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ADVERSE WEATHER AND AIR TRAFFIC DELAYS

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1. INTRODUCTION

Most commercial flights (80%) reliably deliver passengers and cargo on time and within a small fraction of the en route time. Of the remaining 20%, it is widely recognized that about 70% of the delays, diversions and cancellations (DDCs) are related, somehow, to adverse weather.

Only during the past few years have the limitations on *capacity* of the entire National Airspace System (NAS) become apparent when faced with the simultaneous and conflicting interests of air traffic and hazardous weather. This, compounded by the traditional methods of traffic management, limitations of space and runway orientation at congested terminals, and the inability to fully utilize uncertain weather forecasts has led to several studies of the impact of adverse weather on traffic delays. For example, Callaham, et.al., 2001; and Post, et.al., 2002.

The objective of our work is first, to capture the relationship between adverse weather and the DDCs. Armed with this information we hope to define a "weather index" and it's "climatology" so that cause of current traffic delays could be determined. When this correlation is fully documented, the value of traffic management and the value of proposed changes and investments in the NAS could be distinguished from the variable influence of the weather itself.

2. ADVERSE WEATHER AND DELAYS

Adverse weather influences the volume of traffic Arrival Acceptance Rate, AAR) at terminals and accounts for a substantial fraction of system delays that are observed. This accounting depends on the capacity and facilities of each terminal that is always regarded as a constant, but is different at each terminal.

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Adverse weather also affects ground operations, and that is usually included as one of the limiting conditions in operational capacity of the terminal. However, after exceptional events (eg, snow or freezing rain), impacts on airport capacity may be substantial and sustained, even though *current* weather conditions may be excellent.

Finally, hazardous weather that is encountered *en route* is responsible for another fraction of delays, since the federal traffic management system, the commercial traffic dispatch procedures, and the pilot always operate to maintain the safest operating conditions. However this concern for safety comes with a cost; it leads inevitably to traffic delays, diversions, and cancellations (DDCs).

3. METHODOLOGY

This paper is a report on three methods currently under investigation.

3.1 TRAFFIC MODEL

The objective is the determination of the weather constraints on the normal flow of en route traffic and is supported by the MITRE Corporation Center for Advanced Aviation Systems Development, CAASD (J.Strouth, 2004).

A prototype decision support tool, the CAASD Analysis Platform for En Route (CAPER) is used to capture and archive data for subsequent analysis. Specifically, for each sector in the NAS, at 15-minute intervals throughout the day, CAPER collects:

- the percentage of each sector in the NAS that is covered by weather (NOWRAD levels 1 through 6)
- the total number of aircraft that were predicted by the CAPER trajectory modeler to transit each sector in the 15 minute period at 1 to 6 hours prior to the 15 minute period. That is, if t is the current 15-minute period, the predictions are captured at t-1 hour, t-2 hours, etc. These predictions indicate the intended flow of traffic through the sectors.
- the total number of aircraft actually transiting each sector in the 15 minute period

The resulting dataset enables analysis that provides insight into the following questions:

- How much weather – and at what level – does it take to impact the intended flow of traffic in the NAS?

- How much is the intended flow impacted by weather?

- Can a correlation be seen in the percentage of weather coverage and a reduction in the actual levels of traffic?

- Can the degree to which traffic levels are constrained be quantified in such a way that the effects of weather can be normalized, allowing comparative analysis of NAS performance over time without concerns about the varying effects of weather?

Additionally, the dataset displays the effects of weather with another tool, NAS Operational Map Display (NOMAD). NOMAD allows users to visualize the changing levels of weather coverage over time, as well as changes in the actual and predicted levels of traffic, both in chart form and geographically (Fig. 1)

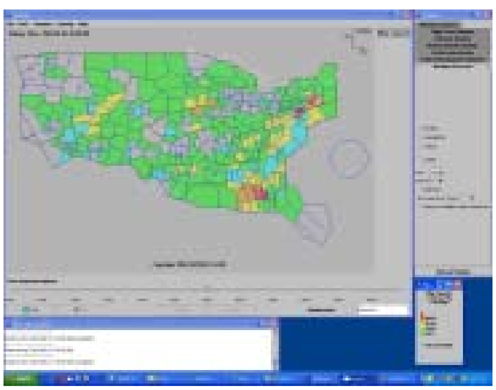

Figure 1 - An example of a NOMAD display of weather constraints according to sector within the CONUS on June 1, 2004. The color scale defines the fractional coverage of convection from national radar coverage (defined in the lower right corner).

These data sets are the basis for subsequent analysis and quantitative understanding of weather constraints on en route traffic.

3.2 WEATHER INDEX ANALYSIS

A second approach was taken by Wine (2004) and has been used by several others. However, Wine classified observed terminal weather into traffic-sensitive categories ranging from none (no influence) to 4 (severe impact). The classification is applied first to the traditional weather variables: weather, weather intensity, ceiling, visibility and wind speed. Subsequently, selected observed traffic parameters are included as surrogates for adverse weather: delays, excess en route miles, and Arrival Acceptance Rates (AARs) at terminals. These data are categorized according to the weighted classification and compared to NAS delay parameters. An example of the results is shown is Figure 2.

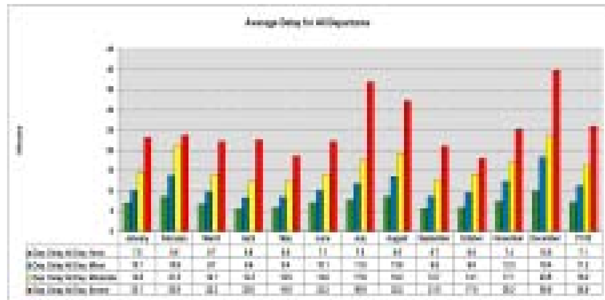

Figure 2 - Example of the impact of a weather index (Wein, 2004) on departure delays.

Although the correlation of this weather-traffic index has not yet been computed, it is expected to be significant. However, the most important en route parameter (thunderstorms) is included implicitly in station data, not with (for example) precipitation coverage or lightning strike information.

Several other investigators have also obtained results by taking this intuitive approach to discovering a sensitive weather index. For example, Callaham, et.al. (2001) obtained a correlation of 0.65 using an index, WITI (Weather Impacted Traffic Index). Post, et.al. used lightning data to compute a weather index that resulted in a correlation of 0.76 with traffic delays. Recently, Liles (2004a,b) computed a weather index for each major terminal and correlated terminal delays at a level of 0.8.

The approach of Wine and previous authors depends on their individual insight into the leading weather elements that are responsible for delays. Their relative success can be measured by a comparison of correlation with the DDCs.

3.3 EFFICIENCY MODEL

A third approach is to conceive a rational model for the behavior of traffic and adverse weather, and let the empirical data deduce the relationship. An efficiency model is:

$$\mathbf{E\ S^{H+W} = constant} \qquad (1)$$

Where **E** = efficiency = 1 - δ/N
S = absence of errors = 1 - ε/M
W = a weather parameter (W=0 indicates no weather influence)

H = an empirical constant that relates E and S when W = 0.
N = number of actual system operations
M = N – number of cancellations

and the constant is a bulk system parameter (**C**) that specifies the level of technology and the methodologies of national traffic management being used.

For this investigation we choose to simplify the expressions for **E** and **S**,

ε = sum of operational errors and operational deviations in the NAS
δ = sum of delays, deviations, and cancellations in the NAS,
H = 1

This concept states that increases in efficiency will be accompanied by an increase in errors (decrease in S). However, improvements in technology (represented by **C,** the bulk system constant) will also improve the efficiency under the same weather conditions without, necessarily, increasing errors.

Taking the logarithmic derivative, we obtain

$$\mathbf{d \ln E / d \ln S = -(1 + W)} \qquad (2)$$

For large N relative to ε and δ, the logarithmic coordinates become linear, as shown schematically in Fig. 3.

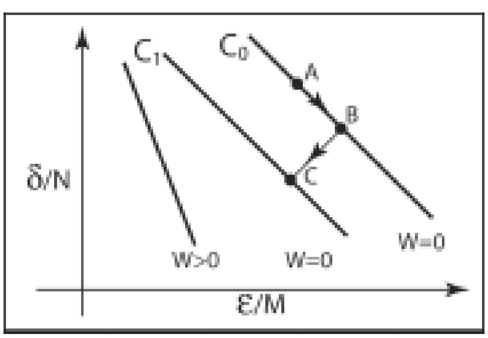

Figure 3 – A schematic description of –lnE (efficiency) as a function of –lnS (errors) for a fixed, bulk traffic technology ($\mathbf{C_0}$), **H** = 1. A condition of no weather influence corresponds to W = 0 on a line with slope, **H** = –1. An improvement in efficiency (AB) cannot be achieved without a commensurate increase in errors unless the bulk operation of the NAS also improves (BC).

There are 2 cases in which the relationship between efficiency and errors becomes trivial, and the original concept (1) is no longer useful. The characterizations are only descriptive of an ideal in a limiting case.

1) Almost Perfect Traffic Control (S = constant)
Traffic management and dispatch operations maintain safety of scheduled aircraft by redirecting flights around hazardous weather. Although efficiency is reduced by adverse weather, errors are determined only by other factors; eg, mechanical failures, or human errors.

2) Almost Perfect Safety (E = constant)
Unscheduled (GA and Business Aviation) pilots maintain safety by favoring safety over efficiency; eg, they refuse to fly until the weather is favorable relative to their operating equipment and skill. Although efficiency is reduced by adverse weather, errors occur only when their equipment and skill are overwhelmed.

To investigate the more general case, we used empirical data for the year 2003 to determine $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$. Subsequently, the intercept constant ($\mathbf{C_0}$) for the bulk system technology, and the slope (W) representing a bulk weather index can be determined. W is the bulk weather index for the system.

The distribution of $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$ are shown in Figs 4 and 5. There values are extremely small relative to N or M, and the shape is similar to a Poisson distribution.

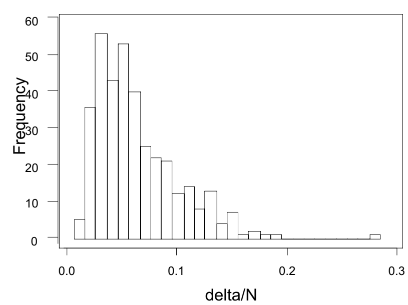

Figure 4 - Frequency distribution of the daily number of delays and deviations (δ), divided by the number (N) of system operations each day for 2003

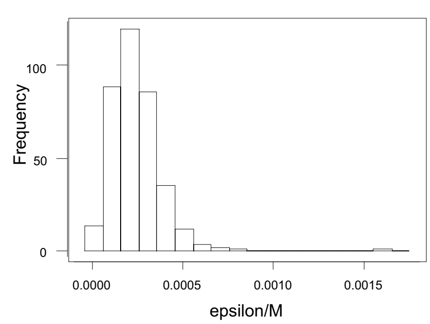

Figure 5 - Frequency distribution of daily operational errors and deviations (ε) divided by the actual number of system operations each day for 2003.

Subsequently, these data are combined and presented in an efficiency diagram (Fig. 6).

This analysis appears to show that the data is close to the idealized case 1), Almost Perfect Traffic Control. If the variations in Efficiency are caused by daily variations in hazardous weather, the number of errors is very small and appears to be independent of weather. This is a superficial conclusion, but if true, would redirect investigations towards an intuitive study of weather indices by Wine or Strouth (as described in the previous sections) or towards station climatology (Liles, 2004a,b).

On the other hand, however close traffic management comes to the ideal case, in reality it is *not* perfect, and these data hold the potential to discover the control that weather (W >>0) has on efficiency through a highly nonlinear control of safety.

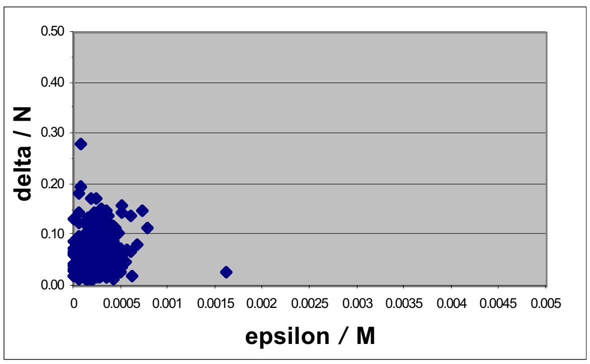

Figure 6 - Delays as a function of Errors for each day of 2003.

4. NEXT STEPS

All three methods deserve further work before substantial results are reported. The immediate objective is to understand quantitatively and separately, the changes in efficiency in the NAS due to weather and traffic management. The ultimate objective is to forecast air traffic impacts of the weather that is forecast. And always, there will be uncertainty due to the hydrodynamic instability of the atmosphere and due to the non-linear behavior of NAS operations.

ACKNOWLEDGEMENTS

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