p* < .01; **p* < .05

to more than 362 (Number of Point Outs) standard deviations. Beyond theoretical issues surrounding the use of frequency data in parametric statistics, such extreme departures from normality confirm the choice of a non-parametric statistic.

Though logistic regression is a "distribution-free" statistic, it is not assumption free. As with other forms of regression, multicollinearity among the predictors can lead to biased estimates (Menard, 1995). None of the Spearman's correlation coefficients shown in Table 3 are of sufficient magnitude to suggest multicollinearity in the predictor set. Tolerance values were >.45 for all predictors, far in excess of the <.20 that would indicate multicollinearity. Correlations of the predictors in the cross-validation sample are shown in Table 4. Although all of the coefficients are statistically significant (no doubt due to the size of the sample), the pattern of associations is similar to that of the model-building sample.

The Model χ^2 represents the difference between the -2 log likelihood for the model containing the predictor variables and that of the model with the constant only. Thus, the Model χ^2 is analogous to the overall F in linear regression because it tests the null hypothesis that the coefficients for all predictors in the model equal zero (Norušis, 1990). The final logistic regression model for this sample generated a Model $\chi^2(3, N=96) = 51.67$, $p <.01$, indicating significantly improved prediction over the model with the constant only. The Hosmer-Lemeshow Test is a particularly robust measure of fit. Cases are divided into deciles of predicted probabilities, and then observed and expected probabilities are compared within each decile. As with most goodness-of-fit measures, a non-significant result is desirable. The Hosmer-Lemeshow $\chi^2 (7, N=96) = 6.10$, $p =.53$ for this sample indicated that the model fit the data reasonably well.

Table 5. ***Logistic Regression Summary (N = 96)***

Variable	*B*	*S.E.*	Odds	95% CI		*p*
Number of Intersecting Flight Paths	1.60	.50	4.94	1.86	13.12	.000
Number of Heading Changes	.46	.21	1.58	1.05	2.37	.019
Number of Handoffs	.25	.11	1.28	1.03	1.59	.019
Constant	-3.10	.71	.05			

Table 6. ***Classification: Model-building Sample (N = 96)***

Observed	Predicted: Routine Operation	Predicted: Operational Error	Total
Routine Operation	41 (85%)	7 (15%)	48
Operational Error	14 (29%)	34 (71%)	48

Table 7. ***Classification: Cross-validation Sample (N = 2667)***

Observed	Predicted: Routine Operation	Predicted: Operational Error	Total
Routine Operation	1829 (71%)	767 (29%)	2596
Operational Error	20 (28%)	51 (72%)	71

Logistic regression coefficients (*B*), standard errors, estimated odds ratios (Odds), 95% confidence intervals for the odds ratios (95% CI), and significance values for the likelihood-ratio tests are provided in Table 5. Note that neither the logistic regression coefficients nor standard errors are inflated. The absence of large coefficients indicates a sufficient ratio of cases to predictors. Variables included in the model were the Number of Intersecting Flight Paths, the Number of Heading Changes, and the Number of Handoffs. In this sample, every one-unit increase in the Number of Intersecting Flight Paths increased the likelihood by a multiplicative factor of 4.94 (i.e., increased the odds by $e^{4.94}$). In other words, each intersecting flight path detected increased the likelihood that the traffic sample was an OE by 394%. Every heading change increased the likelihood by 58%, and each handoff increased the likelihood by 28% that a traffic sample was an OE.

Classification accuracy in the model-building sample is shown in Table 6. In this sample, 41 (85%) of the 48 ROs were correctly classified, and 7 (15%) were misclassified as OEs. Of the 48 OEs in the model-building sample, 34 (71%) were correctly classified and 14 (29%) were misclassified as ROs. Overall, classification reached 78% accuracy in the model-building sample. This represents 28% improvement over prior probabilities (i.e., the number that would be correctly classified by chance).

Classification accuracy in the cross-validation sample is shown in Table 7. Keep in mind that relative group size does not matter in the cross-validation sample because these cases are not being used to build the model. The existing model is simply being *applied* to the sample. Of the ROs in the cross-validation sample, 1829 (71%) were correctly classified and 767 (29%) were misclassified as OEs. Of the OEs in the cross-validation sample, 51 (72%) were correctly classified and 20 (28%) were misclassified as ROs. Overall classification accuracy was 71% in the cross-validation sample.

Although the loss of classification accuracy when the model was applied to the RO samples was somewhat disappointing, the question of whether the samples were similar enough for pooling applied only to the OE samples. The similarity between classification accuracy for the model-building (71%) and cross-validation (72%) OE samples suggested they were homogenous enough to justify pooling for separate logistic regression analyses of the low- and high-altitude sectors.

In the pooled sample of OEs, 40 occurred in the low-altitude sectors and 79 occurred in the high-altitude sectors. The 40 low-altitude OE traffic samples were combined with 40 randomly-selected low-altitude RO traffic samples to produce a total of 80 traffic samples for the low-altitude sector analysis. The 79 high-altitude OE traffic samples were combined with 79 randomly-selected high-altitude RO traffic samples to produce a total of 158 traffic samples for the high-altitude sector analysis. Backward stepwise elimination using the likelihood-ratio test as selection criterion (p =.10) was employed for both the low- and high-altitude sector logistic regression analyses. Appendix A contains a list of the ZID sectors and the number of low-altitude (Table A2) and high-altitude (Table A3) traffic samples associated with each.

Logistic Regression Analysis: Low-Altitude Sectors

As shown in Table 8, the Number of Heading Changes is highly correlated with both the Number of Intersecting Flight Paths (r_s=.62) and the Number of Transitioning Aircraft (r_s=.68). The association between Number of Transitioning Aircraft and the Number of Handoffs (r_s=.61) is also of sufficient magnitude for concern. Nevertheless, Tolerance values were > .40 for all predictors, indicating there is no reason to suspect bias due to multicollinearity in the low-altitude sector sample.

The logistic regression model for the low-altitude sample generated a Model $\chi^2(3, N=80) = 23.82$, $p < .01$, indicating significantly improved prediction over the model with the constant only. The non-significant Hosmer-Lemeshow χ^2 $(8, N=80) = 1.61$, $p=.99$ for the low-altitude sample signifies that the model fit the data well. Logistic regression coefficients (B), standard errors, estimated odds ratios (Odds), 95% confidence intervals for the odds ratios (95% CI), and significance values for the likelihood-ratio tests for the low-altitude sector sample are provided in Table 9. As with the full sample, neither the logistic regression coefficients nor standard errors are inflated, indicating a sufficient ratio of cases to predictors.

In the low-altitude sample model, the Number of Intersecting Flight Paths had the highest odds ratio (2.89), followed by the Number of Point Outs (1.57), and the Number of Handoffs (1.19). In other words, each intersecting flight path increased the likelihood that the traffic sample was an OE by 189%, each point out increased the likelihood by 57%, and each handoff increased OE likelihood by 19%. However, the confidence intervals for the Number of Point Outs and the Number of Handoffs suggest that the parameter estimates for these predictors might not generalize to another sample.

Classification accuracy in the low-altitude sample (Table 10) was similar to that of the combined sample. Of the 40 ROs in the low-altitude sample, 32 (80%) were correctly classified and 8 (20%) were misclassified as OEs. Of the 40 OEs in the sample, 28 (70%) were correctly classified and 12 (30%) were misclassified as ROs. Overall, the low-altitude model had 75% classification accuracy.

Logistic Regression Analysis: High-Altitude Sectors

Although several of the Spearman's correlations shown in Table 11 are statistically significant, none of coefficients are of sufficient magnitude to suggest multicollinearity. Accordingly, Tolerance values were high (.56 and above) for all predictors in this sample.

The logistic regression model for the high-altitude sample generated a Model $\chi^2(4, N=158) = 73.01$, $p < .01$, indicating significantly improved prediction over the model with the constant only. The non-significant Hosmer-Lemeshow χ^2 $(8, N=158) = 3.33$, $p=.91$ for the high-altitude sample verified that the model fit the data. Logistic regression coefficients (B), standard errors, estimated odds ratios (Odds), 95% confidence intervals for the odds ratios (95% CI), and significance values for the likelihood-ratio tests for the high-altitude sector sample are provided in Table 12. As with the full sample, neither the logistic regression coefficients nor standard errors are inordinately large, indicating a sufficient ratio of cases to predictors.

In the high-altitude sample model, the Number of Intersecting Flight Paths had the highest odds ratio (2.00), followed by the Number of Heading Changes (1.36), the Number of Transitioning Aircraft (1.27), and Average Control Duration (1.01). In other words, each one-unit increase in the Number of Intersecting Flight Paths increased the likelihood that a traffic sample was

Table 8. ***Correlation*** [*] ***Matrix: Low-Altitude Sectors (N = 80)***

		1	2	3	4	5
1	Average Control Duration					
2	Number of Handoffs	-.27*				
3	Number of Heading Changes	.21	.40**			
4	Number of Intersecting Flight Paths	.33**	.32**	.62**		
5	Number of Point Outs	-.14	.17	.25*	.06	
6	Number of Transitioning Aircraft	.22	.61**	.68**	.56**	.08

[*] Spearman's rho; ** $p < .01$; * $p < .05$

Table 9. ***Logistic Regression Summary: Low-Altitude Sectors (N = 80)***

Variable	*B*	*S.E.*	Odds	95% CI		*p*
Number of Intersecting Flight Paths	1.06	.36	2.89	1.43	5.83	.00
Number of Point Outs	.45	.24	1.57	.98	2.52	.04
Number of Handoffs	.17	.11	1.19	.97	1.46	.10
Constant	-1.94	.57	.14			

Table 10. ***Classification: Low-Altitude Sectors (N = 80)***

		Predicted		
		Routine Operation	Operational Error	Total
Observed	Routine Operation	32 (80%)	8 (20%)	40
	Operational Error	12 (30%)	28 (70%)	40

Table 11. ***Correlation[a] Matrix: High-Altitude Sectors (N = 158)***

		1	2	3	4	5
1	Average Control Duration					
2	Number of Handoffs	-.14				
3	Number of Heading Changes	.36**	.42**			
4	Number of Intersecting Flight Paths	.49**	.22**	.51**		
5	Number of Point Outs	.11	.24**	.21**	.24**	
6	Number of Transitioning Aircraft	.16*	.43**	.53**	.39**	.19*

[a] Spearman's rho; ***p* < .01; **p* < .05

Table 12. ***Logistic Regression Summary: High-Altitude Sectors (N = 158)***

Variable	*B*	*S.E.*	Odds	95% CI		*p*
Number of Intersecting Flight Paths	.69	.28	2.00	1.16	3.45	.01
Number of Heading Changes	.31	.15	1.36	1.01	1.83	.03
Number of Transitioning Aircraft	.24	.11	1.27	1.03	1.57	.02
Average Control Duration	.01	.01	1.01	1.00	1.03	.01
Constant	-4.43	1.11	.01			

Table 13. ***Classification: High-Altitude Sectors (N = 158)***

Observed	Predicted: Routine Operation	Predicted: Operational Error	Total
Routine Operation	64 (81%)	15 (19%)	79
Operational Error	19 (24%)	60 (76%)	79

an OE by 100%, each one-unit increase in the Number of Heading Changes increased the likelihood by 36%, every Transitioning Aircraft increased the likelihood by 27%, and each one-second increase in Average Control Duration increased the likelihood by 1%.

Classification accuracy in the high-altitude sample (Table 13) was slightly better than that of the low-altitude sample. Of the 79 ROs in the high-altitude sample, 64 (81%) were correctly classified and 15 (19%) were misclassified as OEs. Of the 79 OEs in the sample, 60 (76%) were correctly classified, and 19 (24%) were misclassified as ROs. Overall, the high-altitude model had 79% classification accuracy. This represents a 29% improvement over prior probabilities (i.e., the number that would be correctly classified by chance).

Discussion

The results of the logistic regression analyses indicate that a sufficient model may be constructed from sector characteristics variables. Overall classification accuracy between 75-79% is remarkable for models constructed solely of environmental and contextual factors. After all, other factors (e.g., human elements, organizational influences) also contribute to the occurrence of OEs. Unfortunately, all the logistic regression models were better at classifying ROs than OEs. Classification of OEs ranged from as low as 70% in the low-altitude sector sample to 76% in the high-altitude sample. Although this level of accuracy would be unacceptable for most automation tools, it is unrealistic to expect definitive results from one or two analyses. Moreover, the sector characteristic variables used in these analyses do not represent an exhaustive list of all the potential predictors of OEs.

One of the most unexpected findings was the uniqueness of the preliminary analysis model. The Number of Handoffs had an odds ratio of 1.28, and yet this variable failed to demonstrate a similar level of influence in the low-altitude model and was conspicuously absent from the high-altitude model. The relative influence of the Number of Handoffs when low- and high-altitude sectors were combined is either an indictment of the use of regression techniques in general (i.e., they tend to capitalize on the unique characteristics of the sample) or an indication that traffic count becomes more salient as the level of analysis changes. Most dynamic variables correlate, to a greater or lesser degree, with traffic count. Therefore, traffic count may emerge as unique characteristics of the low- and high-altitude sectors are obscured. That traffic count remains the single best predictor of OEs at the national level, yet fails to predict well at the sector level, may be an example of this phenomenon. Consequently, differences between the low-altitude, high-altitude, and combined models might have implications for the suitability of applying policies based on evaluations made at the national level at the sector level.

Low-Altitude Sector Model

The most influential variable in the low-altitude sector model was the Number of Intersecting Flight Paths (Odds = 2.89), followed by the Number of Point Outs, and the Number of Handoffs (Odds = 1.19). Aside from the addition of the Number of Intersecting Flight Paths, this model was similar to the low-altitude sector model in Pfleiderer and Manning (2007). In the previous study, the most influential predictor was the Number of Point Outs (Odds = 3.30), followed by the Number of Handoffs (Odds = 1.54), and the Number of Heading Changes (Odds = 1.49). Doubts about the validity of the Number of Heading Changes as a genuine predictor in the previous study were due to concerns that much of its effect in the low-altitude model was related to clearances made in an attempt to resolve the OE. As anticipated, the Number of Heading Changes was not included in the low-altitude sector model once this variable was adjusted. Both the Number of Point Outs and the Number of Handoffs lost a considerable amount of reliability, as evidenced by the range of the confidence intervals. On the other hand, the fact that the Number of Point Outs and the Number of Handoffs were also included in the previous model (based on a completely different sample of ROs) somewhat belies the contention that these parameter estimates might not generalize to another sample.

On the whole, classification accuracy in the low-altitude samples was inferior to that of the previous study. Although classification of the RO samples was improved (80% as opposed to 77% in the previous analysis), OE classification was not. The current model, as compared to 82% accurate classification in the previous analysis, accurately classified only 70% of the OE samples.

The predictive strength of the Number of Point Outs and the Number of Handoffs in the Pfleiderer and Manning (2007) results suggested that coordination played a primary role in the development of OEs in the ZID low-altitude sectors. This impression was bolstered by the Pfleiderer et al. (2007) data, in which controllers and supervisors at ZID rated coordination as one of the primary sources of complexity in low-altitude sectors. Consequently, the emergence of the Number of Intersecting Flight Paths as the most influential predictor in the current low-altitude logistic regression model was surprising, because controller and supervisor ratings for this complexity factor were moderate in the low-altitude sectors. The results of the logistic regression analysis suggest that coordination may be a contributing factor, but converging traffic patterns might be of greater consequence.

High-Altitude Sector Model

The Number of Intersecting Flight Paths was the most influential predictor in the high-altitude sector model (Odds = 2.00), followed by the Number of Heading Changes. As anticipated, there was a reduction in the relative influence of the Number of Heading Changes after adjustments were made to exclude changes made in response to clearances to avoid an imminent OE (i.e., the estimated odds ratio was reduced from 2.28 in the previous study to 1.36 in the present study). Nevertheless, it remained a significant predictor in the high-altitude model. Other elements of the model were nearly identical to those of Pfleiderer and Manning (2007). The Number of Transitioning Aircraft had an estimated odds ratio of 1.26 in the previous study and increased to 1.27 in the present one. Average Control Duration had an estimated odds ratio of 1.02 in the previous study and decreased to 1.01 in the present one. Classification accuracy in the high-altitude sample was also relatively consistent between the two studies. Both models correctly classified 81% of the ROs. However, 79% of the OEs were correctly classified in the previous analysis, whereas only 76% were correctly classified in this one.

The influence of the Number of Intersecting Flight Paths was no surprise in this sample, because ZID controllers and supervisors rated this complexity factor one of the most influential in the high- and super high-altitude sectors (Pfleiderer et al., 2007). The Number of Heading Changes remained influential, despite changes to the processing interval and adjustments to the variable itself. This is consistent with Laudeman et al. (1998), in which heading changes received the highest beta weight in a linear multiple regression analysis of controller ratings of activity in four sectors at the Denver ARTCC. In their discussion, the authors attributed the influence of heading changes to the "significant arrival traffic in all the sectors that were observed" (p. 7). Arrival and departure traffic complexity is generally considered to be a low-altitude phenomenon, but this perception may be inaccurate. In the present study, the Number of Heading Changes was extremely influential in the high-altitude model but failed to be included in the low-altitude sector model.

The third most influential factor in the high-altitude logistic regression analysis was the Number of Transitioning Aircraft. Climbing and descending traffic has long been recognized as a contributor to the difficulty of working a sector (e.g., Arad, 1964; Grossberg, 1989; Kopardekar & Magyarits, 2003). This finding is also consistent with Pfleiderer et al. (2007), in which the complexity factor Climbing and Descending Traffic received the highest complexity rating for the high-and super high-altitude sectors.

The fourth variable included in the high-altitude sample model was Average Control Duration. Odds ratios in logistic regression are an indication of effect size. The closer the odds are to zero, the smaller the effect size. Consequently, a 1.01 odds ratio suggests that the effect for Average Control Duration is small. However, it is important to remember that logistic regression coefficients (i.e., the natural logs of the odds ratios) are not standardized. Average Control Duration is based on the number of *seconds* each aircraft was controlled by the sector. Thus, a minimal change in Average Control Duration produced a relatively large 1% change in the likelihood that a traffic sample was an OE.

Future Research

Although logistic regression cannot be used to identify causal factors directly (i.e., prediction is not the same as causation), the logistic regression coefficients do provide information about the *likelihood* of an OE relative to the predictors in the model. Thus, the results have immediate heuristic value in that they invite questions about how the dynamic predictors interact with static sector characteristics. Dynamic elements lend themselves to automation applications, but static characteristics must be addressed by sector restructuring. The dynamic predictors that make up the logistic regression models are indicants of conditions that discriminate between OEs and ROs.

These indicants may be used to reveal aspects of the sector environment that might be altered to reduce the number of OEs. For example, the combination of the Number of Point Outs and the Number of Handoffs in the low-altitude sector model may indicate that the location of sector boundaries increases coordination workload and complexity. As Couluris and Schmidt (1973) observed, handoffs and point outs "result from, or are influenced by, the existence and design (shape) of the sectors" (p. 657). On the other hand, the combination of the Number of Point Outs and the Number of Intersecting Flight Paths may point to problems with the orientation of traffic paths relative to those boundaries. The combination of the Number of Heading Changes and the Number of Transitioning Aircraft in the high-altitude sectors is suggestive of traffic complexity in high-altitude sectors adjacent to low-altitude arrival or departure sectors. Average Control Duration as a predictor of OEs may be a function of the size of high-altitude sectors.

Because of the research that remains to be accomplished, these results must be viewed as preliminary. Given the sample size and consequent restriction of the predictor set, there is no guarantee that these results will generalize to other samples. Multiple studies, with samples sizes that allow for a more inclusive list of predictors, must be conducted at a number of facilities before such models might be reliable enough for practical applications. Nevertheless, the methodology of comparing OE and RO traffic samples is promising. Continued investigations along these lines may highlight complexity factors that must be addressed to ensure that separation is maintained.

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Table A1. *Model-building and Cross-validation Samples*

Sector Number	Sector Name	Sector Strata	Number of Associated Traffic Samples			
			Model-building Sample		Cross-validation Sample	
			Routine Operation	Operational Error	Routine Operation	Operational Error
18	Nabb	LO	2	3	71	4
19	New Hope	LO	1	2	75	1
20	Lexington	LO	2	3	43	1
21	London	LO	3	0	73	1
24	Parkersburg	LO	0	0	76	1
25	Hazard	LO	0	1	60	0
26	River	LO	1	1	74	1
30	Columbus	LO	0	2	76	2
31	Lytle	LO	0	1	75	3
32	Rosewood	LO	0	1	70	1
33	Muncie	LO	3	0	73	1
34	Shelbyville	LO	3	1	73	3
35	Terre Haute	LO	0	0	62	3
66	Madison	HI	1	3	75	3
69	Pike	LO	2	1	74	2
76	Batesville	SH	2	0	63	1
78	Springfield	HI (IM)	1	1	75	1
79	Bobcat	HI (IH)	0	4	73	1
80	King	HI	1	1	73	2
81	Pocket City	HI	3	1	72	3
82	Louisville	HI	2	3	72	5
83	Falmouth	HI	3	1	74	1
84	Rebel	HI	2	0	74	0
85	Charleston	HI	2	1	74	4
86	Beckley	HI	1	3	75	2
87	Appleton	HI	3	3	73	2
88	Dayton	HI	2	2	72	6
89	Indianapolis	HI	1	2	75	5
91	Impel	SH	1	2	62	1
92	Mystic	SH	1	1	51	2
93	Dacos	SH	1	0	75	2
94	Somerset	SH	0	0	74	2
95	Henderson	SH	0	2	76	1
96	Bluefield	SH	0	1	74	0
97	Lockbourne	SH	3	0	73	1
98	Patterson	SH	1	0	48	0
99	Wabash	SH	0	1	68	2
		TOTAL	48	48	2596	71

Table A2. *Low-Altitude Sector Sample*

Sector Number	Sector Name	Sector Strata	Number of Associated Traffic Samples	
			Routine Operation	Operational Error
18	Nabb	LO	0	7
19	New Hope	LO	4	3
20	Lexington	LO	1	4
21	London	LO	2	1
24	Parkersburg	LO	4	1
25	Hazard	LO	2	1
26	River	LO	2	2
30	Columbus	LO	3	4
31	Lytle	LO	4	4
32	Rosewood	LO	3	2
33	Muncie	LO	0	1
34	Shelbyville	LO	2	4
35	Terre Haute	LO	6	3
69	Pike	LO	7	3
		TOTAL	40	40

Table A3. *High-Altitude Sector Sample*

Sector Number	Sector Name	Sector Strata	Number of Associated Traffic Samples	
			Routine Operation	Operational Error
66	Madison	HI	6	6
76	Batesville	SH	3	1
78	Springfield	HI (IM)	5	2
79	Bobcat	HI (IH)	5	5
80	King	HI	4	3
81	Pocket City	HI	1	4
82	Louisville	HI	2	8
83	Falmouth	HI	1	2
84	Rebel	HI	4	0
85	Charleston	HI	1	5
86	Beckley	HI	1	5
87	Appleton	HI	4	5
88	Dayton	HI	3	8
89	Indianapolis	HI	2	7
91	Impel	SH	2	3
92	Mystic	SH	3	3
93	Dacos	SH	6	2
94	Somerset	SH	3	2
95	Henderson	SH	6	3
96	Bluefield	SH	7	1
97	Lockbourne	SH	5	1
98	Patterson	SH	1	0
99	Wabash	SH	4	3
		TOTAL	79	79