# Impact of Maintenance Staffing on Availability of the U.S. Air Traffic Control System

Myron Hecht • SoHaR Incorporated • Beverly Hills
Jady Handal • Federal Aviation Administration • Washington, DC.
Loni Czekalski • Federal Aviation Administration • Washington, DC.
Abraham Rosin • System Resources Corporation • Washington, DC.

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*SUMMARY & CONCLUSIONS*

This paper describes a model for assessing the impact of staffing on outage times and availability in the national network of air traffic control equipment using a finite queuing model. Because of the wide geographic distribution of FAA facilities and equipment, maintenance is provided out of a national network of cost centers. Each such center has a limited number of technicians ("servers") who are responsible for providing scheduled maintenance and repair for the equipment assigned to that center. When an equipment requires service and a qualified technician is available, then the outage time is simply the repair time. However, if there are equipment failures when technicians are busy making other repairs, then there is an additional waiting time until a qualified technician is free. The model determines average outage times as a function of the number of technicians assigned to a cost center, equipment failure rates, and the number of equipment which technicians must support.

Results for a representative cost center are that the average maintenance technician utilization, (is the time spent in repair and associated activities approximately 50%), and the average outage duration was approximately 26 hours. Typically close to 4000 systems await repair due to outages at any given time. More than 80% of the outage time is attributable to awaiting a repair technician. Throughout the National Airspace System (NAS), typically close to 4000 systems (9%) await repair due to outages at any given time.

## 1. INTRODUCTION

The U.S. National Airspace System (NAS) consists of more than 45,000 individual equipment or systems supporting air traffic control which have functions as diverse as lighting to radar tracking, and which incorporate technologies ranging from backup diesel generators to networks of UNIX workstations. Their upkeep requires technicians trained in many different disciplines who must be deployed over the entire geographical area of the United States and its possessions. Providing dependable air traffic control services at a reasonable cost requires the proper allocation of maintenance resources across these systems. Proper allocation is increasingly significant as the average age of NAS equipment increases and air traffic continues to grow. Over the past two years, the FAA Office of Communications, Navigation, and Surveillance, has sponsored research on the business impact of operational availability of Communications, Navigation, and Surveillance (CNS) systems to support its cost-benefits analysis and investment decisions. This paper describes one of the products of this research, a model for assessing the impact of staffing based on a finite queuing model. The specific objectives of this effort are to investigate allocations within the Cost of Service category so that a higher availability can be achieved within a fixed budget.

This paper is organized as follows: Section 2 describes the empirical evidence of a maintenance staffing shortfall (and hence, the motivation for this work). Section 3 describes the mathematical relationships used in the modeling and analysis. Section 4 provides results for a representative cost center which uses average parameters for staffing, equipment, and repair time, and section 5 includes additional discussion.

## 2. EVIDENCE OF A MAINTENANCE STAFFING SHORTFALL

The use of the exponential distribution to measure and predict outage (or restoration) times is a common practice [1] and is used in DoD standards such as Mil-STD-472 and 1388. The extent to which the exponential distribution predicts NAS outage times can be judged by Figure 2-1 which shows an extremely close agreement between the actual and predicted values for the aggregate of 1995 data from the FAA National Airspace Performance Reporting System (NAPRS) [2]. The fit was determined by using a log-linear regression of outage time distributions.

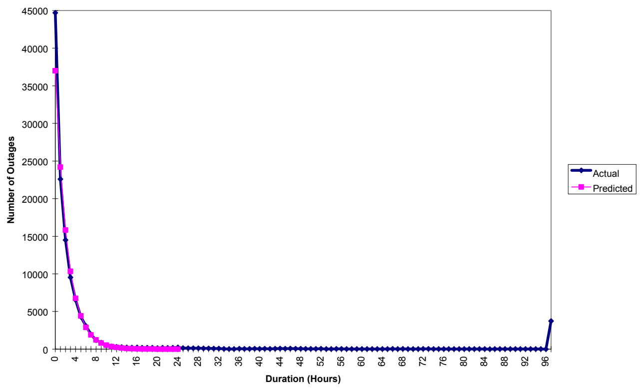


**Figure 2-1 Actual and Predicted Frequency Distribution of all NAPRS reportable outage durations from 1995 data. Unscheduled outage times are net of travel (Predictions are not shown beyond 24 hours in order not to obscure actual data ).**

However, discrepancies begin to emerge when the repair times exceed 11 hours as is visually apparent when Figure 2-1 is transformed into a log-linear plot as shown in Figure 2-2. The result of this transformation is to highly magnify the right bottom portion of figure 2-1.

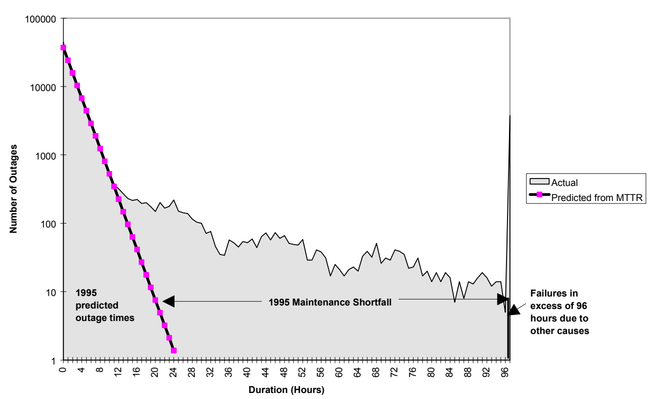


**Figure 2-2. Log-linear representation of 1995 NAPRS Outage Durations**

The graph shows that the outage times predicted using the exponential distribution underestimate the actual experience as reflected in the NAPRS data (i.e., the area to the right of the line). The primary cause of this discrepancy is a shortfall in maintenance staffing (other less important causes include repair parts shortages, travel time, or inclement weather). The outages to the right of the line represent those which are not restored immediately because of inadequate technician or other repair resource availability. The model described in the next sections addresses how increasing or decreasing this shortfall will affect individual equipment availability.

## 3. *MODEL DESCRIPTION*

The model consists of a number of separable submodels, two of which are described here: a maintenance queuing model which predicts the waiting time (and therefore outage time) of equipment in a cost center as a function of the number of technicians, service time, and the number of equipment, and a Failure to Outage submodel, which accounts for the fact that due to redundancy, many equipment failures require maintenance actions (thereby occupying technicians), but do not result in outages. Other models accounting for training, sparing, and travel time were also developed but are not discussed in this paper because of space considerations.

The following nomenclature is used in this paper.

| | |
|---|---|
| c | Average staffing level at a cost center |
| D | Maintenance expansion factor |
| F | Average number of facilities that a technician is qualified to service (qualification breadth) |
| k | Fraction of failures that result in outages |
| L | Expected number of facilities with failures |
| $L_{eff}$ | Effective size of queue length (number of unrepaired facilities) |
| Lq | Number of facilities waiting and not yet repaired |
| MTBO | Mean Time Between Outages |
| MTTR | Mean time to repair |
| k | Integer part of c (number of technicians) |
| m(t) | probability density function for exponential repair time distribution |
| n | Number of facilities in a cost center |
| $N_{equip}$ | NAPRS reportable facilities (NAS wide) |
| $N_{costctr}$ | Number of facilities in a cost center |
| O | Expected number of outages |
| $O_{costctr}$ | Number of outages in a cost center |
| o(t) | Number of outages of duration t |
| $o_g(t)$ | Number of glide slope outages of duration time t |
| $P_M(t)$ | Probability of repair at or before time t |
| po | Probability of an empty queue (technician is available) |
| $r_{avail}$ | Number of available technicians |
| $r_n$ | Average number of required technicians |
| Shift | Shift factor |
| Sp | Number of maintenance specialty categories |
| Stf | Actual staffing level |
| $t_{opt}$ | Optimal average outage time |
| $t_{avgout}$ | average outage time |
| $t_d$ | Documentation time |
| $t_o$ | Time for other delays |
| $t_p$ | Time for obtaining parts |
| $t_t$ | Travel time |
| types | Number of unique facility types at a center |
| U | Unavailability, generic |
| $U_I$ | Unavailability of 1-out-of-2 block |
| $U_p$ | Unavailability of a single channel in a block |
| W | Failure duration |
| Wq | Waiting time for repair by facilities for which repair has not begun |

| | |
|---|---|
| | (queue waiting time) |
| $X_C$ | Fraction of failures leading directly to outages |
| x | Fractional part of c (number of technicians) |
| $x_{log}$ | Fraction of outages affected by an inventory shortfall |
| $\lambda$ | failure rate, generic and for a total facility |
| $\lambda_C$ | failure rate of components that can induce common mode failures |
| $\lambda_I$ | failure rate of block that contains independently failing component |
| $\lambda_o$ | Observed outage rate |
| $\lambda_p$ | failure rate of a single channel in a block |
| | repair rate, generic |
| $\mu_{act}$ | actual repair rate |
| $\mu_o$ | optimal repair rate |

### *3.1 Maintenance Queuing Models*

The objective of the maintainability queuing models is to determine outage time and failure rate as a function of the number of available technicians, and the number of services and facilities (collectively referred to as "equipment") which these technicians must support. A finite queuing model was used for this purpose. The probability of an empty queue is given by [3]

$$po(c\ n\ \lambda\ \mu) = \left[ \sum_{i=0}^{c-1} \frac{n!}{i!\,(n-i)!}\cdot\left(\frac{\lambda}{\mu}\right)^i + \frac{1}{c!}\sum_{i=c}^{n} \frac{n!}{(n-i)!}\,\frac{1}{c^{(i-c)}\cdot c!}\cdot\left(\frac{\lambda}{\mu}\right)^i \right]^{-1}$$

**Equation 3-1**

Where

$p_o$ is the Probability of empty queue (technician being available)

c is the average staffing level (number technicians) for each cost center

n is the number of facilities in each cost center

$\lambda$ is the model failure rate

$\mu$ is the model repair time

The expected number of facilities with failures in each queue is given by

$$L(c\ n\ \lambda\ \mu) := po(c\ n\ \lambda\ \mu)\left[ \sum_{i=0}^{c-1} i\,\frac{n!}{i!\,(n-i)!}\cdot\left(\frac{\lambda}{\mu}\right)^i + \frac{1}{c!}\cdot\sum_{i=c}^{n} i\,\frac{n}{(n-i)!}\cdot\frac{1}{c^{i-c}}\cdot\left(\frac{\lambda}{\mu}\right)^i \right]$$

**Equation 3-2**

where L is the expected number of facilities with failures (also referred to as the queue length).

The number of facilities that are waiting and have not yet been repaired ($L_q$) is given by

$$Lq(c,n,\lambda,\mu) := L(c,n,\lambda,\mu) - c + po(c,n,\lambda,\mu)\cdot\left[ \sum_{i=0}^{c-1} (c-i)\cdot\frac{n!}{i!\cdot(n-i)!}\cdot\left(\frac{\lambda}{\mu}\right)^i \right]$$

**Equation 3-3**

Total failure duration time (W, i.e., the number of facilities waiting to be repaired and actually under repair) is given by

$$W(c,n,\lambda,\mu) := \frac{L(c,n,\lambda,\mu)}{\lambda\cdot(n - L(c,n,\lambda,\mu))}$$

**Equation 3-4**

The number of facilities with failures ($W_q$) waiting for the start of repairs is given by

$$Wq(c,n,\lambda,\mu) := \frac{Lq(c,n,\lambda,\mu)}{\lambda\cdot(n - L(c,n,\lambda,\mu))}$$

**Equation 3-5**

Equations 3-2 through 3-5 require that both the number of technicians (parameter c) and the number of facilities (parameter n) have integer values. However, as will be described below, calculation of the representative cost center parameters results in non-integer values for these parameters. This fractional addition is handled through linear interpolation. For example, if the average number of technicians in a cost center c, is a non-integer, i.e.,

$$c := k + x$$

where k is an integer and x is a non-integer (less than 1), the expected number of failures,

$$L_{eff} = (1-x)\cdot L(m, n, \lambda, \mu) + x\cdot L(m+1, n, \lambda, \mu)$$

**Equation 3-6**

where $L_{eff}$ is the effective size of the queue length (i.e., the number of unrepaired failures within the cost center), represented as a linear combination of m and m+1 technicians. Another way of looking at this interpolation is that for a large number of cost centers with an average number of technicians c, some centers will have m technicians whereas others will have m+1 technicians.

### *3.2 Failure To Outage Model*

The maintainability queuing model provides results on the average duration of a *failure* and the average number of *failures* in each sector. However, because a large proportion of the facilities and equipment used in CNS functions are redundant, a *failure* does not necessarily result in an *outage*. The purpose of the redundant system model is to establish the number of *outages* as a function of the number of *failures* predicted by the maintainability queuing model.

Figure 3-1 shows a block diagram of a model NAS facility. The facility incorporates both redundant elements (e.g., dual transmitters on a glide slope), designated as channel 1 and channel 2 ($c_1$ and $c_2$) and a series element. The series element includes common mode failures such as power or weather, and hence, is labeled "common".

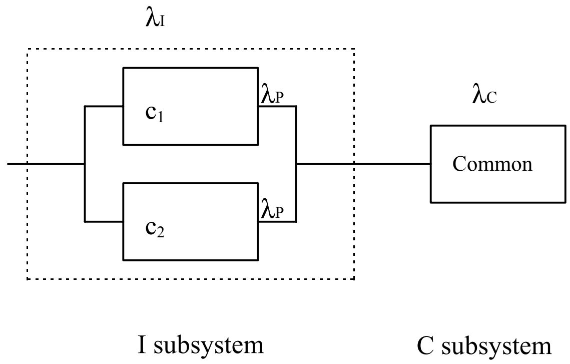


**Figure 3-1. Redundant System Model**

The following are additional assumptions

1. Failures of the I and C susytems are independant
2. Failures of the two channels within the I subsystem are independent
3. All repairs on the facility follow an exponential distribution with a repair rate of $\mu$.

The facility outage rate $\lambda_o$ is then the sum of the failure rates of the two subsystems (with the accepted approximation for small failure rates), i.e.

$$\lambda_o = \lambda_C + \lambda_I \qquad \textbf{Equation 3-7}$$

where $\lambda_I$ and $\lambda_C$ represent the subsystem-level failure of each of the subsystems I and C. The unavailability of subsystem I is denoted by $U_I$ and is determined by

$$U_I = \frac{\lambda_I}{\lambda_I + \mu} \qquad \textbf{Equation 3-8}$$

where $\mu$ is the facility repair time (as noted previously, it is assumed to be identical for all subsystems and channels in the facility).

The I subsystem consists of two channels, each with a failure rate of $\lambda_p$ The unavailability of either *channel* in subsystem I is

$$U_p = \frac{\lambda_p}{\lambda_p + \mu}$$

where $U_p$ is the unavailability of each of the channels of the 1-out-of-2 subsystems, and $\mu$ is the repair rate. Because failures on channel 1 and channel 2 are assumed to be independent, the unavailability of the I subsystem (channel 1 and channel 2) is the product of the individual unavailabilities, i.e.,

$$U_I = U_p U_p \qquad \textbf{Equation 3-9}$$

Using Equations 3-8 and 3-9 and solving for $\lambda_I$ results in the following relation:

$$\lambda_I = \frac{\lambda_p^{\,2}}{2\lambda_p + \mu} \qquad \textbf{Equation 3-10}$$

From Equation 3-7, $\lambda_I = \lambda_o - \lambda_C$. Combining this result from Equation 3-7 and Equation 3-10 yields

$$\lambda_o - \lambda c = \frac{\lambda_p^{\,2}}{2\lambda_p + \mu} \qquad \textbf{Equation 3-11}$$

Another form of Equation 3-11 is

$$\lambda_p^{\,2} - 2(\lambda_o - \lambda_C)\lambda_p - \mu(\lambda_o - \lambda_C) = 0 \qquad \textbf{Equation 3-12}$$

The quadratic equation can then be used to solve for $\lambda_p$ . The result is the following relation between the parallel failure rate, the common mode failure rate, and the observed outage rate:

$$\lambda_p = \lambda_o - \lambda_C + \sqrt{(\lambda_o - \lambda_C)^2 + \mu(\lambda_o - \lambda_C)} \qquad \textbf{Equation 3-13}$$

These relations can now be used to determine the relationship between the number of outages which are recorded in NAPRS and the number of maintenance actions which can be expected for such a system as shown in equations 3-15 and 3-17.

Let $X_c$ be the number of outages on the C subsystem. Then

$$\lambda_C = X_c\lambda_o \qquad \textbf{Equation 3-14}$$

It is possible to estimate $X_c$ using NAPRS outage data cause codes and comment fields[1].

The total number of maintenance actions, for the facility model shown in Figure 3-1 is the failure rate of the C subsystem and each of the redundant channels in the I subsystem, i.e.,

$$\lambda_T = 2\lambda_p + \lambda_c \qquad \textbf{Equation 3-15}$$

The relationship between the observed outage rate $\lambda_o$, common cause failure rate $\lambda_c$, repair rate $\mu$, and the maintenance action rate $\lambda_T$ can be found by substituting equation 3-15 for $\lambda_p$ in Equation 3-14 and simplifying, i.e.,

[1] Using cause codes, it is possible to directly identify the proportion of weather, commercial power, commercial communications. For other cause codes, the comments field must be examined to identify single channel components (e.g., a radar antenna, rotary joint, or drive motors) were responsible for the outage.

$$\lambda_T := 2\cdot\left[\lambda_o + \sqrt{(\lambda_o - \lambda_c)^2 + \mu\cdot(\lambda_o - \lambda_c)}\right] - \lambda_c$$

**Equation 3-16**

Substitution of Equation 3-14 into equation 3-16 results in

$$\lambda_T := \lambda_o\cdot(2 - X_c) + 2\cdot\left[\sqrt{(1 - X_c)^2\cdot\lambda_o^2 + \mu\cdot(1 - X_c)\cdot\lambda_o}\right]$$

**Equation 3-17**

This relation allows the calculation of the total facility maintenance action rate (i.e., the rate of maintenance actions, not outages) based on two quantities which can be determined directly from NAPRS data ($\lambda_o$ and $\mu$) and the parameter $X_c$ which varies between 0 and 1.

## 4. *RESULTS*

Table 4-1 shows the maintenance model results for the representative sector using the parameters defined above. As is shown in the table, the results are in reasonably good agreement with the 1995 NAPRS outage data-derived values.

**Table 4-1. Maintenance Model Results for Representative Sector**

| Result | Obs.erved value | Predicted value | Comment |
|---|---|---|---|
| Cost center effective uptime percentage (availability measure) | 0.98 | 0.99 | Difference can be accounted for in terms of long-term outages of some NAS facilities reflected in NAPRS data which are outside of the scope of this analysis. |
| Technician Utilization | 50% | 48.9% | Approximate upper limit of reasonable technician utilization |
| Mean Outage and Failure duration | 26 hours | 22 hours | Agreement (within the 95% confidence interval) with the observed value of 26 hours for the average outage time). Difference can be accounted for in terms of long-term outages of some NAS facilities reflected in NAPRS data which are outside of the scope of this analysis. |
| Avg. no. of outages in cost center waiting to be repaired | 8% | 9.3% | Consistent with cost center operational availability |

Figure 4-1 shows the resultant expected failure duration time (also outage time) as a function of staffing. The graph shows that a failure time reduction of approximately 4.2 hours per added technician per cost center (the linearity of the plot is due to the interpolation technique to account for the benefit of an incremental increase in staffing described in Chapter 2) until staffing is increased to 14 technicians (approximately 140% of the current level for the representative cost center).

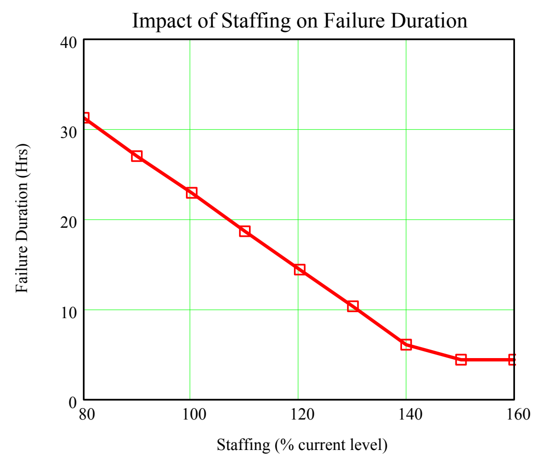


**Figure 4-1. Impact of Staffing on Failure (and Outage) Duration**

As additional staffing are added beyond that point, however, the outage duration asymptotically approaches the assumed effective MTTR level of 4.1 hours, the product of the $t_{opt}$ and D parameter values. This meaning of this result is that at 140% staffing, there is little or no waiting time because a technician can be dispatched as soon as a failure occurs.

Figure 4-2 shows the impact of staffing on the average maintenance backlog (i.e., number of failures awaiting restoration) within the NAS. The curve shows a reduction of approximately 75 outages per percentage of staffing increase. For the representative cost center, this corresponds to a benefit of 1.04 fewer outstanding failures per additional technician. Under the assumption of a 90% common mode failure proportion discussed above, this represents a reduction of 0.075 outages per staff-year, or an increase in availability of 0.192% per staff year. The shape of this curve is identical to that of the previous figure, i.e., with the maximum benefit incremental benefit being achieved up to a staffing level increase of 40%. The curve does not go to zero because facilities that are under repair are by definition, also awaiting service restoration.

The similarity between Figures 4-1 and 4-2 is a result of the linear relationship between the expected duration and the expected number of failures in the regions of interest in this analysis. This result can be expected based on Equation 2-5 when n >> L; it is not driven by any of the assumptions discussed above.

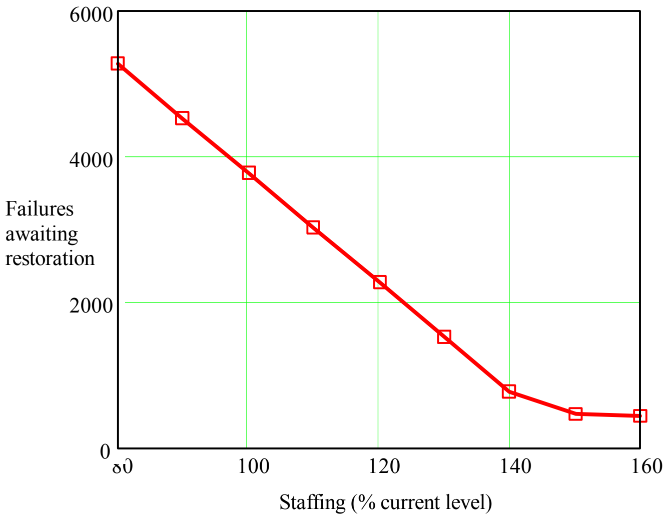


**Figure 4-2. Impact of Staffing Changes on Number of Expected Failures awaiting repair**

Figure 4-3 shows the change of average cost center equipment uptime or availability[2] vs. staffing increase. The curve shows a benefit of approximately 0.00019 (0.019%) per percent change in staffing.

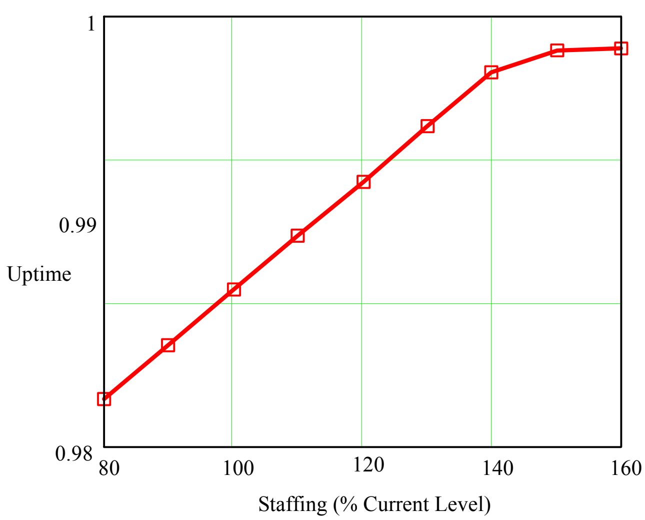


**Figure 4-3. Relationship availability and staffing**

Using the results of Figure 4-3, it is possible to estimate the impact of staffing on the availability of a larger system whose significance can be measured in air traffic delay and other economic terms. For example, at the Los Angeles International Airport (LAX), there are four runways, each equipped with an instrument landing system which consists of 5 subsystems: the glide slope, localizer, distance measuring equipment, runway visual range, and lighting. At LAX, two of the runways are used for arrival, and two of which are used for departure. Under restricted visibility conditions (which occur approximately 20% of the time), equipment-related delays will occur if any of these five subsystems are unavailable at two or more runways (most of these facilities are necessary for landing, not for departure). Thus, unavailability at the individual equipment level will result in delay at the airport level. Figure 4-4 shows the result of combining the maintenance action model described in this paper with the airport availability model. The figure shows that the capacity loss probability can be reduced from approximately 1.15% to 0.9% by increasing staffing by 40% over current levels.

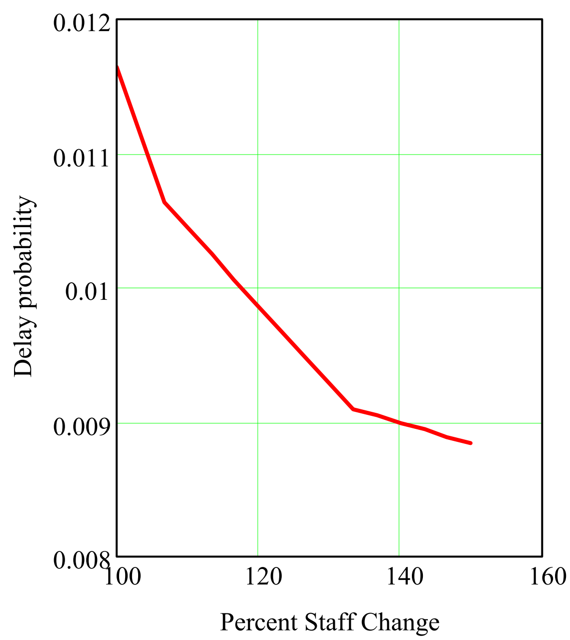


**Figure 4-4. Impact of Staffing Changes on the Probability of a Loss of Airport Runway Capacity (i.e., delay probability).**

## 5. *DISCUSSION*

The model and results described in sections 3 and 4 provide a part of the basis for making an economically-based decisions on expenditures. For example, if the avoidance of the capacity loss at LAX (approximately 23 hours) has an economic benefit greater than the penalty of 40% staffing increase, then the decision to increase staffing can be cost justified. This same approach can be used in other industries where the benefit of service availability can be traded off against the cost of supporting this increased availability. As such, the approach presented here has generality.

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[2] Average cost center equipment availability is defined as the proportion of facilities (equipment) which is operational (i.e., may have failed but has not suffered an outage). It is calculated as

A=1-(Ratio*Leff)/Ncostctr

The analytical queuing model presented in Section 3 has a number of simplifying assumptions including homogeneity of repair times, a “first in first out” queue discipline, a single technician performing the repair under all circumstances (even if more technicians are available and the repair can be performed in fewer hours), that all technicians are qualified to repair all equipment in the cost center, and that given that a repair is started, it will be completed with 100% success (i.e., there will not be any additional complications such as a lack of spare parts or inadequate diagnostics). We are now in the process of addressing the impact of these assumptions through the creation of a simulation against which the simpler analytical approach can be compared. The results of this study will be reported in future publications.

## 6. *ACKNOWLEDGMENTS*

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## *BIOGRAPHIES*

Myron Hecht
SoHaR Incorporated
8421 Wilshire Blvd., Suite 201
Beverly Hills, CA 90211-3204
Phone: (213) 653-4717 ext.111
Email: myron@sohar.com

Myron Hecht, co-founder and President of SoHaR, has worked in the areas of software and systems reliability. He directs SoHaR’s support of the FAA Advanced Automation System which is to replace the current air traffic control system in the early 1990’s. His activities in basic research and development at SoHaR have resulted in new architectures for real time distributed systems, methodologies for the development and verification of fault tolerant software, and he has also developed designs for highly reliable distributed systems for both process control and $C^3I$.

Jady Handal, *PhD*
Federal Aviation Administration
800 Independence Ave. SW
Washington D.C. 20591
Phone: (202) 267-3214
Email: jady_handal@mail.hq.faa.gov

Dr. Jady Handal is the Special Assistant to the Director of Director for Communications, Navigation and Surveillance Systems for the Federal Aviation Administration (FAA). He is responsible for the development of a full context cost benefit analysis system that allows the FAA to make availability centered risk based investment decisions.

Loni Czekalski
Federal Aviation Administration
800 Independence Ave. SW
Washington D.C. 20591
Phone: (202) 267-9467
Email: loni_czekalski@mail.hq.faa.gov

Loni Czekalski, Director for Communications, Navigation and Surveillance Systems for the FAA, is responsible for research, development, acquisition and deployment of communication, navigation, landing and surveillance systems into the National Airspace System (NAS). Ms. Czekalski manages approximately 260 employees, about 1000 contractors, approximately 100 programs and an annual budget in excess of $300 Million. Her organization is responsible for delivering a total of 10,414 systems to an aging NAS in two years, which accounted for 99% of all new systems delivered by the FAA’s Acquisition Organization.

Abraham Rosin
System Resources Corp.
400 Virginia Ave. SW Suite C140
Washington D.C. 20024
Phone: (202) 488-9740
Email: Abe_Rosin_at_SRC-DC@mail.hq.faa.gov

Abraham Rosin is the Lead Reliability Engineer for System Resources Corp. (SRC) where he is working on FAA Communication, Navigation, and Surveillance Systems. Prior to joining SRC, Mr. Rosin worked for Rafael, the Armament Authority for the Israeli Ministry of Defense, for Elscint, a manufacturer of medical device equipment, the U.S. Navy Naval Engineering Support Center (NAVSEC) and the Naval Aviation Integrated Logistic Support Center (NAILSC). Mr. Rosin holds M.S. degrees in Reliability Engineering from the University of Arizona and in Quality Assurance from the Technion-Israel Institute of Technology and a B.S., in Aerospace Engineering from Northrop University.