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COMPARISON OF ANALYSIS STRATEGIES FOR SCREENING DESIGNS IN LARGE-SCALE COMPUTER SIMULATION MODELS

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ABSTRACT

In large-scale computer simulation models it is often necessary to perform a screening experiment to reduce the number of factors to be examined in subsequent analysis. This study evaluated the results of a Plackett-Burman screening design using three different analysis strategies: 1) an approach due to Box and Meyer (1993); 2) an approach due to Hamada and Wu (1992); and 3) a standard Response Surface Methodology (RSM) approach. These strategies or methodologies were used to identify the active/significant factors across 17 different model outputs. The results from these three methodologies were then compared against each other for any notable differences in the identified significant factors. In one instance, where there was a notable difference, further analysis was performed in an attempt to ascertain which methodology was the best predictor for that specific response. A Resolution V design was used in this subsequent analysis to produce a validation model, which was then used to compare the three initial analysis strategies. The strategy/methodology that produced the model with the smallest mean absolute percent error (MAPE), the measurement criteria, was selected as the best for that response.

1 INTRODUCTION

Ideally, the practitioner can identify the significant factors for a large-scale simulation with a relatively small number of runs using a screening design. We assume the practitioners ultimate objective is the development of a linear model with emphasis placed on identifying the active main effects and two-factor interactions. Therefore, in an effort to perform an initial screening of inputs , an experimental design of at least Resolution III should be used. A Resolution III design is a design in which the main effects are not confounded or aliased with other main effects but are confounded with two factor interactions (or higher). Plackett-Burman designs are Resolution III with the additional attribute of requiring the fewest number of runs of any classical design type, but do not allow the estimation of interactions between factors (RS/Discover Reference Manual, 1992:3-10). Although Plackett-Burman designs do not allow the estimation of factor interactions, they have the advantage of parceling out the two factor interactions over many of the main effects, which will limit the amount of bias in any main effect due to the confounded two factor interactions (RS/Discover Reference Manual, 1992:XV). Although the Plackett-Burman design does not allow estimation of interactions between factors, it can identify the significant main factors that make up the possibly significant interactions. Further analysis of the important main factors allows the analyst to identify and estimate the significant interaction terms. Therefore, the use of a Plackett-Burman design is appropriate for screening.

1.1 Simulation Model

The large-scale computer simulation model used in this analysis was THUNDER, Version 5.8. THUNDER is a two-sided computer simulation model that simulates air and ground combat, logistics, and limited airlift at the theater level. It was developed by the Air Force Studies and Analyses Agency (AFSAA) and is the Air Force's premier theater level model. THUNDER is written in Simscript II.5 and has in excess of 700,000 lines of code. The purpose of THUNDER is to provide a detailed comparative analysis of tactical warfare.

The unclassified data base scenario provided with THUNDER, enhanced to more evenly match the opposing forces, was used as the initial input data set or baseline. See Webb, 1994, for the changes to the data base scenario provided with Version 5.8.

1.2 Experimental Design

There are 13 factors and 17 Measures of Outcome (MOOs) considered in the analysis for this paper. Table 1 gives the uncoded settings for the 13 input factors. For a complete definition of the files in Table 1 see Appendix A.

Table 1: 13 Input Factors with Uncoded Settings

FILE/CODE-SIDE	LOW	BASE	HIGH
advsac.dat			
A - Blue	0.75	1.0	1.25
B - Red	0.75	1.0	1.25
airairpk.dat			
C - Blue	0.9	1.0	1.1
D - Red	0.9	1.0	1.1
airgrdpk.dat			
E - Blue	0.9	1.0	1.1
F - Red	0.9	1.0	1.1
detect.dat			
G - Both	0.75	1.0	1.25
airplan.dat			
(CAS/BAI factors)			
H - Blue	2=failure	3=equal	1=success
I - Red	2=failure	3=equal	1=success
airrules.dat			
(GCI Ranges)			
J - Blue(Hi)	90,000	120,000	150,000
Blue(Low)	22,500	30,000	37,500
K - Red(Hi)	60,000	80,000	100,000
Red(Low)	15,000	20,000	25,000
squadron.dat			
L - Blue	-.25	no change	+.25
M - Red	-.25	no change	+.25

In a two-level, Resolution III design it would require 32 runs (2_{III}^{17-12} fractional factorial). However, by using a Plackett-Burman screening design the number of runs required for a Resolution III design is 20 (a multiple of 4 greater than 17). The coded design used in this analysis is given below in Table 2.

Although THUNDER produces numerous output variables, only a small subset of these are to be examined for this paper. The 17 MOOs examined in this paper are provided in Table 3.

Table 2: Twenty Run Plackett-Burman Screening Design (Coded Values)

A	B	C	D	E	F	G	H	I	J	K	L	M
1	-1	1	1	-1	-1	-1	-1	1	-1	1	-1	1
1	1	-1	1	1	-1	-1	-1	-1	1	-1	1	-1
-1	1	1	-1	1	1	-1	-1	-1	-1	1	-1	1
-1	-1	1	1	-1	1	1	-1	-1	-1	-1	1	-1
1	-1	-1	1	1	-1	1	1	-1	-1	-1	-1	1
1	1	-1	-1	1	1	-1	1	1	-1	-1	-1	-1
1	1	1	-1	-1	1	1	-1	1	1	-1	-1	-1
1	1	1	1	-1	-1	1	1	-1	1	1	-1	-1
-1	1	1	1	1	-1	-1	1	1	-1	1	1	-1
1	-1	1	1	1	1	-1	-1	1	1	-1	1	1
-1	1	-1	1	1	1	1	-1	-1	1	1	-1	1
1	-1	1	-1	1	1	1	1	-1	-1	1	1	-1
-1	1	-1	1	-1	1	1	1	1	-1	-1	1	1
-1	-1	1	-1	1	-1	1	1	1	1	-1	-1	1
-1	-1	-1	1	-1	1	-1	1	1	1	1	-1	-1
-1	-1	-1	-1	1	-1	1	-1	1	1	1	1	-1
1	-1	-1	-1	-1	1	-1	1	-1	1	1	1	1
1	1	-1	-1	-1	-1	1	-1	1	-1	1	1	1
-1	1	1	-1	-1	-1	-1	1	-1	1	-1	1	1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Table 3: Measures of Outcome

Blue/Red Aircraft Inventory
Blue/Red Sorties Flown
Blue/Red Ending Strength (% authorized)
Blue/Red Aircraft Losses by Mission
- Air-to-Ground
- Air-to-Air
- Defense Suppression

Blue/Red Aircraft Losses by Defense
- Surface-to-Air
- Air-to-Air

Blue Cumulative FLOT Movement (km)

2 ANALYSIS METHODOLOGIES

Three methodologies are used to identify the significant or active factors in analyzing the results of the experiment described in the previous section. The first is an approach developed by Box and Meyer, the next is an approach developed by Hamada and Wu, and the last is a typical Response Surface Methodology (RSM) approach. Note that examining all 17 MOOs with these three methodologies requires 51 total analyses.

The Box/Meyer and Hamada/Wu screening approaches are both based on the concept that of "the many potentially important variables, it is often the case that only a few are truly important" (Box and Meyer, 1993: 94). This condition is known as the *Pareto Principle* or *factor* (or effect) *sparsity*. Furthermore, the Hamada/Wu approach assumes "that when a two-factor interaction is significant, at least one of the corresponding factor main effects is also significant" (Hamada and Wu, 1992: 132). This is known *as effect heredity*. For example, if the AB interaction term is significant then either factor A or factor B is also significant (or possibly both).

Given these different approaches, it is anticipated that different significant factors or models can be identified, especially with the complex aliasing of the Plackett-Burman design used for this experiment. Therefore, an attempt to ascertain a "truth" model for one of the MOOs that display differing important inputs is to be performed using a Resolution V design. This "truth" model can be used as a vehicle for comparison for the three methodologies. These three methodologies are described in more detail in the following subsections.

2.1 Box and Meyer Approach

This screening methodology improves the likelihood of identifying significant factors that might be overlooked when using typical or conventional methods of analysis, such as an RSM approach. "This is particularly true of Plackett-Burman designs where the number of runs is not a power of two" (Box and Meyer, 1993: 94).

This method examines the possible hypotheses and identifies those that best fit the data. For example, if there are three factors (A, B, and C), then the various hypotheses considered are that a single factor is responsible, that two factors are responsible, and that all three factors are responsible for what is going on. In the single factor hypotheses, only single factors are included in the model. In the hypotheses that two and three factors are responsible, the models considered include the main factors along with all possible interactions, e.g., under the hypothesis that A, B, and C are active, only the subset of these main factors with interactions AB, AC, BC, and ABC are considered. This screening methodology can also be modified to allow the analyst to assume, for example, that three-factor interactions are negligible and thus the models considered would contain at most two-factor interactions.

"A Bayesian framework is used to assign an appropriate measure of fit to each model considered (posterior probabilities) that can be accumulated in various ways (marginal posterior probability)" (Box and Meyer, 1993: 95). "It is analogous to all-subsets regression in that all possible models are evaluated" (Box and Meyer, 1993: 95).

The Bayesian approach to model identification is as follows (see, e.g., Box and Tiao (1968)). We consider the set of all possible models labeled $M_0, \ldots, M_m$. Each model M_i has an associated vector of parameters θ_i so that the sampling distribution of data **y** [or output responses], given the model M_i, is described by the probability density $f(\mathbf{y}|M_i,\theta_i)$. The prior probability of the model M_i is $p(M_i)$, and the prior probability density of θ_i is $f(\theta_i|M_i)$. The predictive density of **y**, given model M_i, is written $f(\mathbf{y}|M_i)$, and is given by the expression

$$f(y|M_i) = \int_{R_i} f(y|M_i,\theta_i)d\theta_i \ ,$$

where $\mathbf{R}_i$ is the set of possible values of θ_i. The posterior probability of the model M_i, given the data **y**, is then

$$p(M_i|y) = \frac{p(M_i)f(y|M_i)}{\sum_{h=0}^{m} p(M_h)f(y|M_h)}.$$

The posterior probabilities $p(M_i|\mathbf{y})$ provide a basis for model identification. Tentatively plausible models are identified by their large posterior probability. Computationally one calculates $p(M_i)f(\mathbf{y}|M_i)$ for each model M_i (the numerator in the above expression) and then scales these quantities to sum to one. The probabilities $p(M_i|\mathbf{y})$ can be accumulated to compute the marginal posterior probability P_j that factor *j* is active as

$$P_j = \sum_{M_i:\ \text{factor j active}} p(M_i|y).$$

The probability P_j is just the sum of the posterior probabilities of all the distinct models in which the factor *j* is active. The probabilities $\{P_j\}$ are thus calculated by direct enumeration over the 2^k possible models M_i, where k is the number of factors (Box and Meyer, 1993: 95-96).

Large values of P_j indicate that factor *j* is significant while small values indicate that factor *j* is not significant. For a more in depth explanation of this method see Box and Meyer, 1993. Box and Meyer developed a software program called MBJQT92 that performs the calculations described in their article and above. By using this program, the analyst does not have to do the calculations manually and is provided with output that indicates which factors are active. An example of this output is provided below in Figure 1. In analyzing the results of the MBJQT92 program, it is up to the analyst to determine what signifies a large posterior probability. "In practice there is no harm in interpreting the posterior probabilities liberally" (Box and Meyer, 1993: 102). For example, from Figure 1, the analyst might conclude that factors 3, 5, 7, and 8 are active. Further analysis on these factors can produce a model that contains these main effects along with any significant interactions.

```
              Posterior
Factor        Probabilities
None          0.001  +                    +
   1          0.136  +**                  +
   2          0.143  +**                  +
   3          0.573  +**************      +
   4          0.245  +*****               +
   5          0.513  +**********          +
   6          0.272  +******              +
   7          0.894  +******************  +
   8          0.704  +**************      +
   9          0.095  +*                   +
  10          0.276  +*****               +
  11          0.229  +****                +
  12          0.053  +*                   +
  13          0.248  +****                +
```

Figure 1: Example Output from MBJQT92

2.2 Hamada and Wu Approach

This method "works well when *effect sparsity* and *effect heredity* hold and the correlations between aliased effects (i.e., aliasing coefficients) are small to moderate" (Hamada and Wu, 1992: 132). Hamada and Wu specifically state that this methodology is useful in analyzing the result of a Plackett-Burman design by taking advantage of the complex aliasing pattern of a Plackett-Burman design. In analyzing the results of a screening design to identify the significant factors the following steps should be performed (Hamada and Wu, 1992: 132):

Step 1: Entertain all the main effects and interactions that are orthogonal to the main effects. Use standard analysis methods such as analysis of variance or half-normal plots to select significant effects. Go to Step 2.

Step 2: Using effect heredity, entertain (i) the effects identified in the previous step and (ii) the two-factor interactions that have at least one component factor appearing among the main effects in (i). Also, consider (iii) interactions suggested by the experimenter. Use a forward selection regression procedure to identify significant effects among the effects in (i)-(iii). Go to Step 3.

Step 3: Use a forward selection regression procedure to identify significant effects among the effects identified in the previous step as well as all the main effects. Go to Step 2.

Iterate between Steps 2 and 3 until the selected model stops changing. (Effect sparsity suggests that only a few iterations will be required.)

The proposed method, however, does have a limitation. Significant main effects can be overlooked when several significant interactions are aliased with a nonsignificant main effect and cause it to appear significant (Hamada and Wu, 1992: 135). To overcome this problem, Hamada and Wu offer two extensions to the above steps (136):

(1) Relax the criterion for significance in Step 1 so more main effects are included.

(2) Replace Step 1 with Step 1' below.

Step 1': For each factor X, entertain X and all its interactions XY with other factors. Use a forward selection regression procedure to identify significant effects from the candidate variables and denote the model by M_X. Repeat this for each of the factors and then choose the best model from all the M_X's. Go to Step 3.

Then iterate between Steps 3 and 2 as before.

By using this approach, it is possible to identify significant effects (either main or two-factor interaction) that explains most of the variance.

For a more detailed explanation and example of its use see Hamada and Wu, 1992. This paper makes use of the second extension provided above (Step 1') in analyzing the results of the screening design. This method should produce better results than the standard analysis techniques normally performed. "Note that the standard analysis of PB [Plackett-Burman] designs ends at Step 1" (Hamada and Wu, 1992: 132). This standard analysis is the final method used in analyzing the results of the screening design experiment, which in this paper will be termed the Response Surface Methodology (RSM) approach.

2.3 RSM Approach

This method uses the standard analysis methods found in many experimental design texts or response surface methodology texts, such as, Box and Draper (1987). These standard analysis methods include: (1) examining the effects of the main factors and identifying which are large compared to the others; (2) examining the analysis of variance (ANOVA) tables; (3) using normal probability plots; or (4) the use of *Pareto* charts (a chart consisting of bars whose length is proportional to the absolute value of the estimated effects). In this study, all of these are used to identify significant factors from the results of the screening experiment.

The approach used to determine the significant effects is an iterative one. That is, the first step is to identify the significant main effects using standard analysis methods as discussed above and then, if enough degrees of freedom are left for such an analysis, examining the interactions between these significant main factors to determine if any of these are significant. A step-wise regression approach is used to identify the final model, containing the identified significant main factors and any significant two-factor interactions.

3 RESULTS

The output from the THUNDER model is analyzed using the three methodologies described above. Where possible, the analysis was divided into two steps: the first step identified only the significant main effects and the second attempts to incorporate two-factor interactions.

The first step of the analysis produced notably different significant factors for each method, especially when comparing the Hamada/Wu screening method with the RSM and Box/Meyer screening methods. A possible reason for this difference is that at the first step of this analyses, the two-factor interactions are not taken into account for both the RSM and Box/Meyer screening methodologies. This helps explain why they, the RSM and Box/Meyer techniques, produced similar significant effects when compared against the Hamada/Wu screening method.

The next step in this analysis attempts to identify the significant two-factor interactions within the RSM and Box/Meyer techniques. The results from this second step produced similar models for each measure of outcome or MOO; that is, they are substantially more consistent in identifying the significant factors across all three methodologies. However, there are a few exceptions; of these exceptions, the MOO that provided the best opportunity for further analysis is Blue Aircraft Losses from Surface-to-Air Defenses, which is the number of Blue aircraft lost from Red surface-to-air defenses (i.e., surface-to-air missiles). For example, THUNDER accumulates Blue aircraft losses over time caused by Red surface-to-air defenses, in this particular instance THUNDER is accumulating the losses over a period of 30 days. This particular MOO produced slightly different models (or identified slightly different significant factors) for the Box/Meyer method (Equation (1)) compared against the Hamada/Wu and RSM methods (Equation (2)).

The Box/Meyer method concluded that the following factors are significant (at an α = .10): A, B, J, L, AB, and AI; which produced the following model

$$\begin{aligned}\hat{Y} &= 13.95 - 1.65 \cdot A + 4.436 \cdot B - 2.291 \cdot J \\ &+ 1.818 \cdot L - 2.228 \cdot AB - 2.432 \cdot AI.\end{aligned} \tag{1}$$

These significant factors can be identified by using Table 1. For this method, "A" (Blue Air Defense to Red Air Probability of Kill or Damage), "B" (Red Air Defense to Blue Air Probability of Kill or Damage), "J" (Blue Ground Control Intercept Radar Ranges), "L" (Blue Sortie Rate), "AB" (the "A" and "B" interaction), and "AI" (the "A" and "I" (Red CAS/BAI Planning Factors) interaction).

The Hamada/Wu and RSM methods concluded that the following factors, defined in Table 1, are significant (at an α = .10): B, AB, AL, BG, CE, and EJ; which produced the following model

$$\begin{aligned}\hat{Y} &= 13.95 + 4.454 \cdot B - 2.294 \cdot AB - 2.44 \cdot AL \\ &- 2.118 \cdot BG + 4.37 \cdot CE - 0.59 \cdot EJ.\end{aligned} \tag{2}$$

In order to determine which of these models best predicts or estimates the actual MOO, a number of runs needs to be completed to provide a validation or "truth" model to compare these different models against. By creating this "truth" model, a measurement criterion can be used to check the accuracy of these models produced from these different methodologies. The measurement criterion decided on for this study is the mean absolute percent error (MAPE); which is defined by the following equation

$$MAPE = \frac{100}{n} \cdot \sum_{i=1}^{n} \frac{|e_i|}{|X_i|},$$

where X_i = (the actual observation), $\hat{X}_i$ = (the estimate of X_i using Equations (1) and (2) for each model), and e_i = (the difference between X_i and $\hat{X}_i$), and n = (the number of runs). A design of at least Resolution V is needed in the validation of the fitted models to ensure that the two-factor interactions are not confounded with main effects or other two-factor interactions, which would might confuse the results of the validation dataset. For the Blue Aircraft Losses from Surface-to-Air MOO, five of the original main effects or factors can be dropped since they are not included in either model as either a main effect or interaction. Therefore, eight main factors are left which allows a Resolution V design with sixty-four runs (2_V^{8-2} fractional factorial).

When the sixty-four run validation dataset is completed, the better methodology can be decided by examining each model (Equations (1) and (2)) against this dataset. The measurement criterion for the Hamada/Wu & RSM screening methodologies is

$$MAPE_{H/W\&RSM} = 43.778$$

and for the Box/Meyer screening methodology is

$$MAPE_{B/M} = 31.393.$$

Equation (3) is the model produced from the Resolution V design (using the forward selection option in SAS), assuming three-factor interactions and higher are negligible.

$$\begin{aligned} \hat{Y} &= 13.95 + 4.43 \cdot B - 0.02 \cdot G - 2.74 \cdot J + 2.04 \cdot L \\ &\quad - 2.09 \cdot AB - 2.38 \cdot AI - 0.90 \cdot BI + 0.52 \cdot BL \end{aligned} \tag{3}$$

Assuming that the best MAPE value possible is obtained from the model produced from the Resolution V design, Equation (3) produces the following MAPE value

$$MAPE_{ResV} = 28.452.$$

Comparing the other models' MAPEs, it is apparent that the Box/Meyer screening methodology is almost as accurate as the model produced from the actual validation dataset.

4.0 CONCLUSIONS

The three analysis methodologies used in this paper eventually converged to similar models or identified significant factors in most cases; however, in a few instances, such as Blue Aircraft Losses from Surface-to-Air, the models did not converge for all three methodologies. In this instance, the validation set of sixty-four runs (Resolution V design) is used to compare the different models produced; specifically, the Hamada/Wu & RSM methodologies produced the same model as contrasted with the model produced by the Box/Meyer methodology. In this particular case the screening methodology developed by Box and Meyer (1993) provided the best predictor of the validation data. However, all three methodologies are useful since the purpose of a screening experiment is to reduce the number of factors to be examined in further analyses. The point to be noted here is that by using the screening methodology developed by Box and Meyer, the results are consistent with the other two methodologies and in some cases better, but at a fraction of the cost or effort; specifically, the number of iterations in refining the final model produced by these different methodologies.

APPENDIX A: INPUT FILES

(AFSAA, 1992:6-3 to 6-8)

Air Rules (airrules.dat) data includes, for each side, aircraft taxi times, main operating base, divert base and dispersal base takeoff and landing delays, crater repair times, rearming and refueling times, minimum distances from FLOT of certain types of missions, radar detection distances, lethality, loss value, vulnerability, error, perception, target priority factors of various facilities, priority and mutual support factors, length of time a flight will wait for other flights at a join point, over-the-FLOT defensive counter air (ODCA) and fighter sweep (FSWP) orbit time, ODCA minimum threats size, size ratio and probability of detection, and mission supported by ODCA.

Air-to-Air Probability of Kill (airairpk.dat) data includes both killer and target ID, and the PK of the killer ID against the target ID, and, for low resolution for each target, the average percent killed per engagement and the time this kill rate becomes effective.

Probability of Detection (detect.dat) of each aircraft type on each side by each aircraft type on the opposing side.

Air Defense to Air Probability of Kill or Damage (advsac.dat) data includes target aircraft IDs for each type of air defense site on each side and the upper and lower limits for probability of kill and probability of damage to the target by the site, and, for low resolutino by side for each AD site, average percent of enemy target types killed per engagement and the time this kill rate becomes effective.

Air-to-Ground Air Munitions vs. Target (airgrdpk.dat) data includes air munition effectiveness for each air munition on each aircraft against each type component, type strategic target, and type equipment; each anti-radiation missile (ARM) and self-protect weapon (SPW) on each aircraft against each radar type; and each mine munition on each aircraft against each arc construction type.

Fighter/Bomber Squadron (squadron.dat) data includes mission class names; ID and name of each squadron on each side, its owning command, main operating base and dispersal base, mission class, quantity and type of aircraft owned, the squadron's relative effectiveness for each mission, and squadron orders.

Air Planning (airplan.dat) data includes side preplanned air tasking order (ATO) support flags and flags that indicate, by side, whether a given autoplanned mission will be supported by escorts. Air planning factors are also contained in this file and are determined by the air planning command and by time. Different air planning factors include squadron planning factors (escort to primary mission aircraft ratios and time over target spacing); battlefield air interdiction (BAI) planning factors (target type priorities); barrier combat air patrol (BARCAP) planning factors (value of assets to be protected); close air support (CAS) planning factors (CAS support planning rule); suppression of enemy air defenses (SEAD) planning factors (depth, planned effectiveness, and desired target drawdown percentage); suppression and support jammer planning factors (planned setback distances and support depths); interdiction planning factors (planned per-sortie effectiveness and desired target drawdowns for each type of interdiction target and depth factor curves); and offensive counter air (OCA) planning factors (planned effectiveness and desired target drawdown percentages).

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