AN EXPLORATORY EXERCISE IN TAGUCHI ANALYSIS OF DESIGN PARAMETERS: APPPLICATION TO A SHUTTLE-TO-SPACE STATION AUTOMATED APPROACH CONTROL SYSTEM

Final Report

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ABSTRACT

NASA is currently exploring strategies which can contribute to increased efficiency in performance of their various activities and is undertaking to evaluate the potential offered by a multitude of techniques in the Total Quality Management area. One such technique that has received considerable attention within the manufacturing community over the last few years is Taguchi design of experiments and optimization of design parameters.

Taguchi methods are concerned with the quality design of an end-product and give specific focus to efficiency in the design process. The underlying philosophy of the Taguchi approach is that through introducing a planned structure to the experimentation carried out in the formative stages of design that a great deal of information regarding product or system performance can be gleaned in less time and at less cost than through traditional methods.

The chief goals of the summer project have been twofold —— first, for my host group and myself to learn as much of the working details of Taguchi analysis as possible in the time allotted, and, secondly, to apply the methodology to a design problem with the intention of establishing a preliminary set of near-optimal (in the sense of producing a desired response) design parameter values from among a large number of candidate factor combinations.

The selected problem is concerned with determining design factor settings for an automated approach program which is to have the capability of guiding the Shuttle into the docking port of the Space Station under controlled conditions so as to meet and/or optimize certain target criteria. The candidate design parameters under study were glide path (i.e., approach) angle, path intercept and approach gains, and minimum impulse bit mode (a parameter which defines how Shuttle jets shall be fired). Several performance criteria were of concern: terminal relative velocity at the instant the two spacecraft are mated; docking offset; number of shuttle jet firings in certain specified directions (of interest due to possible plume impingement on the Station's solar arrays), and total RCS (a measure of the energy expended in performing the approach/docking maneuver). In the material discussed here, we have focused on a single performance criterion —— total RCS. An analysis of the possibility of employing a multiobjective function composed of a weighted sum of the various individual criteria has been undertaken, but is, at this writing, incomplete.

Results from the Taguchi statistical analysis indicate that only three of the original four posited factors are significant in affecting RCS response. A comparison of model simulation output (via Monte Carlo) with predictions based on estimated factor effects inferred through the Taguchi experiment array data suggested acceptable or close agreement between the two except at the predicted optimum point, where a difference outside a rule-of-thumb bound was observed. We have concluded that there is most likely an interaction effect not provided for in the original orthogonal array selected as the basis for our experimental design. However, we feel that the data indicates that this interaction is a mild one and that inclusion of its effect will not alter the location of the optimum.

INTRODUCTION

A critical stage in the performance of the Shuttle's rendezvous and docking maneuvers with the Space Station will be the final approach, initiated at a separation of a few hundred feet between two spacecraft. This procedure can be supported, either entirely or in large degree, by an automated approach program designed to establish the approach path and control the approach velocity and attitude of the Shuttle relative to the Station, thus guiding the Shuttle into the Station's docking port.

A central goal in the assessment of approach design options is that of determining a superior combination of design parameter settings so as to permit an approach/docking maneuver which, when evaluated against several quantifiable criteria, is projected to produce a near-optimal result. The set of design factors whose optimal levels are to be determined include the glide path approach angle ($\emptyset$), the minimum impulse bit setting (MIB) which defines the mode of Shuttle jet firings, and two gains — the path intercept gain ($K_{\partial r}$) and approach gain factors (K_x) — which describe target velocity modification profiles for the approach. The set of performance indicators includes statistics indicative of the terminal conditions at the instant docking is to be achieved (e.g., the terminal velocity and docking offset); fuel expended in the approach (total RCS); and the number of Shuttle firings in specified directions, this last being of concern due to the possibility of plume impingement on the Station solar arrays.

In the summer assignment, we have focused on a single performance criterion, total RCS, which we seek to minimize. Our evaluation medium was a simulation program developed within the Guidance & Prox Ops Section which models the dynamics of the problem and produces estimates for the various performance indicators, all of which are, of course, functions of the design parameter values set by the analyst. The methodology employed in searching for a near-optimum combination of these design factor values was Taguchi parameter optimization, a statistical design of experiments technique, the details of whose analytical steps are given in the sections below.

EXPERIMENTAL DESIGN

The domain for the factor settings in this preliminary study were as follows: Glide Path Angle - $\emptyset = -10°$, $\emptyset = 0°$, $\emptyset = +10°$; Minimum Impulse Bit mode - MIB= norm z, MIB= low z; Path Intercept Gain - $K_{\partial r} = 0.8T$, $K_{\partial r} = 1.0T$, $K_{\partial r} = 1.2T$; Approach Gain - $K_x = 0.8T$, $K_x = 1.0T$, $K_x = 1.2T$, where T for these last two factors is a theoretically derived value posited for each. Thus, our feasible region of interest is defined by four discrete decision variables with three 3-level factors and one 2-level factor.

In an exhaustive search for the optimum set of design factor values, an evaluation of all 54 setting combinations would be performed through a full-factorial experimental design. A by-product of the statistical analysis which follows compilation of the experiment data is a mathematical model which estimates all main factor effects *and* the effects of *all* interactions among these factors on the response variable (here, total RCS). Though derivation of such a detailed model produces considerable insight into the phenomenon being modeled, there are also obvious disadvantages in this approach. The time and expense involved in running experiments is frequently such that a large number of cases cannot be accommodated.

Fortunately, in the majority of instances, it not necessary to perform a complete enumerative analysis. It has been observed that in engineering design problems the effects of the higher-order interaction terms — certainly those involving three or more factors — are very often insignificant and that, in many cases, most of the second-order terms have little effect on the response function. As a result, meaningful information may be gleaned through a considerably smaller battery of experiments, if the experimental design is constructed in a particular manner. These points are, in fact, the premises underlying Taguchi design of experiments.

It not being evident that there would be any significant interactions among the factors, it was decided that we would employ the simplest experimental design that could accommodate all four factors. This was the Taguchi L_9 orthogonal array[1], each of whose four columns could carry a 3-level factor. Note that, as pointed out earlier, one of the design parameters (MIB) was a 2-level factor, the remaining three parameters being 3-level factors. This mismatch between the factor levels of the problem and those provided for in the L_9 array, is only apparent. In actual fact, using a dummy level technique, we simply choose a level designation to repeat as a third level value for the 2-level factor — for example, MIB_1= norm z, MIB_2= norm z, MIB_3= low z. The net result is that the estimate for the mean effect at one level (MIB= norm z) has twice the precision as that at the other (MIB= low z). In addition, the orthogonality of the experiment array is preserved. The L_9 layout for our matrix of experiments is given in Table 1 below.

TABLE 1: L_9 MATRIX EXPERIMENT LAYOUT

Experiment Number	Factors				Response
	Ø	MIB	$K_{\partial r}$	K_x	
1	-10°	norm z	0.8T	0.8T	RCS_1
2	-10°	norm z	1.0T	1.0T	RCS_2
3	-10°	low z	1.2T	1.2T	RCS_3
4	0°	norm z	1.0T	1.2T	RCS_4
5	0°	norm z	1.2T	0.8T	RCS_5
6	0°	low z	0.8T	1.0T	RCS_6
7	+10°	norm z	1.2T	1.0T	RCS_7
8	+10°	norm z	0.8T	1.2T	RCS_8
9	+10°	low z	1.0T	0.8T	RCS_9

[1] A matrix experiment is termed an orthogonal array if the contrasts corresponding to all its columns are pairwise orthogonal (i.e., if the inner product of any two vectors of contrast weightings is zero). See Chapter 3 of Hicks [1] and Appendix A of Phadke [2].

EXPERIMENT RESULTS

Recall that we wished to evaluate the factor contributions with an eye towards minimizing the total RCS response —— i.e., we were operating from a "smaller the better" basis, as termed in the Taguchi literature. For each of the nine response observations, the *squared deviation* from zero (the "ideal" target in the minimization of a nonzero objective) was computed in accordance with Taguchi's concept of a quadratic quality loss function (see Chapter 2 of Roy [3]). The individual squared deviations were then transformed into dB readings[2] as follows: $R_i = -10 \log_{10}(RCS_i)$. In the transformed domain we then wish to maximize the "signal" response.

An analysis of variance was carried out on the transformed data with the result that all factors were statistically significant, with the exception of $K_{\partial r}$. Figure 1 below displays the estimated factor level effects in the original domain so that we see actual RCS projected effects. The optimum factor settings which are predicted to minimize total RCS are Ø = -10°, MIB = norm z and K_x = 1.2T.

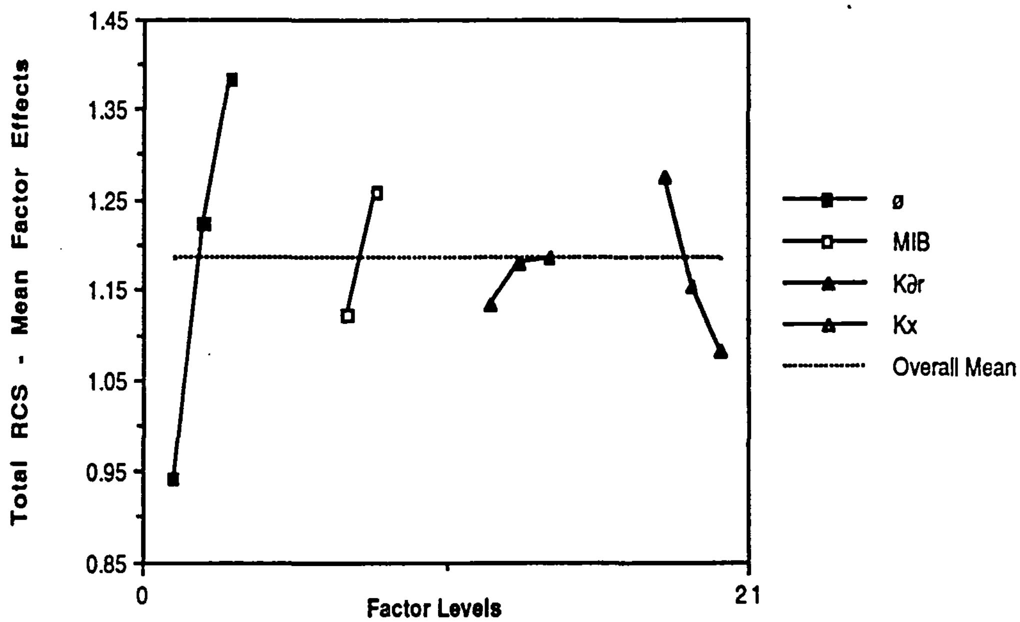

Figure 1: Mean Factor Effects on Total RCS

[2] Transformation of data into decibels is standard procedure in Taguchi analysis and offers an advantage in prediction, particularly when observed values are close to zero but cannot be negative. The transformation concept is also useful in assessing signal-to-noise ratio. See Phadke, Chapter 5.

The sum of squares estimated for $K_{\partial r}$ was pooled with that for the ANOVA error sum of squares to produce an error mean square, or error variance, estimate (this estimate would be used later in comparing predicted values to observed values). The statistical model for the response as a function of the contributing factor settings was then

$$\mu(\varnothing_i, MIB_j, K_{x_k}) = \mu + (\mu_{\varnothing_i} - \mu) + (\mu_{MIB_j} - \mu) + (\mu_{K_{xk}} - \mu)$$

where $\mu(\varnothing_i, MIB_j, K_{x_k})$ is the projected mean response with glide path angle equal $\varnothing_i$, minimum impulse bit mode set to MIB_j and the approach gain equal to K_{x_k};

μ is the overall mean of all observed responses;

$\mu_{\varnothing_i}$ is the estimated effect of $\varnothing$ at setting i;

μ_{MIB_j} is the estimated effect of MIB at setting j;

$\mu_{K_{xk}}$ is the estimated effect of K_x at setting K_{x_k}.

The next step was to compare predicted values to actual observations from the simulation program at various combinations of settings for the contributing factors. Predicted values for the mean response at given factor settings are obtained from the functional description above. Observed means would be estimated (via sample mean values) from several runs made at the corresponding settings through the simulation program, where random initial state errors were included to approximate actual "noise" effects (the nine data points obtained through the experimental design were outcomes resulting from no initial state errors).

Table 2 on the following page lists the model predictions for total RCS at all 18 combinations of the significant design factor levels. Predictions are arranged in ascending order to facilitate a rank-order comparison with observed values in the adjacent column. Observed sample means in the third column are for samples of size 12 at selected level combinations (time did not permit simulation and review of data at all combinations). The standard deviation used in computing the normalized error is a function of the ANOVA estimated error variance and the dispersion observed in the 12 replications at that particular combination of factor levels. We note that the standardized errors are all of reasonable magnitude, except for that at the predicted minimum (factor combination #1), and the rank-order of predicted RCS values agrees closely with that for the observations.

Figure 2, which follows the table, depicts a graphical comparison of the data. The actual range of observed values is about 64% of the range predicted, with the most significant error, again, being that at the optimum combination. However, we note that with this one exception all predictions fall within a 2-sigma error envelope (shown as the area between broken lines in the figure) used as a rule-of-thumb upper bound by some authors. Thus, while the model predictions are not uniformly in close agreement with the corresponding

TABLE 2: COMPARISON OF MODEL PREDICTIONS WITH SIMULATION OUTPUT

Factor Combination Count	Mean - Model Prediction	Mean - Simulation Observations	Error (Percent)	Error (in Std. Dev.'s)
1	.838	.962	-12.88	4.00
2	.895			
3	.940	.997	- 5.68	1.14
4	.990			
5	1.005			
6	1.090	1.112	- 1.96	0.48
7	1.111			
8	1.165	1.180	- 1.26	0.33
9	1.224	1.120	9.29	1.93
10	1.230			
11	1.288			
12	1.307	1.252	4.42	0.94
13	1.314	1.347	- 2.45	0.61
14	1.381			
15	1.445			
16	1.453			
17	1.475	1.369	7.78	1.66
18	1.631			

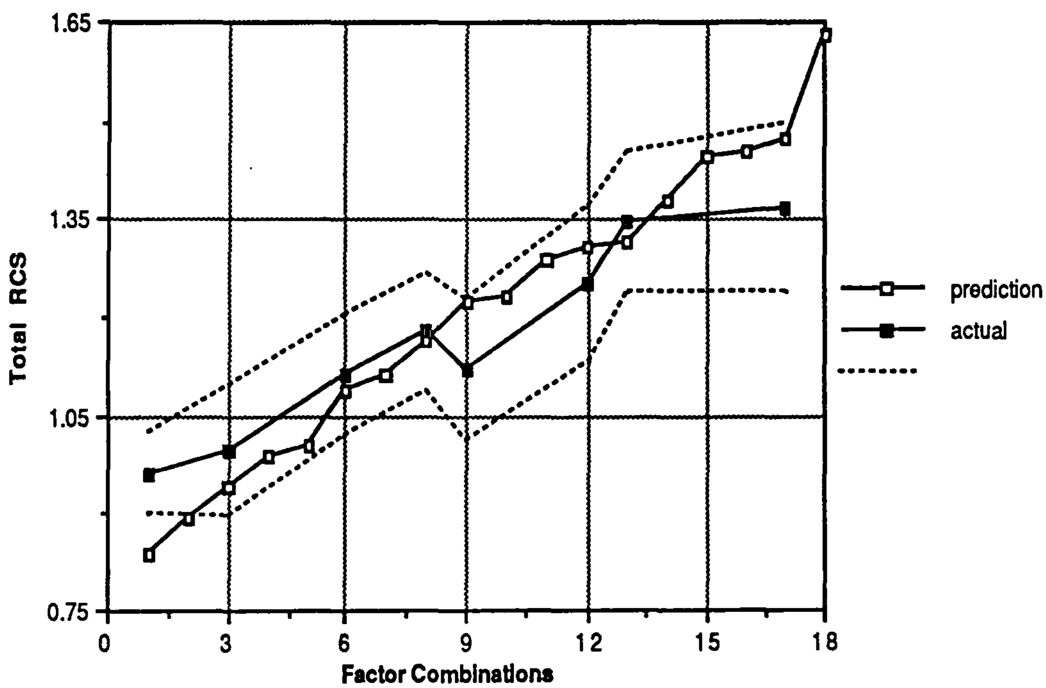

Figure 2: Total RCS Predicted Means vs. Observed Means

observations —— particularly, at the predicted extremes —— the model seems to capture adequately information regarding rank ordering of the possible factor combinations.

CONCLUSIONS

Our assessment is that the primary source of differences between the projections of the statistical model and observations obtained through simulation is most likely a single interaction effect between two of the factors. Recall that the L_9 experimental design employed provided for estimation of no factor interactions. Thus, any interaction effects that are, in fact, present are confounded with some subset of the main effects. However, given the level of agreement between predictions and observations over the range of results, we feel that the postulated interaction effect, though not insignificant, may be a mild one. We emphasize that provision for evaluation of the interaction would likely lead to a mathematical model with improved predictive capabilities; however, our chief objective has been to determine a near-optimum combination of design factor settings, and we feel that we have been able to do that.

For this investigator and the NASA host group, this has been a first exercise with Taguchi methods in a realistic problem setting. Our overall evaluation of the technique is that it can prove to be an efficient analytical tool, particularly once one has gained some experience with the mechanics and develops a feel for its subtleties. As a summary, we express impressions formed and offer some caveats in working with Taguchi analysis.

Rule-of thumb rationale for identifying "significant" factors will not always produce a clear-cut set of contributing variables. In typical ANOVA, a level of significance for statistical tests may be specified, and the F-ratio suggests that either a factor is significant or it is not. This is not the case here. It may be extremely difficult in this application to specify an alpha value in advance and then adhere to the conclusions one is drawn to as a result. A Pareto Principle approach seems more practical. This maxim suggests that approximately half the factors (actually, the factors associated with approximately half the total degrees of freedom) should account for the large majority of the observed variation. These factors are significant, and the sum of squares attributed to the remainder of the variables (i.e., the nonsignificant factors) are pooled with the error variance. This rationale is likely to work well in most instances —— but not always. There will be "borderline" cases where it is difficult to feel confident about assigning a factor to either class. We can only suggest that the best aid in such situations is one's insight into the phenomena under study.

Computation of squared deviations from a target follows from Taguchi's paradigm of the quadratic quality loss function. For cases where deviations from the target are more easily accommodated in one direction than the other, authors in the field offer the useful concept of employing asymmetric penalties wherein computations produce scaled deviations of $k_1\Delta^2$ in one direction and $k_2\Delta^2$ in the other. We feel that in many engineering design problems such asymmetric penalties may be called for.

We have found through our experience with this study that there may be some difficulty, when using small orthogonal arrays with all columns assigned to factors, in determining whether significant interactions are present and in deciding with some confidence which, if any, these might be. The graphical techniques suggested as offering some indication of the presence of interactions are based on comparison of mean effect against mean effect at various levels for two factors. In small experimental designs, these mean effects may be based on a single observation so that the standard error of the mean is relatively large. Evaluation is thus clouded by these uncertainties. A practical method may be to compare predictions against actual observations at various points in the domain as we have done here; lack of close agreement may suggest interaction effects not provided for in the experimental design.

Despite the possibility of overlooking interactions with small, total column-assigned array designs, much information can be gained if we view analysis at this stage as a first step in an iterative process. Frequently, it will be desirable, after performing a preliminary analysis, to "fine tune" the spacing of settings for the significant factors in an attempt to incrementally improve upon the optimum initially identified; thus, a second iteration may be planned as a matter of course. If we conclude that there may exist notable interactions and can determine which these might be, design of the experiment array for the subsequent stage can take this possibility into account.

In evaluating supporting software, we would look for special applications that can assist in selection and modification of the standard orthogonal arrays, advising the analyst as to which experimental design might be most appropriate for the problem at hand. Any software package that performs only the necessary statistical calculations may offer little more than existing nonspecific statistical packages.

Engineering design problems, particularly those undertaken within NASA, typically involve concern with multiple objectives. It may be possible to scale and weight the various individual objectives and pool these so as to enter into the Taguchi analysis with a single (weighted-sum) objective. However, it is not clear whether we can expect results with a similar level of integrity as those deriving from analyses with single-criterion objective functions. It may be necessary to carry out evaluations on a piecemeal basis (i.e., through independent consideration of the various objectives) and then perform a constrained trade-off analysis to ascertain near-optimal solutions.

We should underline the fact that the philosophy of Taguchi design optimization is to produce a quality design through a structured experimentation process which yields a maximum amount of information about the system under study with a minimum investment of time, effort and cost. As with many other methods within the TQM field, realization of increased efficiency depends on a shift of major effort to the early steps in the project. In Taguchi analysis it is *engineering experience and intuition* that are called upon at the beginning of the process in postulating controllable design factors and potential interactions and in establishing a feasible region of parameter settings to produce a desired result. Failure to take advantage of these elements can reduce the return promised by the methodology.

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