THE LINK BETWEEN OPERATIONAL PERFORMANCE AND OPERATIONAL ERRORS IN THE NATIONAL AIRSPACE SYSTEM

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Abstract

We consider the link between the incidence of operational errors (OEs), operations counts, operational conditions, and weather in the US National Airspace System (NAS). Our main aim is to test the hypothesis--suggested by the human factors literature linking cognitive tasks and human error--that adverse operating conditions lead to higher rates of OEs. Poisson regression estimation results support this hypothesis in all three air traffic control domains—en route, tower, and TRACON. Our results also demonstrate that OEs increase supra-linearly with operations volume, that convective weather causes more TRACON and en route operational errors, that low visibility increases tower OEs, and that there are large facility fixed effects for TRACON and tower OEs. One implication of this research is that investments to improve operational performance of the NAS may also improve its safety performance.

1. Introduction

More than 90 percent of the operational errors—defined by FAA as "violations of separation standards that define minimum safe distances between aircraft, between aircraft and other physical structures, and between aircraft and otherwise restricted airspace* (*1*)"—that occur in the US Air Traffic Control system stem from human errors rather than equipment malfunction. The human factors literature, both general and aviation-specific, suggests a link between human error rates and the nature of tasks being performed. The character of air traffic control tasks may be affected by operating conditions, which in turn depend on weather conditions, traffic, and air traffic management actions such as Ground Delay Programs. The effects of these factors are reflected by operational performance measures. Our aim in this paper is to assess the relationship between the incidence of operational errors and daily indices of operational performance based on the Airline Service Quality Performance (ASQP) and Aviation System Performance Metrics (ASPM) data bases.

The remainder of this paper is organized as follows: section 2 of this paper reviews past literature on the relationship between human performance and human error, particularly in the aviation domain; in section 3, we discuss the relationship between NAS operational performance and operational errors in the context of human factors; section 4 presents the general methodology that we used in this study; sections 5, 6, and 7 detail the models, estimation results, and their interpretation; the final section concludes the study.

*According to the event location, OEs are categorized into En Route, TRACON, and Tower OEs. Air Route Traffic Control Centers (ARTCCs) provide services for the en route phase of flights, generally above 10,000 feet. The required minimum horizontal separation is 5 miles, and vertical separation is 2,000 feet for the airspace above 29,000 feet and 1,000 feet for below. Terminal Radar Approach Control (TRACON) provides approach control services within about 5 to 40 nautical miles of an airport. The in-trial separation is mandated to be more than 4, 5, or 6 miles for different TRACONs. Control Towers (Towers) provide services within 5 nautical miles of an airport. The obligatory vertical separation is 1000 feet and the horizontal separation is 2.5 or 3 miles depending on the runway configurations. It is also considered to be an OE whenever the runway is blocked by obstacle when flights need to take off or land. TRACON and Tower facilities can be referred to as Terminals and some TRACON and Tower are co-allocated in one facility.

2. Literature Review

2.1 Human Performance and Human Error

According to Danaher, more than 90 percent of all the Air Traffic Control system errors that do occur stem from human errors rather than equipment malfunction (*2*). Thus any analysis of the OE rates must be informed by knowledge of the phenomenon of human error.

To study human error, it is useful to start by classifying tasks in which errors may occur. One widely recognized classification scheme is Rasmussen's Skill-Rule-Knowledge framework, originally raised in 1974 (*3*). He classified human tasks according to their level of cognitive demand as skill-based (SB), rule-based (RB), and knowledge-based (KB). Reason (*4, p43*) described human performance and human errors at Rasmussen's three levels:

> "*At the SB level, human performance is governed by stored patterns of preprogrammed instructions represented as analogue structures in a time-space domain. Errors at this level are related to the intrinsic variability of force, space or time coordination.*
>
> *The RB level is applicable to tackling familiar problems in which solutions are governed by stored rules. Errors are typically associated with the misclassification of situations leading to the application of the wrong rule or with the incorrect recall of procedures.*
>
> *The KB level comes into play in novel situations for which actions must be planned on-line, using conscious analytical processes and stored knowledge. Errors at this level arise from resource limitations and incomplete or incorrect knowledge*."

The analysis of human tasks and errors can be understood in the context of a more complete model of human performance. Reason (*4*) encapsulated it into three main phases: evaluation, goal-setting, and execution, while Bea represented it in more detail to seven stages of action. The seven stages are defined as following: perceptions of the state of the world, interpretation of perceptions, evaluation of perceptions, goal setting and selection, form intentions to act, develop actions sequence, and execute action sequences (*5*). Bea also charted a ladder figure (Figure 1) to explain their connections. Different performance levels are associated with "shortcuts". In RB performance there is a shortcut between evaluation of perceptions and forming intentions to act, while in SB performance interpretations of perception lead directly to developing actions sequences. Bea pointed out that with increasing expertise, higher level performance modes shift toward lower levels, reducing workload: "Only knowledge-based performance requires plan/goal formulation, which provides a further conservation of attentive resources (*5*)."

The research results of Watson (*6*) and Dougherty and Collins (*7*) showed that the SB performance level permits the greatest human reliability. They calculated the error probability for each level by studying task performance in diverse types of human operations. The KB performance is the most cognitively demanding level, which has the highest error probability about 1×10^{-2} to 1 per task. The error probability of SB is the lowest, falling into the range of 5×10^{-5} to 5×10^{-3} per task. The error probability of RB is in between, at about 5×10^{-4} to 5×10^{-2} per task.

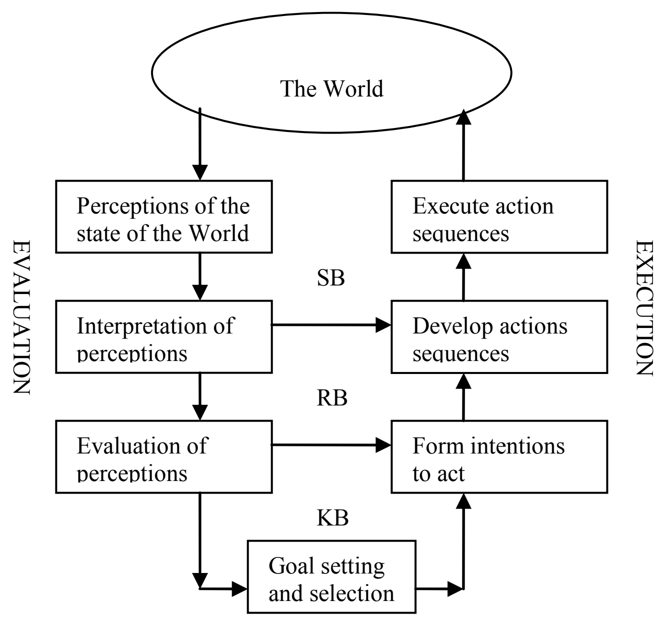

FIGURE 1 Seven stages of human actions (From Bea 2001)

2.2 Controller Operational Errors

An operational error (OE) takes place when an air traffic controller allows less than applicable minimum separation criteria between aircraft (or an aircraft and an obstruction—see note on page 1). There has been considerable research on operational errors.

Kinney et al. studied US OE data from 1974 to 1976 and found that most errors were reported under conditions of low to moderate workload (*8*). However, this is not the evidence that OEs are more likely to occur under such conditions, because these conditions are also far more prevalent in the NAS than high workload conditions. Traffic density is a generally acknowledged factor in controller workload analysis. Other traffic factors, identified by Laudeman et al. (*9*), include the number of aircraft heading, speed, and altitude changes; minimum Euclidean inter-aircraft distances, and predicted conflicts within 0-25, 25-40 or 40-70 nautical miles.

The research of Rodgers et al. (*10*) reveals that OEs were reported when sectors had a traffic volume significantly higher than normal. The controllers in high-OE sectors experience higher workload as a result of more problematic weather, higher radio frequency congestion, and higher traffic complexity. Rodgers et al. designed an experiment to isolate the air traffic conditions for operational errors by using the Systematic Air Traffic Operations Research Initiative (SATORI), which is a computer display and analysis system. Through it, the recorded data at an air traffic control facility was replayed and shown on a radar display during a specified period of time together with the occurrence of OEs. In addition, the voice recordings of the radio communications were provided so that the interviewed controllers could see and hear what happened then and there. The interviewed controllers were asked to describe their workload by ranking fifteen air traffic complexity factors. Then controller workload was calculated for OE occurrence periods and non-OE occurrence periods. The results suggested that the workload was much heavier when an OE occurred than two minutes beforehand

To study air traffic controller workload, Empson (*11*) applied a human error classification system to military air traffic controllers in the United Kingdom for two years. Two types of controllers, termed radar directors and radar approach controllers, were compared. Radar directors give heading and altitude instructions to the aircraft, keeping them separated and sequencing them onto the airfield. The task of the radar approach controller is to guide the landing or departure of the aircraft within a 30-mile radius of the airfield. Although the radar approach controllers handle twice as much traffic as the radar director, they made fewer errors than directors. Epson postulated that this is because the directors' job was more difficult, and also that directors were force paced and faced more time pressure.

3. Operational performance and Operational errors

We postulate that when NAS operational conditions degrade, there will be more RB and KB level tasks on the part of controllers, leading to more OEs. In regular conditions, most air traffic activity consists of flights following regular routes at regular times so air traffic controllers perform highly routinized tasks in familiar circumstances using skills acquired through intensive training and on-the-job experience. In these cases, controller performance is Skill-Based (SB). As conditions degrade, there is more deviation from the schedule and normal routes. For instance, under adverse weather conditions, the capacity of sectors affected by the weather condition is reduced; controller may encounter some circumstances that differ from regular days. In such cases, controllers must respond to more varied conditions, relying on a standardized rule database in their memory. Their performance in these cases involves selecting the appropriate rules from that database; it is therefore Rule-Based (RB) task increases. Even worse, controllers may have to make decisions in real time, according to their knowledge. In other words, more knowledge-based performance is possibly required compared to regular days. Based on the arguments from the previous section, we expect that as high cognitive level tasks increase, performance demands shift from SB to RB and KB, requiring more stages of processing, and hence result in increase of more error.

There is also reason to believe that degraded operating conditions increase the risk of SB slips as well as RB and KB mistakes by increasing controllers' workload. Non-normal operating conditions increase controllers' workload by forcing them to perform more communication and coordination. Mogford (*12*), based on interviews with controllers, found that the amount of radio frequency congestion is one of the factors determining the level of ATC complexity. Fowler (*13*) suggested that handoff coordination is an important determinant of ATC complexity. Although the hand offs have become silent, flight plan changes require more coordination between controller teams and communication between controllers and pilots. Schroeder and Nye (*14*), reviewing FAA's OE reports between 1985 and 1988, found evidence that communication and coordination factors are associated with OE incidents.

In summary, general human factors research, human factors studies of air traffic control, and specific studies of OEs suggest that operational conditions in the NAS may affect the occurrence of OEs through multiple causal sequences. The effect can be revealed by estimating mathematical models including weather, traffic and operational performance measures as explanatory factors of OEs.

4. Methodology

We investigate how operating conditions and other factors affect OEs using multivariate regression. We take the daily OE count as our dependent variable because we can treat each day as an independent observation, ignoring interrelationships whereby performance in one time period affects performance in some other period *(15)*. The Poisson model is used to analyze the daily OE count data. The Poisson distribution is appropriate for "small count" data, particularly when the counts involve infrequent events such as accidents, incidents, or OEs. Poisson and Negative Binomial regression has been applied extensively in transportation risk prediction and modeling (*16*). The primary difference between these methods is that Poisson regression assumes that the variance of the error is equal to the expected value, while Negative Binomial regression relaxes this assumption. Previous researchers suggested that the Poisson regression model should be used to establish the relationship between dependent variable and explanatory factors. If the results from the Poisson suggest that the assumption about error variance is incorrect, Negative Binomial regression models can be investigated. Therefore, we will focus on Poisson regression initially.

The probability density function (PDF) for the Poisson regression model of OEs is:

$$\mathrm{Prob}\,(\mathrm{Y_t} = \mathrm{y}) = \frac{\mathrm{e}^{-\lambda_t}\lambda_t^{\,y}}{\mathrm{y}!} \qquad (1)$$

where:

$\mathrm{Y_t}$ is a random variable corresponding to the observed number of operational errors at date t;

y is a possible value for $\mathrm{Y_t}$;

λ_t is the mean number of errors to be expected at date t.

The mean of the distribution, λ_t , is a function of certain explanatory variables x_{it} .

$$\lambda_t = e^{\alpha + \sum_i \beta_i x_{it}} \qquad (2)$$

where:

x_{it} is the i^th^ explanatory variable for date t.

α is an intercept capturing the general rate of incidence of operational errors;

β_i is the regression coefficient for explanatory variable i.

We estimate separate models for en route, TRACON, and tower OEs. We model en route OEs at the national level, since it is difficult to define operating conditions at a more disaggregate level. TRACON and tower OEs, in contrast, are analyzed at the facility level, because in these cases facility-level metrics for operating conditions are easily obtained. Our TRACON analysis considers only those facilities that serve the busiest airports, where the TRACON and tower are not co-located.

The OE data comes from the FAA Operational Error/Deviation Reporting System. Since 1985, the FAA has employed this system to investigate each operational error and maintained a database of the resulting reports. Information such as the location of the OE, separation between aircraft at the time of the error, date and time of error occurrence are included in the report. OEs are categorized into tower, TRACON, and en-route. Daily counts of OEs from 1997 to 2002 for the continental United Stated were used in this study. Only centers have an automatic OE reporting system. At other facilities, OE reporting is somewhat judgmental and may vary over time or across supervisors responsible for making the reports (*17*). Our models attempt to control systematic reporting differences by including fixed effects for time period and facility.

A second data source used for all of our OE models is daily counts of flight operations. We obtained these data from the Air Traffic Activity Data System (ATADS) database, maintained by the FAA Office of Aviation Policy and Plans (APO). The ATADS is the official source of the historical air traffic operations for center, airport, instrument and approach counts.

Other variables and associated data sources included in our analyses are OE-type-specific, and described in the following subsections.

5. En-route OEs

5.1 Operational Performance Metric (Daily Flight Time Index DFTI) and Weather Index

For our en route OE model, we use an operational performance metric based on Airline Service Quality Performance (ASQP) obtained from the FAA. These data include schedule and actual departure, arrival, and airborne times for all scheduled passenger flights of major U.S. airlines.

DFTI is defined as a weighted average of daily flight time from scheduled departure to actual arrival for selected city pairs *(15)*. The DFTI is the sum of four components: the origin departure delay index (DODI), the taxi-out time index (DTOI), the airborne time index (DABI), and the taxi-in time index (DTII). The weights used in the averaging are constructed to maintain day-to-day comparability in the event of changes in the city-pair distribution of flights. Also, by measuring times instead of delays directly, DFTI avoids distortions resulting from changes in schedule padding.

The DFTI used in this analysis is based on 776 city-pairs, each of which has at least one completed flight in each day for which the DFTI was computed. The index was computed for all but 33 days for the eight years from January 1, 1995 to December 31, 2002. In this study, only six years of data, from January 1, 1997 to December 31, 2002, are used to be consistent with the OE data. The 33 excluded days had low city-pair representation; excluding them allows a much larger number of city-pairs to be included in the DFTI. The weight for each city-pair is calculated based on its proportion of total flights for all 776 city-pairs over the 8-year period.

To create a weather metric for the en route model, we used a daily summary of weather information obtained from the National Climatic Data Center, called the Federal Climate Complex Global Surface Summary of Day (*18*). The data includes mean temperature, dew point, wind speed, precipitation amount, and indicators for occurrence of fog, rain/drizzle, snow/ice pellets, hail, thunderstorms, and tornado/funnel cloud for each of 8000 weather stations around the world, including about 1500 in the US. Using the latter, we calculated the daily proportion of stations reporting thunderstorms as weather index in our model.

5.2 Regression Results

We employ a log-linear specification for the daily en-route OE model with fixed effects for year and season. The model is thus:

$$\begin{aligned}\ln \lambda_t = {} & \alpha + \beta_0 \times \ln(OP_t) \\ & + \beta_1 \times \ln(DFTI_t) \\ & + \beta_2 \times WI_t \\ & + \sum_m \gamma_m \times D_{mt} \\ & + \sum_n \eta_n \times DS_{nt}\end{aligned} \qquad (3)$$

where:

$\ln(OP_t)$ is the logarithm of national operation at date t;

$\ln(DFTI_t)$ is the logarithm of delay index at data t;

WI_t is thunderstorm ratio at data t;

D_{mt} are yearly dummy variables: if date t is in year m then D_{mt}=1, otherwise, D_{mt}=0, m = 1997, 1998, 1999, 2000, 2001, 2002 ;

DS_{nt} is seasonal dummy variable, if date t is in season n then DS_{nt}=1, otherwise, DS_{nt}=0, n = 1.. 4 ;

α, β, γ, η are regression coefficients;

TABLE 1 Estimation Results for Daily En-Route OE Count Models

Variable	Definition	Estimates	Standard error
	Intercept	-24.46	2.407
ln(OP)	Logarithm of operations	1.79	0.152
ln(DFTI)	Logarithm of DFTI (daily index of total flight time)	0.75	0.373
WI	Weather index (thunderstorm ratio)	0.70	0.269
D98	yearly dummy variable for 1998	0.11	0.074
D99	yearly dummy variable for 1999	0.25	0.071
D00	yearly dummy variable for 2000	0.35	0.071
D01	yearly dummy variable for 2001	0.35	0.069
D02	yearly dummy variable for 2002	0.41	0.069
DS2	seasonal dummy variable for Summer	0.02	0.049
DS3	seasonal dummy variable for Fall	0.06	0.052
DS4	seasonal dummy variable for Winter	-0.14	0.046
Scale		1.092	

It is obvious that the number of OEs is related to the number of operations in the system. The coefficient of this term in equation (3) indicates whether this relationship is linear (in which case the coefficient will be about 1), quadratic (in this case it would be about 2), or some other degree. Previous research (*19, 20)* suggests a quadratic relationship because the number theoretical intersections for N aircraft is $(N^2-N)/2$, which approaches $N^2/2$ for large N. The yearly fixed effects capture changes in the composition of air traffic, controller procedures, OE reporting policies, and technology that may affect the incidence of operational errors over time. The seasonal fixed effects capture influences such as weather and traffic patterns, and also control for seasonal patterns in the DFTI metrics that are due to winds rather than operational performance.

Estimation results appear in Table 1. The estimated coefficient of operations is 1.79, consistent with the quadratic hypothesis.

The estimated coefficient of DFTI is about 0.75, telling us that with other variables constant, a one percent increase in DFTI will bring about a 3/4 percent increase of number of OEs. The estimated coefficient for the weather index is of a similar magnitude.

In considering the DFTI result, it is important to remember that most of the variation in the DFTI is related to time at the origin airport rather than time in the airspace. Thus the effect does not derive from changes in exposure. Rather, we conjecture that it captures differences in the nature of the cognitive demands placed on controllers on days with poor operating conditions.

All the coefficients of yearly dummy variables are positive and significant, showing that, all else equal, OEs are more likely to occur (or at least be reported) in the years after 1997. Moreover, the coefficients of the yearly dummy variables show a steady increase from 1998 to 2002. This adverse trend may come any of the various factors (traffic composition, procedures, etc) suggested above. The results of quarterly dummy variables are not statistically significant in our model. This means that, while OEs counts may vary by season, such differences are explained by the other variables in the model.

6. Tower OEs

6.1 Operational Performance Metrics and Visibility Index

The operational performance and weather variables for our tower OEs come from FAA's Aviation System Performance Metrics (ASPM) data base. ASPM contains detailed daily, hourly, and 15-minute operational and weather information for 55 major US airports. While using the ASPM data forced us to consider OEs only since 2000, we considered this an appropriate tradeoff because of the richness and comprehensiveness of the ASPM data. We aggregated hourly data to obtain daily performance metrics. These included average arrival delay and departure delay against flight plan; taxi-out, airborne, and taxi-in delay, Expected Departure Clearance Time (ground holding) delay for flights departing this airport and at other airports for flights arriving at this airport. For a daily weather metric, we use the ratio of high visibility hours (visibility>3 miles) to total operating hours.

There is collinearity between the operational performance metrics. We therefore used factor analysis to reduce the number of variables and to detect structure in the relationships between variables. The results of the factor analysis are summarized in Table 2.

TABLE 2 Factor Pattern of Loading (Operational Performance Metrics of Tower OEs)

Principle Component Analysis

	Factor 1	Factor 2	Factor 3	Factor 4
Departure delay	0.982	-0.065	0.051	0.055
Arrival delay	0.918	0.329	0.075	-0.043
Taxi-out delay	0.882	-0.269	-0.149	0.039
Taxi-in delay	0.725	-0.302	-0.077	-0.014
Airborne delay	0.789	-0.138	0.055	-0.099
Upstream ground holding	0.590	0.580	-0.120	0.022
Downstream ground holding	0.436	-0.035	0.220	0.060

Rotation strategy (Promax)

	Factor 1	Factor 2	Factor 3	Factor 4
Departure delay	0.748	0.447	0.462	-0.006
Arrival delay	0.476	0.735	0.425	0.098
Taxi-out delay	0.860	0.268	0.248	-0.040
Taxi-in delay	0.739	0.144	0.237	0.020
Airborne delay	0.652	0.286	0.358	0.136
Upstream ground holding	0.156	0.813	0.123	-0.013
Downstream ground holding	0.264	0.152	0.388	0.003

Rotation strategy (Varimax)

	Factor 1	Factor 2	Factor 3	Factor 4
Departure delay	0.601	0.188	0.313	-0.008
Arrival delay	0.192	0.589	0.177	0.151
Taxi-out delay	0.928	0.068	-0.022	-0.029
Taxi-in delay	0.806	-0.087	-0.015	0.071
Airborne delay	0.584	0.000	0.062	0.251
Upstream ground holding	-0.072	0.955	-0.084	-0.042
Downstream ground holding	0.073	-0.065	0.496	-0.020

There are various rotational strategies that have been proposed. The goal of all of these strategies is to obtain a clear pattern of loadings, that is, factors that are somehow clearly marked by high loadings for some variables and low loadings for others. In this study, we tried standard rotational methods and picked the Varimax since it best satisfied the above criteria. To decide the number of factors should be included into the model, we applied the scree test firstly proposed by Cattell in 1966 (*21*). According to this test, four factors should be taken into account.

The specification for the tower OEs is thus:

$$\begin{aligned}\ln \lambda_{tj} &= \alpha + \beta_0 \times \ln(OP_{tj}) \\ &+ \sum_i \beta_i \times Fact_{itj} + \beta_5 \times VI_{tj} \\ &+ \sum_m \gamma_m \times D_{mt} + \eta_j\end{aligned} \qquad (4)$$

where:

$\ln(OP_{tj})$ is the logarithm of operation of airport j at date t, j= 1….55;

$Fact_{itj}$ is the value of Factor i for airport j on date t, i= 1, 2, 3, 4;

VI_{tj} is the visibility ratio at airport j on day t;

D_{mt} are yearly dummy variables: if date t is in year m then D_{mt}=1, otherwise, D_{mt}=0, m = 2000, 2001, 2002 ;

α, β , γ, η are regression coefficients and η represent the fixed effect of an airport.

Maximum likelihood estimation results appear in Table 3. The coefficient on log of operations is 1.97, indicating that for towers, as for ARTCCs, OEs increase quadratically with the volume of operations. The visibility variable is negative and significant. The value of -0.682 implies that a day in which visibility is always over 3 miles has 50 percent fewer OEs than a day when visibility is consistently less than 3 miles.

Three of the operating performance factors have significant effects on OEs. Factor 1 captures airfield and airspace delay. This factor thus reflects local conditions at the airport being observed. As can be seen from Table 3, the increase of these delays, i.e. degraded airport performance, is associated with more OEs. Factor 2 is captures to arrival delay, including ground holding of flights bound for the observed airport. Such ground holding is used to alleviate severe congestion at the destination airport and reduce total delay cost. Severe congestion at destination airports usually occurs at peak periods or when there is adverse weather. Our results show that such conditions lead to increased OEs, but the effect is considerably weaker than that of Factor 1. Factor 3 captures delay at an airport caused by downstream congestion. Estimation results show that, all else equal, tower OEs decrease with this type of delay. This is reasonable because such delay is normally taken at the gate where it is impossible for an aircraft to be involved in an OE. The remaining factor was found to be insignificant in our initial estimations and is thus excluded from the model presented here.

TABLE 3 Estimation Results for Daily Tower OE Count Models

Variable	Interpretation	Estimates	Standard error
	Intercept	-16.999	0.570
ln(op)	Logarithm of operations	1.968	0.088
Factor1	Airfield and Airspace delay	0.327	0.027
Factor2	Arrival delay	0.040	0.020
Factor3	Downstream congestion	-0.153	0.035
VI	Weather index: visibility ratio	-0.682	0.075
D2002	yearly dummy variable for 2002	-0.082	0.033
D2001	yearly dummy variable for 2001	0.221	0.029
D2000	yearly dummy variable for 2000	0	0
Scale		0.2635	

The yearly dummy variables show a decrease in 2001 and an increase in 2002 compared to 2000, controlling for the other factors. The airport fixed effects—not reported in the Table 3 to conserve space--range from -3 to 3.8, using Tampa International as a basis for comparison. Dallas-Fort Worth has the largest negative fixed effect and Teterboro airport shows the highest positive fixed effect. Taking into account the exponential relationship of fixed effect with OE accounts, the numbers of OEs at different airports vary from 0.04 to 44 times that at TPA, all else equal.

7. TRACON OEs

7.1 Operational Performance Metrics and Weather Index

In the TRACON OE model, performance metrics of the dominant airport served by a particular TRACON are calculated from Airline Service Quality Performance (ASQP) rather than ASPM data. This enabled us to model TRACON OE's beginning in 1997. The ASQP metrics include average arrival or departure delay for aircraft arriving at or departing from the airport, average departure delay for aircraft departing from other airports to that airport, average arrival delay for aircraft arriving at other airports from the airport, and the average taxi-out and taxi-in time at the airport.

The weather index for this model comes from the same source as that discussed in section 4. For a particular TRACON, we calculate the thunder storm ratio of the state where the TRACON is located.

7.2 Regression Results

Factor analysis is again used to reduce the number of variables and to detect structure in the relationships between TRACON operational performance metrics. We used promax rotation since this yielded a clearer pattern of loadings. Three factors were identified, of which two were found to be significant in the OE model.

The model for TRACON OEs is thus:

$$\ln \lambda_{tk} = \alpha + \beta_0 \times \ln(OP_{tk}) + \sum_i \beta_i \times Fact_{itk} + \beta_3 \times WI_{tk} + \sum_m \gamma_m \times D_{mt} + \eta_k \quad (5)$$

where:

$\ln(OP_{tk})$ is the logarithm of operation of TRACON k at date t, k= 1….25;

$Fact_{itk}$ is the ith, i=1,2, factor score for TRACON k on day t , i= 1, 2;

WI_{tk} is the weather index, thunderstorm ratio of TRACON k on day t;

D_{mt} are yearly dummy variables: if date t is in year m then D_{mt}=1, otherwise, D_{mt}=0, m = 1997, 1998, 1999, 2000, 2001, 2002 ;

α, β, γ, η are regression coefficients and η is the fixed effect of a TRACON.

The estimated coefficient of the operations is only about 1.4, which is quite different from the quadratic relationship that we found with en-route and tower OEs. To understand this, consider how a TRACON operates. There are four controller positions in TRACON: high altitude descent controller, low altitude descent controller, approach controller, and feeder controller *(22)*.

> *The high altitude controller will hand off the aircraft to the low altitude controller who then hands off the aircraft to the approach controller. The approach controller merges the many descending aircraft flying toward the same destination airport into one line of air traffic maintaining safe separation. When the aircraft reach about 50 miles outside the destination airport the approach controller performs an electronic transfer and hands the aircraft off to the Feeder Controller. Once the arriving aircraft are within the airport's airspace, they are handed off to the Local Controller located in the airport's control tower.*

From the above description, we can see that TRACON procedure reduce the possible intersections between aircraft. Combining the effects of the increase of operations before and after the aircraft are lined up, it is not surprising that the estimated coefficient of operations is less than 2.

Both operational factors have significant, positive, effects on TRACON OE count. Factor 1 captures the average delays of all flights going through the TRACON and Factor 2 reflects ground delays at the TRACON airport. Both of these factors are associated with deviation from the original scheduling. As discussed, these deviations are likely to generate high cognitive level tasks to TRACON controllers and lead to more OEs. The estimated coefficient of WI is about 0.8, implying that OE count is roughly proportional to the amount of thunderstorm activity in the area.

From estimated coefficients of yearly dummy variables, we can see a steady reduction in the number of TRACON OEs from 1997, with a reversal in 2001, and then a resumption of the downward trend in 2002.

Statistically significant TRACON fixed effects are shown in Figure 6. The range of the fixed effects is from -1.2 to 0.5, with Yankee TRACON (Y90) baselined to 0. The results show that, all else equal, Omaha TRACON is twice as likely to have OEs as Yankee TRACON (Y90), while the likelihood of an OE occurring at Houston (I90) or Boston TRACON (A90) is half of that at Yankee TRACON.

TABLE 4 Estimation Results for Daily TRACON OE Count Models

Variable	Interpretation	Estimate	Standard Error	p Value
	Intercept	-14.487	0.557	<.0001
ln(op)	Logarithm of operations	1.370	0.079	<.0001
Factor1	System performance	0.151	0.013	<.0001
Factor2	Airport ground operational performance	0.134	0.018	<.0001
WI	Weather index	0.814	0.212	0.0001
D2002	yearly dummy variable	-0.256	-0.167	<.0001
D2001		-0.062	0.020	0.1373
D2000		-0.322	-0.237	<.0001
D1999		-0.249	-0.164	<.0001
D1998		-0.119	-0.037	0.0045
A11	Fixed effect of TRACONs	0.419	0.730	0.0081
A90		-1.119	-0.809	<.0001
C90		-0.516	-0.220	0.0006
D10		-0.466	-0.167	0.0022
D21		-0.458	-0.191	0.0008
I90		-1.129	-0.832	<.0001
L30		0.013	0.261	0.918
M98		-0.062	0.188	0.626
MCC		-0.923	-0.582	<.0001
N90		0.281	0.618	0.1029
NCT		-1.008	-0.278	0.0068
O90		-0.372	-0.096	0.0083
P31		-0.391	-0.081	0.0134
P50		-0.037	0.214	0.774
P80		0.151	0.423	0.2741
R90		0.465	0.788	0.0048
S46		-0.109	0.145	0.3992
S56		0.104	0.351	0.4092
SCT		-0.609	-0.261	0.0006
T75		-0.027	0.221	0.8337
U90		-0.426	-0.062	0.0217
Scale		0.3451		

8. Conclusion

In this paper, statistical models of daily en route, tower, and TRACON OEs are specified and estimated. The explanatory variables in the models, operations, operational performance metrics, and weather, are suggested by previous literature on human factors, both general and aviation-specific. The Poisson distribution is used to describe the number of daily OEs. The quadratic relationship between OEs and operations for en route and tower OEs confirms the hypothesis that OEs are proportional to the number of aircraft pairs in these domains. The coefficients for the various operational performance metrics support the qualitative argument that, by increasing cognitive load, high-delay, off-schedule operating conditions lead to a higher incidence of OEs; these results also offer some first-order quantification of that effect. Weather factors—thunderstorm activity for the en route and TRACON domains and visibility in the tower domain—also have the hypothesized effects.

These results suggest that investments in operational improvements—for example measures that will ensure good weather capacities in most weather conditions—may result in increased safety as well as reduced delay and improved reliability. Traditionally, business cases for such improvements focus on the latter; our results suggest that the former should also be considered. While our results focus on controller errors, there is every reason to think that pilots and other personnel engaged in safety-critical functions may also be more prone to errors under non-normal operating conditions.

Finally, we find, in our estimates of fixed effects, significant differences between facilities and across time in the incident of operational errors. The explanation of these differences is not clear. Differences in reporting criteria, technology, airspace and airfield geometry, facility culture, and controller performance may all play a role. Sorting out these contributions is an important challenge for future research.

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Air Traffic Control, Aviation Safety, Operational Errors, Poisson Regression, Human Factors, Cognitive Tasks, Aviation Operational Performance, National Airspace System

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