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**Authors:** Nozer D. Singpurwalla, Carlos M. Talbott

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**Abstract:** (Continue on reverse side if necessary and identify by block number)
A TIME SERIES ANALYSIS OF SOME INTERRELATED LOGISTICS PERFORMANCE VARIABLES*

Nozer D. Singpurwalla
The George Washington University
Washington, D.C.

Carlos M. Talbott**
Air Force Institute of Technology
Wright Patterson AFB, Ohio

ABSTRACT

This paper is a case study. We show how the powerful methods of time series analysis can be used to investigate the interrelationships between Alert Availability, a logistics performance variable, and Flying Hours, an operational requirement, in the presence of a major change in operating procedures and using contaminated data. The system considered is the fleet of C-141 aircraft of the U.S. Air Force. The major change in operating procedures was brought about by what is known as Reliability Centered Maintenance, and the contaminated data were due to anomalies in reporting procedures. The technique used is a combination of transfer function modeling and intervention analysis.

1. INTRODUCTION AND SUMMARY

In January 1976, the U.S. Air Force began some experimental modifications to the existing maintenance policies for the fleet of C-141 aircraft. These modifications were a part of a Department of Defense project known as "Reliability Centered Maintenance," henceforth denoted by RCM. The modifications involved an extension of the maintenance intervals and a reduction in the amount of scheduled maintenance. The experimental phase of the project ended in June 1977, and the modified policies were officially and permanently instituted at that time. The anticipated benefit from RCM was a decrease in scheduled maintenance activity, with a consequent increase in "alert availability." Alert availability, henceforth denoted by AA, is the instantaneous probability that a typical aircraft is available to react to an execution order. In practice, its average value, over say a month, is computed by dividing the monthly total number of "fleet operational hours" by the total number of "fleet available hours."† A plot of AA from October 1973 through November 1979 is shown in Figure 1.

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**Major, USAF
† Fleet available hours is the cumulative time of possession across a fleet of aircraft, whereas fleet operational hours is the cumulative amount of operational time (i.e., up-time) for the fleet.
In a previous study (Singpurwalla and Talbott [5]), we investigated the effects of RCM on several variables which describe what is known as the "logistics performance" of the fleet. Our conclusion was that there was no evidence of an improvement in the logistics performance of the fleet due to RCM; on the contrary, in some cases there was a clear indication of deterioration in performance. These conclusions were particularly true of AA, which is considered to be an important logistics performance variable. One criticism of this previous study, and a valid one, is that it did not take into consideration the influence of other "operational variables," which in addition to RCM may affect the logistics performance variables. An important operational variable, which is suspected of being strongly related to the AA, is "flying hours." Flying hours is the total number of hours flown by the fleet of the C-141's over a certain period of time, say one month. A plot of the monthly flying hours, from October 1973 through November 1979, is shown in Figure 2. Another criticism of our previous study, and again a valid one, is that it did not adequately account for the fact that some of the AA data were "messy." Specifically, there were some revisions to the information system for reporting the operational status of the aircraft that resulted in some possible anomalies in the reported values of the AA.

The analysis that is described here was initiated with a view towards rectifying the limitations of our previous study. Here, using the AA and the flying hours as examples, we demonstrate how a procedure for investigating the interrelationships between the two, using messy data and RCM as an intervention, can be developed and used. The approach we take is a combination of those described in Box and Jenkins [1], pp. 335-420) for the analysis of multiple time series, and in Box and Tiao [2] for intervention analysis. Our conclusion is that the AA is
indeed related to the flying hours, as has been conjectured, but that even after taking this relationship into consideration, and in the presence of messy data, our previous conclusion still holds, namely, that there is no clear evidence of improvement in the AA after the initiation of RCM.

Before going into the details of our analysis, we want to emphasize that the above conclusion and its practical implications are not intended to be the main theme of this paper. Rather, our aim is to suggest and to demonstrate how the powerful methods of time series analysis can be used to analyze the messy and interrelated data that often arise in a study of the reliability and the logistics performance of large military systems.

In what follows, we presume that the reader has a knowledge of autoregressive integrated moving average (ARIMA) processes and is familiar with the notation, terminology, and methodology described in Box and Jenkins [1].

2. NOTATION, PRELIMINARIES, AND AN OUTLINE OF THE PROCEDURE

Let $X$ and $Y$ be two variables of interest, and let $X_i$ and $Y_i$ be their values at time $i$. In our case, we let $X_i$ denote the total flying hours for the fleet of C-141's during the $i$th month, and $Y_i$ the alert availability during that month; $i$ varies from October 1973 through November 1979. A sequence of values $X_i, X_{i-1}, \ldots$ will be denoted by $\{X_i\}$.

To discern the relationship between $X_i$ and $Y_i$, we strive to obtain a linear transfer function model (Box and Jenkins [1], p. 379) of the form

$$(1 - \delta_1 B - \ldots - \delta_p B^p) Y_i = (w_0 - w_1 B - \ldots - w_q B^q) X_{i-b} + N_i,$$
where $B^mY_t = X_{t-m}, m = 0, 1, \ldots,$ and $\delta_1, \ldots, \delta_r, w_0, \ldots, w_i$ are unknown constants to be estimated; $b$ represents the lag of $Y$ with respect to $X_t$ and $N_t$ denotes a noise component described by a suitable ARIMA process.

Equation (2.1) describes the alert availability at time $t$ in terms of the previous values of the alert availability and the present and previous values of the flying hours.

Following the procedures suggested by Box and Jenkins [1] and by Haugh and Box [3], we first consider the sequence (series) $\{X_t\}$ and transform it to a "white noise series," $\{a_t\}$, by way of an appropriate univariate time series model. Similarly, we also reduce the sequence $\{Y_t\}$ to a white noise series, $\{b_t\}$, using an appropriate "intervention analysis model" (see Box and Tiao [2]). Such a model is necessary here in order to account for RCM as well as for the presence of some anomalous observations in $\{Y_t\}$. This procedure of reducing $\{X_t\}$ and $\{Y_t\}$ to $\{a_t\}$ and $\{b_t\}$, respectively, is known as prewhitening the respective series. We then cross correlate the two prewhitened sequences $\{a_t\}$ and $\{b_t\}$ in order to obtain an indication of the relationship between $\{X_t\}$ and $\{Y_t\}$. The cross correlation function is used to suggest values for $r, s,$ and $b$ in (2.1). Finally, we use the prewhitened sequences $\{a_t\}$ and $\{b_t\}$ to estimate the constants $\delta_1, \ldots, \delta_r, w_0, \ldots, w_i$, for some selected values for $r, s,$ and $b$.

Regarding the prewhitening of $\{Y_t\}$ using a model for intervention analysis, we remark that intervention due to RCM can be described by a sequence of indicator variables, say $\{Z_t\}$, where $Z_t$ takes a value of 0 for all $t$ representing the months prior to January 1976, and a value 1 for all $t$ thereafter. Recall that January 1976 is the date of intervention—the date at which experimental RCM was initiated. The response of the sequence $\{Y_t\}$, the output sequence denoting $AA$, to the input sequence $\{Z_t\}$ can take various functional forms. These are depicted in Figure 2; they have been taken from Box and Tiao [2]. We strive to use the most appropriate form of the response function for the situations at hand.

3. PREWHITENING THE FLYING HOURS SERIES $\{X_t\}$

An inspection of Figure 2 finds that the fluctuations of the series about its mean changes over time. In such situations it is common to take the natural logarithms of the data. Accordingly, our analysis of flying hours involves a logarithmic transformation of the original data.

We find that flying hours can best be described by an ARIMA $(2,0,0) \ast (2,0,0)_4$ process. However, the residuals from this model reveal significant autocorrelations at lags 5, 10, 15, \ldots, etc. Consequently, we fit an ARIMA $(0,0,0) \ast (0,0,1)_5$ model to these residuals. Based upon these considerations, an appropriate model for prewhitening can be written as

\[
(1 - .54B + .11B^2)(1 + .38B^4 + .37B^6)(X_t - 10.09) = (1 + .18B^5)a_t.
\]

This model produces residuals whose autocorrelation function (ACF) and log spectral density are shown in Figure 4, in (a) and (b), respectively. These residuals are listed in Table 1.

4. PREWHITENING THE ALERT AVAILABILITY SERIES $\{Y_t\}$

In our previous study we considered alert availability as two separate series, one ending prior to January 1976 and the other beginning with January 1976. We found that the loga-
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Form of Input \( \{ Z_t \} \)

1

0 .............

Jan 76

Forms of Output \( \{ Y_t \} \)

a. Jump Response

\[
Y_t = a Z_t
\]

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b. Slope Response

\[
Y_t = \frac{a}{1-\delta B} Z_t \\
= aZ_t + a\delta Z_{t-1} + a\delta^2 Z_{t-2} + \ldots
\]

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c. Ramp Response

\[
Y_t = \frac{a}{1-B} Z_t \\
= aZ_t + aZ_{t-1} + aZ_{t-2} + \ldots
\]

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d. Step Response

\[
Y = \frac{a}{1-Bs} Z_t \\
= aZ_t + aZ_{t-s} + aZ_{t-2s} + \ldots
\]

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FIGURE 3. Typical forms of the response \( \{ Y_t \} \) to the input \( \{ Z_t \} \)
Figure 4. Behavior of the ACF and the log of the spectral density of the residuals from an ARIMA (0,0,0) * (0,1,0) and an ARIMA (2,0,0) * (0,0,0) model fit to residuals from an ARIMA (2,0,0) * (0,0,0) model.
TABLE 1 — Residuals from Prewhitening Models for Flying Hours and Alert Availability

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<th>TIME</th>
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Algorithms of the observations in both these series could best be described by an ARIMA \((1,0,0) * (1,1,0)_6\) model. Here, we prewhiten the entire series by considering the onset of RCM as an intervention and incorporating this effect into the ARIMA \((1,0,0) * (1,1,0)_6\) model.

Figure 1 indicates clearly that the AA had been decreasing after January 1976, the onset of RCM. However, the rate of decrease of the AA during the experimental phase of RCM is greater than the rate of decrease during the post-RCM phase. This suggests that the effect of RCM during the experimental phase may be different from the effect after the experimental phase. One possible reason for this difference is that there was a piecemeal introduction of RCM, air base by air base, during the experimental phase, along with several trial revisions in the maintenance policies. We also notice some large spikes in value of the AA during October, November, and December 1977 and January 1978. A cause for these large values may be that the information system for reporting the operational status of aircraft was revised during this period. The AA may have been artificially increased during this period due to anomalies of reporting. Thus, it appears that we need three distinct components to our intervention analysis model. We represent these components by three indicator variables, \(J_t\), \(K_t\), and \(L_t\), where:

\[
J_t = \begin{cases} 
1 & \text{for Jan 76} \leq t \leq \text{May 77} \\
0 & \text{otherwise}
\end{cases}
\]

\[
K_t = \begin{cases} 
1 & \text{for Jun 77} \leq t \leq \text{Sep 77} \\
0 & \text{for Feb 78} \leq t \leq \text{Nov 79} \\
1 & \text{for Oct 77} \leq t \leq \text{Jan 78} \\
0 & \text{otherwise}
\end{cases}
\]

\[
L_t = \begin{cases} 
1 & \text{for Oct 77} \leq t \leq \text{Jan 78} \\
0 & \text{otherwise}
\end{cases}
\]

Note that the union of the three sequences \(\{J_t\}, \{K_t\},\) and \(\{L_t\}\) constitutes the series \(\{Z_t\}\), defined earlier.

As for the functional form of the response (series \(\{Y_t\}\)) to these components (see Figure 3), we remark that ramp and step responses appear to be possible candidate forms for \(\{J_t\}\) and \(\{K_t\}\), whereas a jump response is appropriate for \(\{L_t\}\). We exclude a jump response for the first two because it would not account for the gradual decline evident in the data, and we consider a slope response to be inappropriate due to the absence of a sustained leveling of the data. We conjecture that a step response might have a period of three months, which coincides with the length of time between scheduled minor inspections. Our aim now is to compare the functional forms of the ramp response versus the step response in order to determine which combination might best represent the relationship between AA and the series \(\{Z_t\}\).

We fit all reasonable combinations of response forms with the variables \(J_t, K_t,\) and \(L_t\), and find that step type responses, along with the original ARIMA model, i.e., a model of the form

\[
Y_t = \frac{\alpha_1}{1 - B}J_t + \frac{\alpha_2}{1 - B^2}K_t + \alpha_3L_t + N_t
\]

(4.1)
where \( N \), denotes an ARIMA \((1,0,0) \ast (1,1,0)_6\) process, produces residuals that are most satisfactory (see Figure 5). The model (4.1) describes the series \( \{Y_t\} \) as a step function with three-month incremental decreases of size \( \alpha_1 \) during the experimental RCM phase, as a step function with three-month incremental decreases of size \( \alpha_2 \) after implementation of RCM, and as a jump function with height \( \alpha_3 \) during the October 1977-January 1978 time frame. Thus we have the prewhitening model

\[
(1 - .18B)(1 + .35B^6)(1 - B^6) Y_t = \frac{-02}{1 - B^3} J_t + \frac{-01}{1 - B^3} K_t + .15L_t + b_t.
\]

We remark that the estimated parameters \( \alpha_1 \) and \( \alpha_2 \) are negative, as expected, with \( \alpha_1 \) greater than \( \alpha_2 \). Also, the estimated parameter \( \alpha_3 \) is positive, which is intuitively apparent. We also remark that in the residual series (see Figure 5) there remain some significant auto-correlations at lag 12. We can account for this by fitting an ARIMA \((0,0,0) \ast (2,0,0)_12\) model to the residuals. However, this would provide us with only 34 observations with which to perform a cross correlation analysis. Since paucity of data can lead us to questionable results,* we elect to continue working with the residuals of the model (4.2). These residuals are given in Table 1 as values of \( b_t \); also given there are values of \( a_t \), the prewhitened flying hours.

*Actually, we did perform a cross correlation analysis with only 34 observations and obtained results that were counter-intuitive.
5. CROSS CORRELATION ANALYSIS

Using the prewhitened series \( \{a_i\} \) and \( \{b_i\} \), we now develop the transfer function model (2.1). We remark that the \( \{a_i\} \) series with its 59 observations must be modified by omitting the January 1975 observation so that it will match the \( \{b_i\} \) series, which has 58 observations.

Following procedures of Box and Jenkins and using the estimated "impulse response weights," \( V_k \), shown in Figure 6, we remark that possible values of \( (r,s,b) \) in (2.1) are \( (1,3,0) \) or \( (2,3,0) \). From the autocorrelation functions of the generated noise series (see Singpurwalla and Talbott [4]), we remark that a possible model for the noise \( N_i \) is an ARIMA \((1,0,1)\).

<table>
<thead>
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</table>

Figure 6. Estimated impulse response weights \( V(K) \) from a cross correlation of prewhitened flying hours and alert availability

We fit both the \( (2,3,0) \) and the \( (1,3,0) \) transfer function models with an ARIMA \((1,0,1)\) noise component to the data and find that the more parsimonious \( (1,3,0) \) model results in better residuals. This estimated model, whose residuals have an ACF as shown in Figure 7, is

\[
(1 + .53B)b_i = (25 + .51B + .24B^2 + .1B^3)a_i + \frac{1 - .11B}{1 + .12B}e_i.
\]

where \( e_i \) is random noise.

6. THE COMBINED INTERVENTION ANALYSIS TRANSFER FUNCTION MODEL

We can expand the transfer function model (5.1) for the prewhitened series \( \{a_i\} \) and \( \{b_i\} \) by using the following relationships from (3.1) and (4.2):

\[
a_i = \frac{(1 - .54B + .11B^3)(1 + .38B^4 + .37B^8)(\hat{x_i})}{1 + .18B^3}
\]
TIME SERIES ANALYSIS OF LOGISTICS PERFORMANCE

![Figure 7](image)

Figure 7. A (1,3,0) transfer function model between flying hours and alert availability; graph of the ACF of the residual series

\[
(6.2) \quad b_i = (1 - .18B)(1 + .35B^4)(1 - B^6)Y_i + \frac{.02}{1 - B^3}J_i + \frac{.01}{1 - B^1}K_i
\]

\[\quad - .15L_i,\]

where \( \bar{X}_i = (X_i - 10.09) \).

Substituting (6.1) and (6.2) for \( a_i \) and \( b_i \) in Equation (5.1), we obtain a multiplicative transfer function model relating the input series \( \{X_i\} \) to the output series \( \{Y_i\} \) as

\[
(1 + .18B^3)(1 + .35B^4)(1 - .18B)(1 + .35B^4)(1 - B^6)(1 + .12B)Y_i
\]

\[\quad - (.25 + .51B + .24B^3 + .1B^3)(1 - .54B + .11B^3)(1 + .38B^4 + .37B^6)
\]

\[\cdot (1 + .12B)\bar{X}_i - \frac{(1 + .12B)(1 + .53B)}{(1 + .18B^3)(1 - B^3)}[.02J_i]
\]

\[\quad - \frac{(1 + .12B)(1 + .53B)}{(1 + .18B^3)(1 - B^3)}[.01K_i]
\]

\[\quad + \frac{(1 + .12B)(1 + .53B)}{(1 + .18B^3)}[.15L_i] + (1 - .11B)e_i.
\]

Note that \( X_i \) and \( Y_i \) in (6.3) are in terms of the logarithms of the original data.

Expanding the polynomials and rewriting Equation (6.3) in conventional notation (in the interest of parsimony, coefficients with a value less than .1 are arbitrarily deleted), we can reduce the transfer function model to...
\[ Y_t = -0.47Y_{t-1} + 0.1Y_{t-2} - 0.18Y_{t-5} + 0.59Y_{t-6} + 0.31Y_{t-7} + 0.12Y_{t-11} \\
+ 0.39Y_{t-12} + 0.17Y_{t-13} \]
\[ + 0.25\bar{X}_t + 0.68\bar{X}_{t-1} + 0.11\bar{X}_{t-3} + 0.26\bar{X}_{t-5} + 0.25\bar{X}_{t-9} \\
+ 0.42e_{t-1} + 0.18e_{t-5} \\
+ Z_t + 0.65Z_{t-1} - 0.18Z_{t-5} - 0.12Z_{t-6} \]

where, following the notation of Section 4,
\[ Z_t = \{[-0.02J_t - 0.02J_{t-3} - 0.02J_{t-6} - 0.02J_{t-9} - \ldots] \\
+ [-0.01K_t - 0.01K_{t-3} - 0.01K_{t-6} - 0.01K_{t-9} - \ldots] + 0.15L_t\}. \]

7. CONCLUDING REMARKS

From Equation (6.4), we remark that the nonzero coefficients associated with the \( \bar{X} \)'s imply that flying hours do have an effect on the alert availability in a manner specified by the functional form of the equation. Furthermore, an examination of Figure 2, together with the prewhitening transformation, Equation (3.1), reveals that there was no upward or downward trend in the flying hours during the period of study. However, there does appear to be a reduction in the variability of the flying hours as of the inception of RCM. In any case, it appears that Equation (6.4) supports the adage that "the more you fly, the less you fail," within limits.

The negative coefficients (albeit small) associated with the variables \( J_t \) and \( K_t \) in Equation (6.4) do, in the absence of any upward or downward trend in flying hours, support our premise that RCM has a tendency to reduce the alert availability.

The model, Equation (6.4), can be used not only for interpretative purposes as is done above, but within limits and with proper care, it can also be used to predict future availability given its previous values, and the present and previous values of the flying hours.

REFERENCES


