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WHEN IS A SATELLITE NOT A TOASTER?

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ABSTRACT

We repair our automobiles but discard inexpensive appliances at the first sign of trouble: they "cost too much to fix." Comparing $50M satellites with toasters may seem odd, but the analogy can be appropriate. The too-much-to-fix argument can be used in deciding whether to replace or to repair Earth satellites. We investigated (1) when cost considerations dictate using constellations of expendable satellites to be routinely replaced and discarded on failure, and (2) when circumstances indicate using constellations of satellites to be repaired on-orbit by exchanging failed modules.

1 BACKGROUND

Since it began its activities in space, the United States has routinely used satellites that must be replaced when they fail - assuming that their functions are to be continued. Because building and launching replacements for these expendable satellites is expensive, the idea of repairing and servicing satellites on-orbit has long appealed as a potential source of cost savings. The high cost of conducting space operations, however, makes it difficult to assess when this potential can be realized and when it is a chimera. It makes good sense to ask when the satellite is like a toaster in not being economical to fix, and when repairing it is a superior option.

On-orbit satellite maintenance was first discussed as a profitable mission for the then conceptual space shuttle. On-orbit shuttle-based repairs have, in fact, been performed on several satellites that were not designed for repair. NASA has also built or has under development several satellites that will rely on replenishment of expendables, repair, and even limited modification on orbit. One of these, the Hubble Space Telescope (HST), has recently been launched. Other examples of ongoing NASA programs that have considered repair options are the Gamma Ray Observatory (GRO), the Advanced X-Ray Astrophysics Facility (AXAF), and the Space Infrared Telescope Facility (SIRTF).

NASA is apparently headed toward a future in which satellite repair will be routine. The situation facing the Department of Defense (DoD), however, is not that facing NASA. While NASA is contemplating on-orbit maintenance of expensive one-of-a-kind satellites at low altitude and low orbital inclination, DoD often deals with multisatellite constellations of substantially less costly satellites in geosynchronous (GEO) or other hard-to-access orbits.

Are the two situations similar enough for DoD to begin planning for on-orbit maintenance of all its satellites? The answer is decidedly "no," but delineating the boundaries separating discard and repair is a complex problem. Initially, we examined this question for specific existing satellite constellations. Recently, we extended our models and techniques in an attempt to achieve a general understanding of the problem. This follow-on effort is called the Comprehensive On-Orbit Maintenance Assessment (COMA) [Feuchter et al 1989].

2 APPROACH

COMA focuses on constellation support, which consists of establishing a constellation and keeping it functional throughout its life. We chose cost to evaluate competing expendable and repairable constellation support strategies and tactics. Cost, in turn, is dependent upon the resources needed to provide the support.

Resource requirements in COMA are determined by our GAP_PLUS FORTRAN simulation model, which we developed in-house on our Concurrent Computer Corporation 3230 super minicomputer. This model is able to determine support resources as a function of the probability that the satellite constellation will function at a minimum desired level throughout its life. This probability is called `constellation availability`. By comparing constellation support costs for scenarios characterized by the same availabilities, we ensure that the same job is performed within all scenarios.

GAP_PLUS is an event stepped model, all of whose random events are generated by satellite failures.

Historically, these failures have been modelled by the two parameter Weibull distribution, with reliability given as a function of time, t, by

$$R(t) = \exp[-(t/\alpha)^{\beta}]$$

Here the scale parameter, α, is related to the mean life of the satellite, and the shape parameter, β, characterizes the failure rate as the system matures.

Events modeled in addition to satellite failures include successful and failed launches to establish the constellation or replace failed satellites, successful and failed satellite repairs, and substitution of on-orbit spares for failed satellites. Assets tracked include the number of launch and repair missions by the equipment required, the number of satellites and modules used, and the total mass moved from the Earth to low earth orbit (LEO) - approximately 280 km above the Earth's surface. The output from GAP_PLUS is used as input to the COMA cost model.

We also developed the COMA cost model in-house in FORTRAN. Rather than assessing all constellation support costs, thus producing life cycle costs, this model considers only those costs that vary substantially from scenario to scenario. Such differences in cost depend primarily on differing satellite investment costs and upon differing operation and maintenance costs. The COMA model can be described as a differential life cycle cost model. Our model estimates the cost of satellite research, development, test & evaluation (RDT&E); satellite investment; and constellation operations and support(space transportation). It ignores costs for manufacturing facilities; site activation; communications and ground team facilities; and significantly, space platforms used in constellation support, for which no reliable cost estimates seem to exist.

Both expendable and repairable satellite models consist of six subsystems (Figure 1). Satellite RDT&E and investment cost are modeled as simple functions of subsystem mass after Apgar et al. [1987]. COMA determined subsystem masses from historical data as functions of satellite mass. Satellite mass is one of the fundamental parameters of the COMA analysis. Functionally equivalent expendable and repairable satellites are expected to have different masses.

Normally, satellites can be classified as either sensor-type satellites, containing a sensor or other payload but with a minimal communications subsystem; or as communications satellites with no sensor and a payload consisting of a full-blown communications subsystem. We would like to have carried out a complete analysis for both types of satellites, but the necessary resources were not available. Consequently, we decided on a compromise that seemed to best satisfy the overall COMA goal. Both sensor and full-blown communications subsystems were included in our generic satellite model. Because both of these subsystems are costly, our hypothetical generic model was more expensive for a given satellite mass than either a sensor type or a communications satellite. This high cost means that repairable satellites are favored over expendables, as it increases the cost of satellite replacement relative to satellite repair. Even with this advantage, our results show no automatic cost advantage for repair, a position that has been erroneously argued on occasion.

The cost of space transportation is based on the masses moved to support the constellation. This cost depends on estimates of investment cost derived from existing expendable upper stages and from projections for the reusable orbital maneuvering vehicle (OMV) and orbital transfer vehicle (OTV). Both the OMV and the OTV remain conceptual.

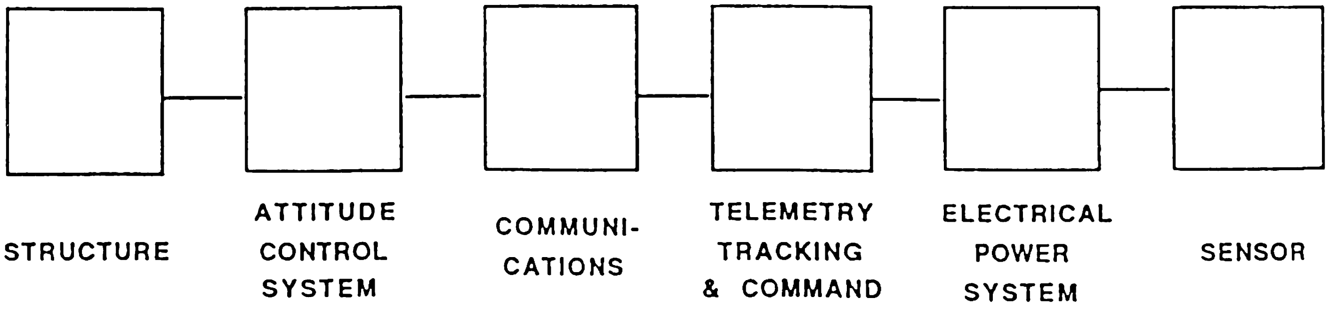

Figure 1: The COMA Satellite Model Contains Six Subsystems

Today DoD constellations are supported by replacing failed or failing expendable satellites with new satellites or with improved satellites. This strategy represents our baseline. Contrasted with this baseline are strategies that allow on-orbit satellite maintenance by remote telerobotic replacement of failed modules.

In COMA we examined a number of combinations of support strategies and tactics to identify the most cost-effective scenarios. Tactics, and to a lesser extent strategies, are dependent on parameters that describe the size, shape, and spatial orientation of the satellite orbit.

Figure 2 shows the altitude and inclination ranges of the orbits examined in COMA. We refer to these regions as high altitude, mid-inclination; GEO; and low altitude polar-, mid- and low-inclination. These regions were initially identified (with a minor modification) for the Space Assembly, Maintenance and Servicing Study (SAMSS) [Waltz 1987]. In COMA we focused on four circular orbits to represent the five orbital regions. Most satellite orbits today are approximately circular and can be found in one of these five regions.

The high altitude, mid-inclination region is represented by a 12-hour orbit at 67.5 degrees inclination. The GEO region is represented by a 24-hour orbit at 0 degrees inclination. The three low altitude regions (low-, mid-, and polar-inclination) are represented not by single specific orbits, but by the collection of all circular orbits at 1,300 km and 3,700 km with appropriate inclinations. Because our methodology characterizes access to different inclinations of low altitude orbits entirely by differences in the cost to travel from the Earth to LEO (a study parameter), we do not need to consider specific inclinations for the 1,300-km and 3,700-km orbits.

The strategy options include reacting to satellite failures as they occur, acting in anticipation of upcoming failures, and relying on a fixed schedule of support visits to the constellation. Our tactics options involve expendable and reusable transfer vehicles and, depending on circumstances, possibly one or two orbital platforms per scenario to serve as warehouses and transportation nodes. One possible platform is the proposed NASA space station at approximately

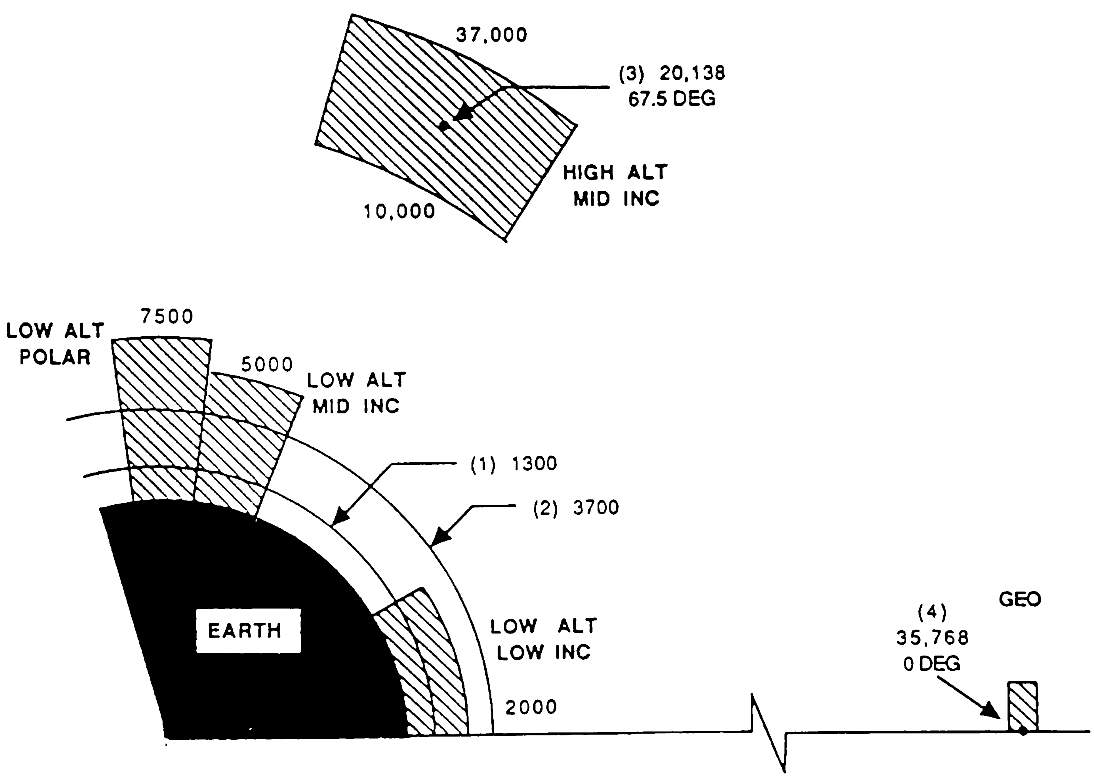

Figure 2: US satellite orbital altitudes and inclinations typically fall in one of the five cross-hatched areas shown in this schematic diagram. The four representative orbits used in COMA correspond to the two circular orbits at 1,300 and 3,700 km; the GEO orbit at 0 degrees and 35,785 km; and the high altitude, mid-inclination orbit at 67.5 degrees and 20,138 km. The figure is not to scale.

400 km and 28.5 degrees inclination. Other reasonable options are platforms coorbital with the satellites they serve, and platforms at a lower altitude but with identical inclinations to the supported satellites.

We verified four constellation parameters and five satellite parameters as being statistically significant in determining constellation support cost. These parameters are

Constellation Parameters
- Size, that is, the number of operational satellites;
- Time over which the constellation is maintained;
- Cost to transport mass from earth to LEO; and
- Transportation efficiency;

Satellite Parameters
- Mass;
- Modularization mass penalty;
- Reliability;
- Truncation lifetime; and
- Value of retrieving failed satellites and modules.

Transportation efficiency is a measure of the efficiency with which the mass used to support the constellation is moved from LEO to the satellite orbit. This mass consists of such things as replacement modules, satellite working fluids, and servicing equipment. Because many scenarios allow this mass to be stored on-orbit in anticipation of its use, some estimate must be made of how efficiently it has been selected and transported. Efficiency will be lowered if materials transported to orbit are never used or if needed items have not been transported in advance. A modularization mass penalty is recognition that a repairable modular satellite will necessarily have a different, probably greater, mass than its expendable equivalent [DeRocher et al. 1978]. There are many reasons for this, for example, the need for a suitable docking point to accommodate the satellite servicer, module-to-satellite interfaces, and likely improved failure diagnostic capability. The truncation of a satellite's lifetime is caused by such factors as mechanical wearout or the exhaustion of consumables and is relatively predictable. Finally, retrieval refund is the value of bringing failed satellites and modules back from orbit, measured as a percentage of their initial investment cost. Retrieval has many possible benefits, including limiting debris in space and allowing examination of failed components.

The issue of when to use expendable or repairable satellites is clearly complex, involving as it does a variety of satellite orbits, scenarios, and constellation and satellite parameters. Fortunately, one member of our study group is experienced with response surface methodology (RSM) techniques [Sparrow 1984]. This methodology combines experimental design with multivariate regression to estimate the dependent variable (in our case constellation support cost) as a surface in N-dimensional space based on parameter values selected by the experimental design. The dimensions are the problem's N independent parameters. For COMA, there are nine regression parameters; the four constellation parameters and the five satellite parameters.

The most useful aspect of RSM for our study is that it allowed us to minimize the number of GAP_PLUS runs needed to obtain our regression equations. Previous analysis showed that constellation support cost as a function of the nine parameters was at least a second-order nine-dimensional surface. Appropriate designs to estimate second-order surfaces are the full 3^k design (k being the number of parameters), fractional 3^k design, and central composite design. For nine parameters the full 3^k design requires 19,683 data points. The fractional 3^k design requires 243 data points, and the central composite design requires 177. Since we needed prediction equations for each of the 66 scenarios (for functionally equivalent expendable and repairable constellations), GAP_PLUS run time became the deciding factor. Therefore, we chose the central composite design. Even with this choice for our regression, and considering that many GAP_PLUS cases could be applied to multiple scenarios, over 2,000 GAP_PLUS cases (1,000,000+ replications) were required for the 66 scenarios. This equated to approximately one month of continuous computing 24 hours per day.

For the COMA experimental design, a regression analysis for a single scenario requires varying six of the nine constellation and satellite parameters in 113 GAP_PLUS cases. The results from GAP_PLUS serve as input to the cost model where the additional three parameters are varied. This results in 177 individual costs for each scenario. The corresponding regression analysis of the data for all scenarios produced 66 approximation equations containing 55 coefficients each (one intercept term, nine linear terms, nine squared terms, and 36 interaction terms). It also assesses the statistical significance of the prediction equations and each of the terms in the equations, and allows confidence intervals to be assigned to cost projections calculated from the equations. Once the regression equations are determined, it is easy to calculate the predicted cost for any independent parameter values within the ranges as specified in the experiment. The appendix contains an abbreviated regression example for one of the cases described below.

3 RESULTS

COMA's nine independent parameters make it impossible to present a comprehensive picture of all potentially significant parametric interactions. One method of circumventing this problem is to examine the individual impact on comparative cost of each of the nine parameters (Table 1) and then select a set of parametric values that favors expendable satellites and a set that favors repairable satellites. Comparing expendable satellites with repairable satellites obtained for these two sets allows us to establish a range of representative results.

Many of the trend directions in Table 1 can be understood by keeping in mind two points. First, RDT&E, investment, and operations and support costs are modelled as monotonically increasing functions of satellite mass. This monotonic nature is embodied in the historically based satellite cost-estimating relationships and the obvious dependence of space transportation cost on mass moved. Second, COMA adopted the premise that all mass-based costs apply identically to both expendable and repairable satellites.

Additional insight can be achieved by recognizing that constellations of expendable satellites are more expensive to maintain because it is more expensive to replace an entire expendable satellite than to exchange one or a few modules of a repairable satellite. The repairs involve both buying and moving less mass. Of course, repaired satellites are less reliable than replacement satellites because of the advancing age of unreplaced modules. The cost of repairing the additional failures that result from this lower reliability is usually not significant.

Using the trends we had identified, we selected the sets of parameter values that favor expendable satellites and those that favor repairable satellites to illustrate the results (Table 2). We chose these values to avoid the large expected errors at the extremes of our parameter ranges, yet to be consistent with values characteristic of today's satellites.

Figures 3 and 4 show typical COMA results based on this approach for the GEO expendable-favorable case, and Figures 5 and 6 show the results for the repairable-favorable case. Where parameters were selected to favor expendable satellites, there is really no advantage to either expendable or repairable satellites (Figures 3 and 4). On the other hand, for the case favoring constellations of repairable satellites, repairable satellites offer fairly large absolute and percentage cost advantages (Figures 5 and 6). The percentage advantage can be determined by comparing the absolute advantage against the expendable cost.

At an α-level of 0.05 the cost difference contours in Figure 4 are not statistically significant; yet the cost difference contours in Figure 6 are statistically significant at an $\alpha = 0.05$ level. We used confidence prediction intervals to evaluate the statistical significance of the cost difference contours in both cases. An example of this process is illustrated in Figure 7.

Table 1: Of the COMA constellation and satellite parameters, all but one have a predictable effect on the expendable-repairable cost comparisons. These trends are defined in this table and indicate how each parameter must change to favor repairable over expendable satellites.

Parameter	Trend Direction	Explanation
<u>Constellation Parameters</u>		
Size	No Trend	No Inherent Economies Involved
Time Maintained	Increase	More Repair/Replace Tradeoffs
Transportation Efficiency	Increase	Reduce Waste
Cost To LEO	Increase	Accentuates Transportation Savings
<u>Satellite Parameters</u>		
Satellite Mass	Increase	Accentuates Repair/Replace Differential
Modularization Mass Penalty	Decrease	Less Difference in RDT&E, Investment, and Launch Cost
Reliability	Decrease	More Repair/Replace Tradeoffs
Truncation Life	Decrease	More Repair/Replace Tradeoffs
Retrieval Refund	Decrease	Satellite Worth More Than Module

Table 2. For our example, we chose parameter values to favor expendable and repairable satellite constellations that are comparable with values found on existing satellites. Constellation size and satellite mass were chosen as independent parameters.

	Parameters Values That Favor	
Parameter	Expendable Satellites	Repairable Satellites
Constellation Parameters		
Size	-	-
Time Maintained (yr)	12.75	19.25
Transportation Efficiency (%)	50	70
Cost To LEO ($/kg)	3000	5000
Satellite Parameters		
Mass (kg)	-	-
Mass Penalty (%)	30	10
MTBCF (yr)	10.75	7.25
Truncation (yr)	10.75	7.25
Retrieval (%)	30	10

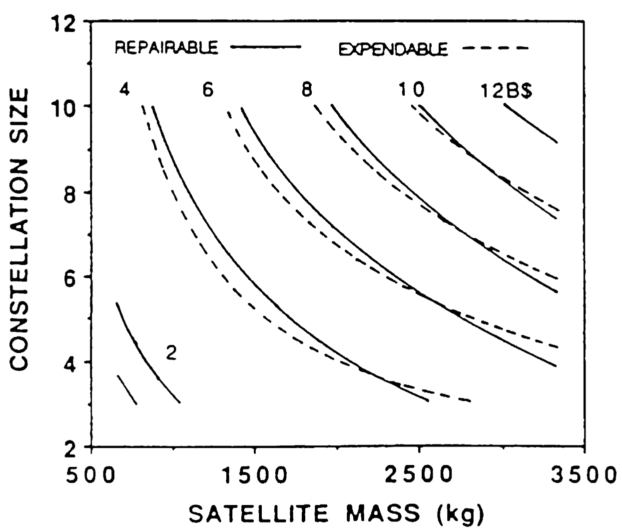

Figure 3: Total expendable and repairable constellation maintenance costs for the GEO expendable-favorable case are similar. The repairable scenario, however, makes use of a coorbital platform whose cost has not been included.

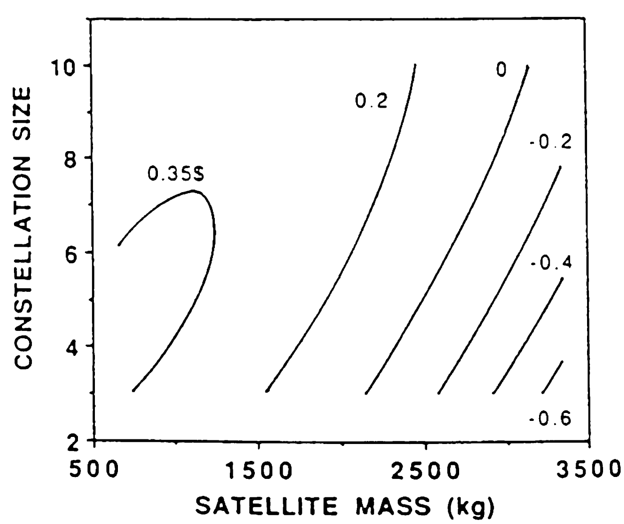

Figure 4: The differential life cycle costs in the GEO expendable-favorable comparison are small, as might be expected from Figure 3. Analysis indicates that they are not statistically significant.

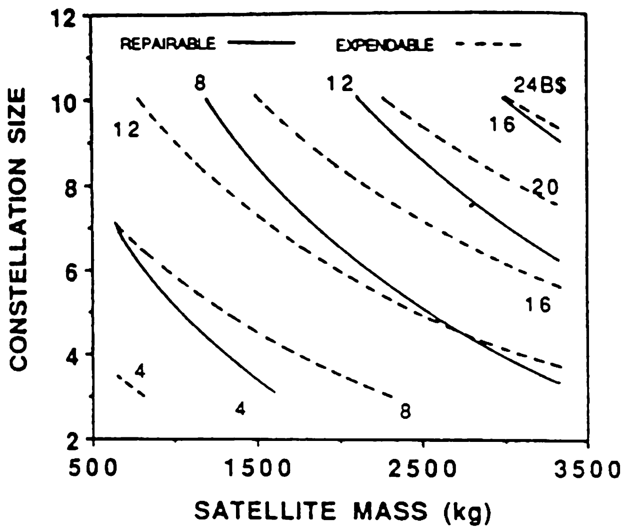

Figure 5: Total expendable and repairable constellation maintenance costs for the GEO repairable-favorable comparison are substantially different. As in the expendable-favorable case, the repairable scenario makes use of a coorbital platform whose costs have not been included.

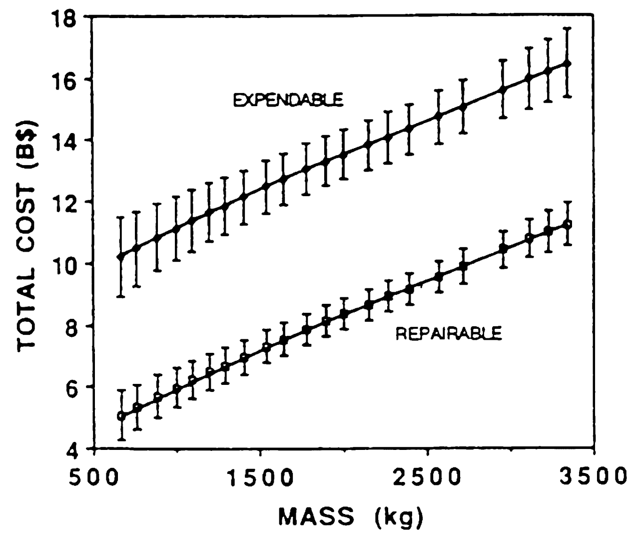

Figure 7: The 95 percent confidence intervals for the total expendable and repairable costs corresponding to the $5-billion cost difference contour of Figure 6 demonstrates the statistical significance of the difference. Since the results in this figure depend upon digitizing the $5-billion contour, the spacing of points is irregular.

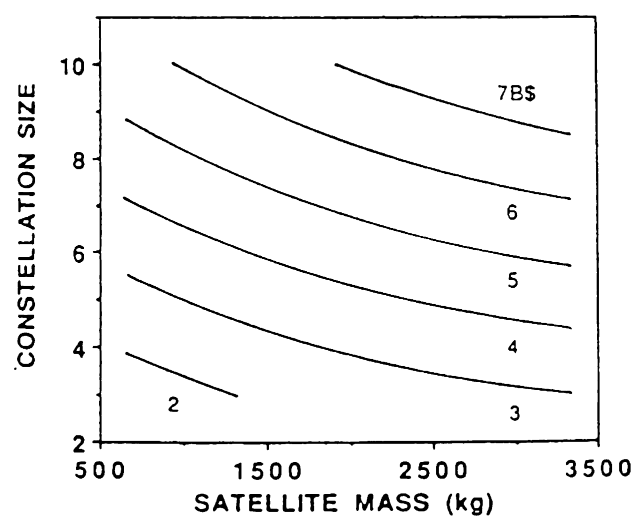

Figure 6: The differential life cycle costs in the GEO repairable-favorable comparison are substantial. These differences are shown to be statistically significant in Figure 7.

4 CONCLUSION

The results shown in Figures 3, 4, 5, and 6 are typical of the results found for the other representative orbits discussed earlier. In total, they demonstrate conclusively that a cost-based decision to adopt repairable satellites can properly be made in a given case only if the basic parameters of both constellation and satellite have been defined and the appropriate analysis conducted.

In another aspect of the COMA analysis, we identified some generic future constellations whose support costs can potentially be reduced by employing repairable satellites. However, engineering questions must still be resolved before we can begin to think of the cost reductions as real rather than potential.

One critical question is whether repairable satellite functions can be augmented or improved by replacing modules. Historically, later satellites of virtually every enduring expendable satellite program have periodically benefitted from the incorporation of preplanned product improvements (P^3I) including satellite redesign. In COMA, we assumed P^3I (upgrading) of repairable satellites could be implemented via limited module exchange, and P^3I was costed for both expendable and repairable satellites. However, should P^3I for repairable satellites also require complete satellite redesign with subsequent replacement of the earlier satellite version, repairable satellites will lose much, if not all, of their potential cost advantage.

If we were to consider present DoD satellites, we would find that some are potential candidates for repairable versions, and others are not. Without specific knowledge of future values of the constellation and satellite parameters (which are dependent upon future missions and technologies), we can only speculate about the possible proliferation of repairable satellites and the necessary support infrastructure. Perhaps, if the historical trend to build fewer and fewer more capable and more costly satellites continues, this will favor the development of repairable satellites. On the other hand, perhaps a decision to build simpler, less capable, and less costly satellites, will tend to perpetuate the replace-on- failure strategy employed today.

As an aid to further investigation of the overall COMA issue of when to use expendable satellites and when to use repairable satellites, we included in our COMA documentation the regression equations for all evaluated scenarios. This will allow future planners to reexamine the question of discarding or repairing satellites as long as the basic COMA premises remain valid.

ACKNOWLEDGMENTS

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APPENDIX

This appendix contains a summary of regression results used to calculate the repairable total cost contours shown in Figures 3 and 5.

The first result, Table 3, is the standard analysis of variance table (ANOVA). This is followed by the F- and R-squared statistics. The F-statistic for the regression model is 2208.86 with degrees of freedom 55,122. Its associated critical value at an α-level of 0.05 is 1.53. Since the F-statistic is greater than the critical value, the regression model proposed is statistically significant at an $\alpha = 0.05$ level. The F-statistic for lack of fit is 187.136 with degrees of freedom 92,30. Its associated critical value at an α-level of 0.05 is 1.90. This significant lack-of-fit is due to higher-order terms not included in our proposed second order regression model. Based on previous analysis, we anticipated that this might be the case for the variables mean time before critical failure (MTBCF) and constellation size. However, the cost comparisons are valid since all equations are used on a comparative basis. Approximately 99 percent of the variation in our total cost is explained by our proposed regression model, as shown by the R-squared statistics.

Another statistic is the standard error of an estimate which can be used to form a confidence interval around a future prediction if all the variable values

Table 3: This table shows the sum of squares (SS) and mean square (MS) terms for the ANOVA results. The F-statistic and R-square terms indicate that the model is statistically significant and that it explains almost all variation in total cost.

Source	d.f	SS	MS
Regression	55	6301721000.00	114576700.00
Residual	122	6328320.00	51871.48
Pure Error	30	11008.00	366.93
Lack of fit	92	6317312.00	68666.44
TOTAL	177	6308049320.00	

F-statistic for regression model = 2208.86 d.f. = 55, 122
F-statistic for lack of fit = 187.136 d.f. = 92, 30

F-square (corrected for mean) = 0.989084
R-square (not corrected for mean) = 0.998997

are near their respective means. The value for the statistic in this case was 227.753. We didn't use this statistic often since our regression program calculated future prediction confidence intervals using the expression

$$Y_f \pm t\sqrt{MSE\left(1 + X_f^T(X^TX)^{-1}X_f\right)}$$

where X is the normalized data matrix used in the regression, X_f is the vector of future proposed variable levels, t is the appropriate t-statistic from Student's t-table, MSE is the mean square error read from the ANOVA table, and Y_f is the future predicted total cost from the regression equation evaluated at X_f.

We calculate the normalized coefficient estimates, standard errors, and T-statistics of the 55 variables for each of the 66 regression equations. The critical value with 122 degrees of freedom and $\alpha = 0.05$ is 1.98. Many of the coefficient estimates are not significantly different from zero and could be dropped from the equation. However, when we dropped non-significant variables from the expendable and repairable prediction equations before differencing them, the resulting equations predicted inconsistent results. This resulted because the variables dropped from the expendable cases for lack of significance were not the same as those dropped from the repairable cases. In order to get consistent predictions of total cost differences, we used all 55 variables to evaluate the equations.

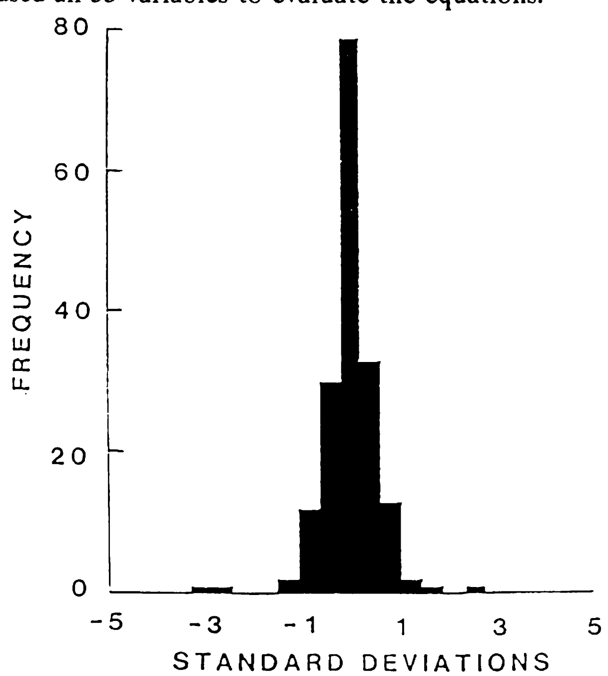

Figure 8: The histogram of normalized residuals appears normal except for kurtosis.

The residual table for this case has not been included to conserve space. It contains 177 rows and five columns. Each of the rows represents one of the 177 cases from the experimental design. The columns contain actual total cost, estimated total cost, the residuals, and the normalized residuals.

Figure 8 is a histogram of the omitted normalized residuals from our example. The graph looks fairly normal except for kurtosis. This kurtosis can be explained by the fact that the regression model displayed a significant lack-of-fit because it did not include higher-order terms for at least the variables MTBCF and constellation size. From the deleted residual table, we know 98.3 percent of the residuals are within ±3 standard deviations, 97.2 percent are within ±2 standard deviations, and 93.2 percent are within ±1 standard deviation.

Again, in the interest of economy of space, we have not included the uncoded coefficient estimates. These estimates are used to formulate the second order equation used to predict total cost by substituting appropriate variable levels.

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