A STATISTICAL ANALYSIS OF AIRCRAFT MAINTENANCE COSTS

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This paper outlines the merits of the recursive regression model in analyzing aircraft-failure and manhour-cost data. The parameters of this model are estimated from maintenance data generated by the entire Boeing B-52 fleet during the period August 1965 to August 1966. Failure rates and manhours of repair are found to be a significant function of the calendar age of the aircraft, the length of the missions flown, the time spent in low-altitude flight, and the technological developments in newer aircraft. The estimated parameters are used to develop a marginal cost analysis that can be used by the decision maker in evaluating his maintenance operation. Although the paper is based on a specific military operation, the method outlined can be used to determine maintenance costs for any large jet aircraft.

STATISTICAL COST analyses based on the technique of multiple regression have received increased emphasis in the past ten years. Although this method has proven valuable in a number of cost areas,[1] its use in the field of aircraft maintenance has met with limited success, the primary reason being the difficult problem of quantifying the causal structure of maintenance in both the military and commercial sectors. After an extensive review of military maintenance operations and data, I have found that the maintenance activity can be described most accurately by a recursive regression model. Certain exogenous factors affect aircraft system failures, and the number of manhours expended repairing these failures is a function of both these factors and the number of failures experienced. This paper describes this recursive model and the data that were collected to support it. Actual estimates based on the maintenance operation of the Boeing B-52 are then presented and discussed.

THE GENERAL RECURSIVE MODEL

GUY H. ORCUTT has defined two models that can be of particular value to the policy maker.[2]

The Forecasting Model. Given all variables which are predetermined and known at the time of forecast, the purpose of a pure forecasting model is to predict future values of criterion variables with as little inaccuracy as possible. The role of undetermined policy variables is either ignored or the forecast is made on the assumption of a continuation of past behavior.

The objective of a forecasting model is to predict either that which is predetermined as of the time of forecast and/or to predict what will be the consequences of a continuation of the past behavior of policy makers. Success of a forecast is determined solely in terms of the accuracy with which criterion variables are predicted, as measured by their actual development.

If successful, forecasting models may serve to forewarn policy makers of the need for alteration of policy. Since the effect of a policy alteration will lag the actual alteration, forecasting may enable a more timely alteration of policy than would otherwise be possible.

The Policy Response Model Given all variables which are predetermined and known at the time of application of a policy response model, the purpose of this type of model is to predict the dependence of criterion variables on, as yet, undetermined policy variables. The function of policy models is to enable policy makers to determine the likely effects of alternative changes in policy.

The success of a forecasting model depends upon the smallness of the forecasting error actually achieved. The value of a policy response model depends upon the extent to which the dependence of criterion variables on undetermined policy variables is correctly represented. Such dependence may be correctly and usefully shown even though sizable unexplained variations of the criterion variables do occur. Accuracy of the prediction of the values of criterion variables is not necessarily an appropriate measure of success of a policy response model.

The model presented in this study is classified as a policy response model. At the present time it is impossible to forecast accurately the number of failures an aircraft will experience on a given mission—there are too many unexplained exogenous and random factors that influence failure rates. This is evident in the low R^2 statistics for the estimated model presented in a later section.

As Orcutt states, the fact that the R^2's are low does not detract from the value of the model. The R^2 statistic indicates the proportion of the total variance of the dependent variable that is explained by the regression equation; it is not a measure of the reliability of the estimated parameters of the equation. For small samples, the R^2 can be high, although the sampling variances of the estimated parameters are quite large. On the other hand, a large sample may yield an exact estimate of the parameters, although the R^2 is fairly low.

In a cost analysis, primary attention is directed toward the parameters in the cost equation. We are interested in accurately allocating the cost of an operation to factors over which the policy maker has some control. It is then possible to estimate the changes that will occur in the dependent variable for each alternative policy that is considered. For example, the coefficient of a flying-hour variable indicates, on the average, what change will take place in the number of malfunctions independent of the influence of other factors if the length of a mission is increased by one hour.

As mentioned above, it was found that a recursive model reflected more accurately the causal chain of maintenance activity than did other specifications. An extensive analysis of individual flight data indicates that certain exogenous factors cause malfunctions and the number of manhours expended in repairing these malfunctions is a function of both these factors and the number of malfunctions experienced. This recursive relation can be specified in the following regression model:

$$\text{malfunctions} = \alpha_1 + \sum_1^n \beta_{1i} X_i + u_1,$$

$$\text{manhours} = \alpha_2 + \gamma_2(\text{MF}) + \sum_1^n \beta_{2i} X_i + u_2.$$

The recursive model provides several features that are not found in other formulations. First, the influence of policy variables on the number of failures can be determined. These results are of interest, not only to the cost analyst, but also to the reliability engineer who in the future must take these factors into consideration in the development of new and improved equipment. Since parts and capital equipment costs are, in part, also predicated on equipment failures, these results should prove beneficial to cost analyses beyond the scope of the present study. Second, the coefficients of the policy variables in the manhour equation, with the effect of malfunctions held constant, indicate whether these factors also increase the severity of malfunctions.

Finally, a dollar cost can be placed on the number of manhours that are allocated to the separate factors. Normally in statistical cost equations, the dollar cost of a particular operation is initially specified as a function of several output variables. The recursive formulation used in this study adds dollar costs only at the end; thus, it permits one to adjust cost figures for changing wage scales without reestimating the failure and manhour parameters.

The wage rate utilized to cost manhours in the study was \$4.66 an hour. This was the average wage (plus 10 percent for fringe benefits) that prevailed in the 1967–68 period for two-year mechanics with most major airlines. This airline wage has the benefit of also representing the true or opportunity cost of a trained Air Force mechanic during that period; it is the price he could command in his best alternative line of endeavor with the airlines. If this amount is not paid either explicitly or implicitly through some factor such as *esprit de corps*, the mechanic will leave the service for this alternative. The airline wage can therefore be considered the true cost of retaining and utilizing mechanics in the Air Force.

When multiple regression is utilized, certain assumptions are made about the character of the error term u in the regression model $Y = \alpha + \beta X + u$. Specifically, we assume that the error term has a mean equal to zero and is independently and randomly distributed. In addition, for efficiency, the variance of the error term should be constant from one observation to the other. For a recursive model, however, an additional stipulation is required: that the error terms of the two equations, u_1 and u_2, must not be correlated. If they are, the malfunction variable in the second equation and the error term u_2 will not be independently distributed. This will result in a biased estimate of the malfunction variable coefficient if the method of ordinary least squares is used.

An extensive review of the data and residuals generated in the regression process revealed that, for the most part, these assumptions had been fulfilled in the estimated equations of this study.[2] For this reason, the method of ordinary least squares was utilized to estimate the parameters presented in the following sections.

THE DATA BASE

THE PARAMETERS OF the recursive model described above were estimated with data provided by The Boeing Company on the entire B-52 fleet. The sample period ran from August 1965 to August 1966. Air Force Manual 66-1 failure and manhour data were subjected to an intensive sorting, purging, and merging program to eliminate all but true failure data. These data were then mated with AFTO Form 16 operational data on a monthly basis by aircraft serial number to provide 6,326 aircraft-month observations (*see* Note 1). These 6,326 observations contained data on approximately 35,000 stateside B-52 flights for a total of 343,000 flying hours, 1,320,000 malfunctions, and 3,720,000 manhours required to repair these malfunctions.

It must be emphasized that only true failure data were considered. Depot, servicing, and general-maintenance manhour data were not included in the sample. It should also be noted that the failures ranged from those that required only minor repairs, such as replacing or adjusting airframe panels, to those of a more critical nature that required the mission to be aborted. Any failure, however, that resulted in manhours being expended for repair was included.

Unfortunately it was impossible to obtain the data for such a large sample on an individual flight basis at this time. The monthly quantitative data for each aircraft were therefore deflated by the number of missions the aircraft flew. This deflation was not effected to improve the statistical properties of the data but because the information was desired on the individual-flight basis. There is no problem then in interpreting the meaning of the constant term in the regression equation. Actually, one will find that the number of malfunctions experienced during a month will be highly correlated with the number of sorties flown, for no other reason than the fact that the more an aircraft flies the more it is inspected, and the more it is inspected, the more chance there is of discovering malfunctions. Averaging by the number of sorties helps to eliminate this effect.

There are both advantages and disadvantages in using monthly average data. First, averages are means, and the central limit theorem states that mean values will approach a normal distribution as the sample size is increased; the method of least squares works best when the variables are normally distributed. Second, the process of averaging tends to minimize the effects of extreme values caused by data inaccuracies and other exogenous influences that are not considered pertinent to the analysis. Averaging, however, may also have opposite effect of eliminating the variance we are trying to explain. For example, if malfunctions are a function of flying hours and there is a tendency to equalize the total flying time among the aircraft at a particular base, a loss of information is experienced when monthly data are utilized.

TABLE I

System Malfunction Equations

		T
	Airframe System	
Malfunctions =	2.065	
	+2.231 (flying hours)$^{1/2}$	2.56
	+0.227 (lagged malfunctions)	4.19
	Flight Controls System	
Malfunctions =	0.281	
	+0.443 (flying hours)$^{1/2}$	2.63
	+0.181 (lagged malfunctions)	2.87
	Power Plant System	
Malfunctions =	0.027	
	+0.638 (log flying hours)	2.05
	Pneudraulics System	
Malfunctions =	0.003	
	+0.498 (log flying hours)	1.96
	+0.086 (lagged malfunctions)	1.64
	Fuel System	
Malfunctions =	0.152	
	+0.023 (flying hours)	2.51
	+0.108 (lagged malfunctions)	2.08

There are two other disadvantages of utilizing monthly observations. First, the effect of past maintenance cannot be analyzed adequately, since it makes little sense to utilize malfunctions from the previous month to explain the current month's malfunctions. Second, it is difficult to incorporate the established fact that failure rates are nonconstant over a mission's length because flying time is added together to get a monthly total for the aircraft.[3] To determine these effects accurately, individual flight data rather than monthly total data should be utilized. As an example, regression equations for five B-52 systems utilizing past malfunctions and nonlinear flying time variables are presented in Table I. These estimates are based on individual mission data for 238 sorties flown out of Westover Air Force Base during the summer of 1965. The T column provides the Student T ratios based on 235 degrees of freedom and computed for the null hypothesis that the regression coefficient is zero.

Ineffective maintenance appears to be the best explanation for the relation between past and current malfunctions. Maintenance probably fails to repair the system adequately after the first flight, and the subsequent work on the system is the result of a repeat write-up. If we do classify this effect as ineffective maintenance, we can obtain an estimate of its significance by multiplying the mean number of lagged malfunctions by the coefficient of the lagged malfunctions variable and dividing by the mean number of current malfunctions. Actually, since the mean number of lagged malfunctions and the mean number of current malfunctions are approximately equal, we need only look at the coefficients of the lagged malfunctions variable. These coefficients imply the following percentages of ineffective maintenance for the four systems:

System	Percent
Airframe	22.6
Flight controls	18.1
Pneudraulics	8.8
Fuel	10.8

These figures are close to those obtained in an independent study conducted by The Boeing Company.[4] If we generalize, it appears that approximately 10 to 20 percent of maintenance actions result from inadequate repair or diagnosis of previous failures. Although it is improbable that ineffective maintenance can ever be completely eliminated, these results do point to an area in which considerable savings can be made.

Now turn to the flying-hour or mission-length variables depicted in the regression equations of Table I. A nonlinear form denoting a nonconstant failure rate provides the best fit for all except the fuel system; this is probably due to the additional air refueling required on longer flights. The square root form provides the best fit for the airframe and flight-control systems, while the natural logarithm form is best for the power-plant and pneudraulics systems.

A graph of the regression equations holding the effect of lagged malfunctions constant at their respective means is presented in Fig. 1. The solid lines denote the regression lines that are valid in the range from 3 to 24 hours; the dashed-line extensions indicate how the regression lines might appear under the assumption that each aircraft begins its flight with zero malfunctions.

However, in light of the knowledge we now have on the significance of ineffective maintenance, this assumption appears unrealistic. Some

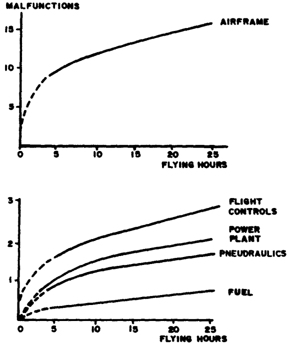

Fig. 1. Nonconstant failure rates.

failures can be discovered only after takeoff when the aircraft is airborne. If the influence of lagged malfunctions can indeed be attributed to ineffective maintenance, a rough estimate of the mean number of malfunctions with which an aircraft begins its flight can be obtained by multiplying the mean number of malfunctions by the coefficients of the lagged malfunctions variable in the regression equations presented in Table I. This figure would provide a more realistic estimate for the intercept of the regression line at the point where the flying-hour variable equals zero.

These regression lines do indicate, however, that a fair approximation for failure rates within the normal range of from 4 to 12 flying hours could be provided by a linear fit based on monthly observations if the 24-hour airborne alert flights are classified separately. A variable defined as an airborne alert adjustment was constructed for this purpose. This variable acts like a dummy variable, but it is not a dummy in the strict sense of the word. It is a type of quasi-dummy constructed by dividing the number of airborne alert missions by the number of sorties flown during the month. This hybrid variable was used as a proxy to reflect the lower failure rates experienced on the longer missions. Its main purpose was to increase the slope of the regression surface so that the failure rate for the normal range

TABLE II

THE B-52 AIRCRAFT MODEL

		T
	Malfunction Equation	
Malfunctions =	24.263	3.88
	−47.101 (age in 100's of months)	3.22
	+44.891 (age in 100's of months)^2	5.00
	+1.739 (flying hours)	5.92
	+2.965 (low-level hours)	3.83
	−21.403 (airborne-alert adjustment)	4.53
R^2 (corrected) = 0.04		
Std. error of est. = 33.10		
	Manhour Equation	
Manhours =	7.171	2.12
	+1.534 (malfunctions)	94.04
	+3.976 (flying hours)	10.32
	+2.159 (low-level hours)	2.14
	+4.483 (B-F model dummy)	4.04
	−42.675 (airborne-alert adjustment)	6.90
R^2 (corrected) = 0.60		
Std. error of est. = 43.19		

of flying hours was more accurately depicted. Because of the hybrid nature of this variable, its coefficient should not be taken seriously. At the most its value could be used in conjunction with the flying-hour coefficient to reflect the failure rate for the 24-hour airborne alert missions.

THE B-52 AIRCRAFT MODEL

THE MODEL FOR the aggregate number of malfunctions and the man-hours expended in repairing malfunctions for the B-52 aircraft is presented in Table II. Both the malfunction and manhour equations with their estimated parameters are given. These ratios are based on over 6000 degrees of freedom and are predicated on the null hypothesis that the parameter equals zero. Below each equation is the R^2 statistic corrected for the appropriate number of degrees of freedom and the standard error of estimate.

T ratios are also presented for the constant terms in these equations. If all factors that cause malfunctions and manhours were known and included in a correctly specified model, the constant term would equal zero. The constant terms that we actually do observe in these empirical regressions are therefore the result of both the mean positive influence of omitted variables and nonlinearities in the lower ranges of the variables that are included.

The coefficients and T ratios in the aircraft-malfunction equation indicate there is a significant relation between aircraft malfunctions and the age of the aircraft, the mission duration, and the time the aircraft spends in low-level flight. The negative coefficient on the age variable and the positive coefficient on the age-squared variable define the U-shaped failure

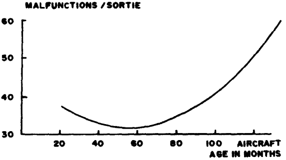

Fig. 2. The effect of aircraft age on failure rates.

curve. This relation, with the effect of all other variables held constant at their means, is plotted in Fig. 2. The age of the aircraft in the sample ranged from 2.5 to 11 years and was based on the Boeing delivery date. Although accumulated flying time on the aircraft could also have been used to describe this relation, its explanatory influence was not as great as calendar age. (*See* Note 2.)

The significant coefficients for the flying-hour and low-level-hour variables in the manhour equation indicate that these two factors influence not only the number of malfunctions but also that severity of the malfunctions. The positive coefficient for the B-F model dummy variable (1 for B-F B-52 models, 0 for G-H models) in the manhour equation implies that more time is spent repairing malfunctions for this model group than for the G-H model group; this is the result of a provision for faster diagnosis and repair of failures built into the more advanced equipment of the later models. It is the benefit of experience and technology that accrues to the maintenance organization.

The negative coefficients on the airborne alert adjustment variable indicate that failure rates are indeed nonconstant throughout a mission. Because of the hybrid nature of the variable, it is not used in cost analysis of this section. Its main purpose is to increase the slope of the regression surface so that a more valid estimation of the influence of flying hours in the normal range, 4 to 12 hours, can be obtained.

TABLE III

B-52 Aircraft Marginal Cost Estimates

Mean manhour cost per sortie = $498.00			
	Flying Hours		
MF/fly hr	MH/fly hr		MH cost/fly hr
1.739	6.644		$30.96
	Low-Level Hours		
MF/fly hr	MH/LL hr		MH cost/LL hr
2.965	6.707		$31.26
	B-F Models		
	MH/sortie		MH cost/sortie
	4.483		$20.89
	Changes Effected by Age		
Calendar age in years	Change in MF/sortie	Change in MH/sortie	Change in MH cost/sortie
2–3	−2.420	−3.712	−$17.30
3–4	−1.127	−1.727	−8.06
4–5	0.165	0.253	1.18
5–6	1.459	2.238	10.43
6–7	2.751	4.220	19.67
7–8	4.044	6.203	28.91
8–9	5.337	8.187	38.15
9–10	6.631	10.172	47.40
10–11	7.923	12.154	56.64
11–12	9.215	14.136	65.87

A marginal cost analysis based on the coefficients depicted in Table II is presented in Table III. A brief explanation of how these estimates were derived is presented below.

Derivation of the cost estimates for linear variables is relatively simple. As an example, take the influence of flying hours on the three criterion variables in which we are interested. First, the coefficient of the flying-hour variable, 1.739, in the malfunction equation indicates how many additional malfunctions we can expect if the mission length is increased by one hour in the relevant range. To determine how many manhours we would expect to expend on this increase of malfunctions, the figure 1.739 is multiplied by the coefficient of the malfunction variable in the manhour equation:

$$1.739 \times 1.543 = 2.668 \text{ manhours/flying hour.}$$

If the flying-hour variable did not appear in the manhour equation, this would be the only calculation needed to determine the number of manhours required to repair the number of malfunctions that result from the increase in flying time. However, the fact that it does appear in the manhour equation indicates that more time is spent on malfunctions as the mission length is increased. The above figure must therefore be adjusted by the value of this coefficient to determine the true increase in manhours: $2.668 + 3.976 = 6.644$ manhours/flying hour.

To determine the manhour cost of the increase in flying time, the above figure is multiplied by \$4.66, the cost figure specified in a previous section:

$$6.644 \times \$4.66 = \$30.96 \text{ manhour cost/flying hour.}$$

The cost of an hour of low-level time is derived in the same manner.

The influence of the B-F model dummy variable is calculated on a per sortie basis. The coefficient of this variable in the manhour equation indicates that 4.483 more manhours are expended on malfunctions per sortie for the B-F models than the G-H models. The value of the advanced technology built into the later equipment is then:

$$4.483 \times \$4.66 = \$20.89 \text{ manhour cost/sortie.}$$

The influence of age on the criterion variables is nonlinear—the slope of the age surface changes throughout the valid age range. This means that we must pick some base point on the age surface from which to calculate the effect of a year's change in the age of the aircraft. As an illustration of the calculations required, we determine the changes that take place in the criterion variables as the age of the aircraft increases from nine to ten years (age is in 100's of months):

$$\{-47.101[(1.20)-(1.08)]\} + \{44.891[(1.20)^2-(1.08)^2]\}$$
$$= 6.631 \text{ change in malfunctions/sortie,}$$
$$6.631 \times 1.534 = 10.174 \text{ change in manhours/sortie,}$$
$$10.174 \times \$4.66 = \$47.40 \text{ change in manhour cost/sortie.}$$

It can be seen that the calculations are more burdensome for the nonlinear estimates than they are for linear approximations. There is a definite tradeoff to be considered between linear and nonlinear specifications for cost variables. If there is no great curvature in the regression surface over the operational range of the explanatory variable, a linear approximation of this surface often provides an effective and more convenient means of estimating the influence of changes in this variable on costs.

Attention is now directed to the cost estimates of Table III. The mean manhour cost per sortie is given at the top of the table to provide the reader with an idea of the significance of the various policy variables in the total mission cost. The influence of flying hours on the criterion variables has already been discussed. The estimates indicate, for instance, that if an organization flies 100 sorties per month and it is directed to increase the length of the sorties by one hour, it would expect to repair 173.9 additional malfunctions. To repair these malfunctions, 664.4 additional manhours would be required for an increased cost of $3,096. If there were no slack in the system and the policy objective were to work personnel only 40 hours a week or approximately 172 hours a month, four additional mechanics would be needed. If the mechanics could not be procured, it would be necessary to resort to overtime employment, which increases the cost of wages for the airlines and degrades morale in the military.

The cost of an additional hour of low level for a given mission is $31.26. Since an hour at low level is also a flying hour, this means that the total cost of a low-level hour is approximately twice that of a high-level hour for the aircraft. This should not be surprising to those who are familiar with the increased turbulence sustained during low-level flight.

The expected changes that will take place in the three criterion variables as the aircraft ages from 2 to 12 years are outlined in the bottom portion of the table. Costs decrease until the minimum point on the age curve is reached (4.5 years) and then begin to increase at an increasing rate. Between 5 and 6 years a year of age costs $10.43, whereas between 9 and 10 years it costs $47.40, an increase of almost 400 percent.

The difference in costs between any two years can be calculated by adding the changes in costs between those years. For example, it costs $144.56 more in manhours per sortie to repair a 10-year-old aircraft than it does a 5-year-old aircraft. If one organization is assigned 5-year-old aircraft and another is assigned 10-year-old aircraft and each unit flies 100 missions, we would expect 3,102 more manhours to be expended by the unit possessing the older fleet for an increased cost of $14,456.

SUMMARY

THE PRECEDING DISCUSSION was directed, first, at showing how the recursive model can provide statistically significant cost parameters, and, second, how these parameters can be utilized to aid the decision maker in the difficult task of evaluating his maintenance operation. Although only the general aircraft model is described here, the recursive formulation is not limited to this level of maintenance. Models were also estimated in my original study for six common aircraft systems—airframe, landing gear, flight controls, power plant, pneudraulics, and fuel. Although the influence of the particular input variables differed, all of these models showed characteristics similar to the general aircraft model presented here.[2]

NOTES

1. Throughout this process, only 4 percent of the original failure data were rejected.

2. Other studies have indicated that aircraft maintenance requirements, taken over the life of an aircraft, decrease and finally level off in a relatively stable state.[5] These results, for the most part, have been derived using manhour data, and may reflect a learning curve and qualitative improvements in the maintenance operation. The panel data used in this study traced the failure rates on approximately 650 aircraft over a year's experience. It was therefore comprised of both time series and cross-sectional data. Although it may be inappropriate to draw time-oriented inferences from cross-sectional data such as consumer budget studies where changes in environment, tastes, and attitudes are involved, it is doubtful whether the same phenomenon would apply in the case of aircraft failure rates. The B-52 aircraft used in this sample operated in a relatively stable environment over their life-span. An attempt to separate the effect of technological differences in B-52 model types from that of age by the use of dummy variables did not provide statistically significant results in the malfunction equation, the reason being that there are only minor differences within the C-F model and G-H model categories. Additional analyses using only C model data did confirm the relation of rising failure rates with aircraft age within that model type and a recent study has shown the same phenomenon for KC-135 tanker aircraft.[6] The additional argument that a steady maintenance state is reached as components are replaced over time certainly has merit for certain individual aircraft systems such as avionics. Component age in other more extensive systems such as the airframe, however, are more correlated with aircraft age and could account for the rising failure rate.

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