

## THE EFFECTS OF CHANGING FORCE STRUCTURE ON THUNDER OUTPUT

THESIS

Michael Ryan Farmer, Captain, USAF

AFIT/GOA/ENS/96M-01

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### THESIS APPROVAL

STUDENT: Capt M. Ryan Farmer

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COMMITTEE:

NAME/DEPARTMENT

Advisor: Lt Colonel Kenneth W. Bauer Associate Professor of Operations Research Department of Operational Sciences, AFIT/ENS

Reader: Lt Colonel Paul F. Auclair Department Head Department of Operational Sciences, AFIT/ENS

SIGNATURE

Jan IL Wannen

#### AFIT/GOA/ENS/96M-01

## THE EFFECTS OF CHANGING FORCE STRUCTURE ON THUNDER OUTPUT

### THESIS

Presented to the Faculty of the Graduate School of Engineering

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Operations Research

M. Ryan Farmer, B.S.

Captain, USAF

MARCH, 1996

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#### M. Ryan Farmer

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#### Acronyms and Useful Definitions

- <u>AFM 1-1</u>: Air Force Manual 1-1, *Basic Aerospace Doctrine of the United States Air Force*.
- Air Kills: Targets destroyed by aircraft.
- <u>Air Superiority</u>: "Gaining and Maintaining freedom of action in the air and also freedom of enemy air attack." --General Charles L. Donnelly, Jr. (AFM 1-1)
- <u>Air Supremacy</u>: That degree of air superiority wherein the opposing air force is incapable of effective interference (AFM 1-1).
- <u>CAS</u>: Close Air Support; the air participation in the combined effort of the air and ground forces, in the battle, to gain objectives in the immediate front of these ground forces." (AFM 1-1).
- CCD: Central Composite Design

FA: Factor Analysis

- <u>FLOT</u>: Forward Line of Troops
- <u>Interdiction</u>: "An action to divert, disrupt, delay or destroy the enemy's surface military potential before it can be used effectively against friendly forces." (AFM 1-1)

Jamming: Limiting or blocking the enemy's use of the electromagnetic spectrum.

MOE: Measure of Effectiveness

MAPE: Mean Absolute Percentage Error

MSE: Mean Square Error

MSPR: Mean Square Prediction Error

<u>Neutralize FLOT</u>: Returning the FLOT to the original boundaries set at the start of the war, usually achieved by the invaded country's ground war success.

PCA: Principal Components Analysis

 $\underline{\mathbf{R}}^2$ : Coefficient of Multiple Determination

 $\underline{R}^2$ , adjusted: Coefficient of multiple determination accounting for degrees of freedom.

**<u>RSM</u>**: Response Surface Methodology

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#### Abstract

In today's reduction of America's national defense, campaign level models are being used more in the development of force structure. The effects of drawdown are of significant interest to those at the highest levels of authority. Campaign models can bring those high ranking officials the answers they seek with high confidence. THUNDER is a campaign model used frequently by the United States Air Force and many of its contractors. The effects of changing the force structure within THUNDER require modifying variables before executing a new experimental run. Changes in such issues as force structure cannot be immediately addressed.

Response Surface Methodology (RSM) can be used to provide a quick answer to effects of changing force structure by executing several experimental runs at a variety of settings. The creation of a "response surface" interlinks each scenario. Factor analysis is a multivariate statistics method of reducing dimensionality of data sets and determining relationships between measures on an observation. From this, relationships can be found among different measures of effectiveness to create new, simpler variables.

The methods used in this thesis provide a means for creating accurate, "quick turn" analysis tools which a decision maker can use to make timely decisions.

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# THE EFFECTS OF CHANGING FORCE STRUCTURE ON THUNDER OUTPUT

#### I. Introduction

The Department of Defense (DoD) compares alternative investment and policy choices to obtain the highest level of effectiveness possible with its limited resources. Recently, modeling, simulation, and analysis have become an integral part of the DoD decision process. Large scale computer simulations, ranging from high resolution one-onone scenarios to aggregate models of large scale campaigns, have been developed to model the combat environment. These simulations provide a basis for comparing the relative effectiveness of alternative weapons systems, force structures, operations concepts, and defense policies. Weapons system options, for example, may range from a small modification in avionics or munitions to an entirely new aircraft, such as the Lockheed F-22 Excalibur.

The number and type of aircraft assigned to a large scale campaign can be a contentious issue, resulting in heated debates over resources, roles, and missions. A typical issue concerns the relationship between the air forces assigned to a Joint Force Air Component Commander (JFACC) and the effectiveness of the resulting theater-level air campaign. Air Combat Command (ACC) is frequently involved in these type of issues. When developing its positions, the Command usually employs a computer simulation called THUNDER. Unfortunately, THUNDER generally requires hours of computer time to conduct a sufficient number of simulation runs to aid in the staffing and planning processes.

Due to time constraints and deadlines, the analysis support of the staffing process rarely has enough time to simulate all alternatives under consideration. Command analysts must anticipate a variety of potentially provocative questions and develop "quick turn" tools or models to respond to them in a timely, accurate manner. This thesis explores two possible methods of this "quick turn" analysis.

#### II. Background

#### Introduction

This chapter provides a background on the materials and methods used in this thesis. The topics covered in this chapter include THUNDER, aircraft force structure, response surface methodology (RSM), model validation, principal components analysis, and factor analysis. The material presented in this chapter is intended to familiarize the reader with the topics covered and provide references, via the bibliography.

#### THUNDER

THUNDER is a two-sided, theater-level combat simulation model that simulates air and ground combat, as well as logistics. An aggregated, deterministic ground war is used in conjunction with a detailed stochastic air war to simulate theater-level conflict (TAC THUNDER Analyst's Manual, 1992). While ground units are modeled at the regiment and division level, aircraft sorties are modeled individually.

Simulating the same theater-level campaign under different conditions, such as the number of and type of aircraft available, provides the basis for estimating the effect of those changes on measures the campaign objectives (Forsythe, 2-4).

THUNDER uses over sixty files to define the simulated campaign scenario. One data file, titled *squadron.dat*, provides information on each aircraft used in the simulation. Besides the number and type of aircraft available, *squadron.dat* provides the mission class (air superiority, ground attack, deep strike, multi-role, jammer, etc.), sortie rate, days in theater, and apportionment of aircraft to mission classes. THUNDER takes into account

the percentage of each aircraft allotted to each mission type and creates an appropriate air plan to meet defined war objectives (TAC THUNDER Analyst's Manual, 1992).

The THUNDER database contains the information for type of scenario, weapon systems, terrain, and force structure. Analysts using this model have the option of changing the database in order to study the effects of the changes in plans, tactics, weapons systems, and force structures. This thesis examines changes only in the force structure portion of the database. The unclassified baseline scenario consists of a preemptive Iraqi attack. The scenario posits that the Iraqi forces penetrate Saudi Arabian territory, forcing the allied forces mobilize to deter the attack. Each side fights to meet predetermined objectives, measured in terms of attrition, movement of the forward line of troops (FLOT), and the time needed by each side to accomplish objectives (TAC THUNDER Analyst's Manual, 1992).

THUNDER is written in SIMSCRIPT<sup>®</sup> II.5. It requires over 500 megabytes of space on a hard disk drive and can be run on any machine that supports SIMSCRIPT<sup>®</sup> II.5. A SUN or DEC workstation is required to support the terminal graphics used in THUNDER's situation map and grapher (TAC THUNDER Analyst's Manual, 1992). Aircraft Force Structure

THUNDER models aircraft from the inventories of the Air Force, Army, Navy, and Marine Corps. The Air Force inventory includes the Fairchild A-10 Thunderbolt II, McDonnell-Douglas F-15 Eagle, Lockheed F-16 Fighting Falcon, Lockheed F-111 Aardvark, and Lockheed EF-111 Raven.

The Fairchild A-10 Thunderbolt II is a ground attack/close air support aircraft. The McDonnell-Douglas F-15 Eagle is primarily assigned to air-to-air engagements; however, the F-15E is modified for ground attack. In this study, the F-15 was strictly employed as an air-to-air aircraft. The Lockheed F-16 Fighting Falcon is a "multi-role" aircraft that serves as both an air-to-air and ground attack aircraft. The Lockheed F-111 Aardvark performs deep strike missions behind enemy lines. The sole mission class of the Lockheed EF-111A Raven is jamming, and the aircraft is designated to perform all jamming mission types. The Air Force aircraft listed were the only aircraft modified throughout the study. The study scenario included other Naval and enemy aircraft, but their force levels were not modified in this study.

#### Response Surface Methodology (RSM)

RSM consists of a collection of statistical techniques for empirical model building and model exploitation. This methodology seeks to relate a *response*, or *output variable*, to the levels of a number of *predictors*, or *input variables*, that affect it (Box and Draper, 1). The set of outputs or responses forms a *response surface*. Since the response surface in this research corresponds to the output of simulation, which itself is a model, the response surface is a model of a model, or a *metamodel* (Kleijnen, 1987: 147-148).

In estimating a response surface, the true response function is unknown; however, the assumption is made that the function can be locally approximated by a polynomial or some other type of function. Designed experiments provide the data needed to develop these local approximations.

Experimental designs induce purposeful changes in the input variables in order to observe changes in the responses (Box and Draper, 1987:17). The nature of the design depends on several factors:

- Which input variables should be studied?
- Should input variables be transformed and then examined?
- How should the response be measured?
- At which levels of a given input variable should experiments be run?
- How complex a model is necessary?
- How should qualitative variables be chosen?
- What experimental design should be used? (Box and Draper, 1987: 4-7)

The last question is obviously answered by the first six. Available resources and time available should also be considered in designing an experiment.

The information needed from an experiment implies the minimum acceptable resolution for the design. The resolution of a design determines the degree to which the estimates of factor effects will be aliased or confounded. Two or more factors are confounding if their effects cannot be distinguished from one another. A design is of resolution k if all  $n^{th}$  order terms are not aliased with any other terms lower than order k-n, where n < k. In a Resolution III design, k=3 and first order (n=1) terms are aliased with second order or higher terms (k-n=2). Resolution III and Resolution IV designs are considered first order designs since no first order terms (or main effects) are aliased with any other first order terms. Although first order terms in a Resolution IV design are not aliased with any terms lower than third order, second order terms can be aliased with other second order terms. Designs of Resolution III and IV are most often used in screening designs to determine *which* of many variables under consideration are important.

Resolution V designs are generally used for establishing *how* the input variables affect the responses. If found necessary in analysis, this design resolution is ideal for implementing a quadratic model, since the first order terms are not aliased with any terms lower than fourth order, and the second order terms are not confounded with any terms lower than third order.

The designs in this study set each input variable at either its high or its low level. These levels were coded as

$$x_{i} = \frac{\xi_{i} - \xi_{i0}}{S_{i}} , \qquad (1)$$

where  $x_i$  is the coded variable,  $\xi_i$  is the actual variable setting,  $\xi_{i0}$  is the center of the region, and  $S_i$  is the half-range, or half-width. The coded value for the high level is +1, and -1 for the low level. The coded design points and responses comprised the data used to generate the response surface metamodels.

Multiple linear regression techniques were used to create a response surface of the simulation output. Several statistical tests are available for assessing the "goodness of fit" of the estimated metamodel. Most of these measures are included in an ANOVA (analysis of variance) table, or a regression diagnostics report. The coefficient of multiple determination, or  $\mathbb{R}^2$ , expresses the percentage of variance explained by the model (Neter, Wasserman, and Kutner, 241). An  $\mathbb{R}^2$  value of one means the model fits the data perfectly, or 100% of the variance is explained. Adding terms to a model will always improve the value of  $\mathbb{R}^2$  (or at least maintain the previous value). Since  $\mathbb{R}^2$  can be made large by the simple inclusion of additional independent variables, a modified measure

adjusts for the number of independent variables in the model. The adjusted coefficient of multiple determination, here noted as "adj  $R^{2}$ ", adjusts  $R^{2}$  by taking into account the number of degrees of freedom, or observations, in the model. Taking this into account provides for a means to maintain a realistic look at the variance explained by the model.

The Mean Square Error (MSE) is an estimate of the variance of the model. When the model is properly specified, MSE is an unbiased estimator. The square root of the MSE is the standard error, and by definition is an estimate of the standard deviation of the residual error of a model. The predicted variance of a model is larger at locations furthest from points used to create the model. The maximum predicted variance of a model is found with

$$MPVar = (1 + x^{T} (X^{T} X)^{-1} x) \cdot MSE$$
(2)

where MPVar is the maximum predicted variance, X is the coded design matrix, and <u>x</u> is the vector of maximum coded settings (all ones--these settings provide the greatest variability of the model). Here again, the square root of (2) gives an indication of the maximum predicted standard deviation. This measure aids in judging model adequacy between design points.

The overall F statistic is a measure of determining if the output is a function of any of the input variables, and can thus be considered a measure of adequacy for the overall model. Another measure of statistical significance is the *p*-value, or attained significance *level*. This value is the smallest level of significance for which the observed data indicates that the coefficient in question is not actually zero (Mendenhall, 448). In other words, if

the *p*-value is smaller than the desired level of significance (noted here as  $\alpha$ ), then the term associated with that *p*-value is significant to the model.

A plot of the residuals versus the predicted output may indicate that a higher order model is needed for the data used. Finding a pattern in the plot may indicate a better model is needed to describe the data. A plot that has a "shotgun pattern" does not discredit any indications the model is adequate. A plot having a diagonal pattern indicates a poor model, and another attempt at modeling should be made. A plot that forms the pattern of an arch indicates a need for quadratic or cross-product terms. Finding any of these patterns indicates a violation of the original assumptions (Neter, Wasserman, and Kutner, 1990: 116-121).

The use of these statistical measures and plots adds confidence and credibility to model adequacy. If a linear metamodel is not adequate for the data used in the model building, a quadratic model may be a path for exploration for gaining an adequate model. Augmenting a Resolution V design with additional runs that incorporate other coded levels proves to be of particular value in determining all quadratic and other second order terms in the model.

A central composite design (CCD) is a design that finds quadratic terms by using center point replications and "star," or "axial," points. Central composite designs contain the following:

A "cube," consisting of a 2<sup>k</sup> factorial, or a 2<sup>k-p</sup> fractional factorial, made up of points of the type (±1, ±1, ±1,..., ±1), of resolution R ≥ 5 (Box and Hunter, 1961a, b) replicated r<sub>c</sub> (≥ 1) times. There are thus n<sub>c</sub> = r<sub>c</sub> 2<sup>k-p</sup> such points (where p may be zero).

- 2. A "star," that is, 2k points ( $\pm \alpha$ , 0, 0,...,0), (0,  $\pm \alpha$ , 0,...,0),..., (0, 0, 0,...,  $\pm \alpha$ ) on the predictor variable axes, replicated  $r_s$  times, so that there are  $n_s = 2kr_s$  star points in all.
- 3. Center points (0, 0, 0, ..., 0),  $n_0$  in number, of which  $n_{c0}$  are in cube blocks and  $n_{s0}$  in star blocks (Box and Draper, 457).

The value chosen for the distance from the center of the design to a star point,  $\alpha$ ,

can provide for the model aspect of rotatability. The value of  $\alpha$  is usually set at a value which is greater than 1, thus putting the star points outside the original design space. The number of center point runs determines orthogonality. With some designs, having these qualities is not feasible. These qualities are also not always essential. While desirable to have these design qualities, options such as the "face centered central composite design" provide for a means to determine quadratic terms with a limited operability region. This design sets the value of  $\alpha$  to be set at the limits of the design upper and lower levels; namely +1 and -1. Figure 2-1 shows the differences in design for a central composite design, in two dimensions.



Figure 2-1. CCD (left) and Face Centered CCD (right)

When the value of  $\alpha$  for rotatability extends beyond the design region, the face-centered CCD proves to be a acceptable alternative, provided the quality of rotatability is not important.

#### Model Validation

Model validation serves to provide confidence in the final model. Three basic methods provide a means for validating a regression model. They are:

- 1. Collection of new data to check the model and its predictive ability.
- 2. Comparison of results with theoretical expectations, earlier empirical results, and simulation results.
- 3. Use of a hold-out sample to check the model and its predictive ability. (Neter, Wasserman, and Kutner, 1990: 465).

The best means for model validation is collecting new data. This new data could be used in estimating a new model and comparing the coefficients of the validation and original model. Credibility is added to the model if the coefficients of the new and validation models have consistency.

Metamodels generated in this thesis are validated using new data to examine predictive ability. When a regression model is developed from a given set of data, the selected model is inevitably chosen because that model is the best for the given data. A different model consisting of different independent variables, interaction terms, and intercept term could be arrived at using different random outcomes. From this model development process, the MSE tends to understate the variance of the predictive ability of the selected model (Neter, Wasserman, and Kutner, 1990: 465). To determine the actual predictive capability of the selected regression model, the model is used to predict the results of the new data set. Each case is predicted and used to estimate *mean square prediction error*:

$$MSPR = \frac{\sum_{i=1}^{n^*} (Y_i - \hat{Y}_i)^2}{n^*} , \qquad (3)$$

where  $Y_i$  is the value of the response in the *i*th validation case,  $\hat{Y}_i$  is the predicted value for the *i*th validation case based on the model-building data set, and  $n^*$  is the number of cases in the validation set.

If the mean squared prediction error *MSPR* has a value fairly close to the model MSE, then the regression model is not seriously biased and gives an appropriate indication of the predictive ability of the model. If the MSPR has a value much larger than the MSE, the mean square prediction error should then be used as an indicator of how well the selected regression model will predict in the future (Neter, Wasserman, and Kutner, 1990: 466).

The use of theory, empirical evidence, or simulation results also serves to determine how well a regression model will predict. If a data set is large, the method of "data splitting" can be used to create a "construct data set" and a "validation" or "prediction" set. This procedure is also called "cross-validation" (Neter, Wasserman, and Kutner, 1990: 466-467). These particular validation methods are not used in this research and thus are not discussed in detail here.

#### Multivariate Analysis

Multivariate Analysis is defined as the application of methods that deal with reasonably large numbers of measurements (i.e., variables) made on each object in one or more samples *simultaneously*. Multivariate analysis deals with the *simultaneous relationships among variables*. While univariate and bivariate analysis examines the mean and variance of a single variable or a pairwise relationship between two variables, multivariate analysis "examines the covariances or correlations which reflect the extent of relationship among three or more variables" (Dillon and Goldstein, 1-2). In this research effort, the multivariate approaches of Principal Components Analysis and Factor Analysis are used.

#### Principal Components Analysis (PCA)

Principal Components Analysis "transforms the original set of variables into a smaller set of linear combinations that account for most of the variance of the original set" (Dillon and Goldstein, 24). For example, several measures of effectiveness (MOEs) in THUNDER that measure Red performance may be combined to form a new variable that measures how well the Red forces performed in the battle. The advantage of performing such analysis is that instead of tracking four or five of the original MOEs, one variable is observed that gives an overview of the original MOEs.

One of the first considerations in PCA is to decide whether a covariance matrix or correlation matrix will be used in extracting the principal components from the data set. If the variables under consideration are of the same unit of measurement, a covariance matrix is acceptable. If the variables under consideration have grossly different units, the

composition of the derived components can be influenced by scale effects. Hence, the data should be standardized and the correlation matrix used (Dillon and Goldstein: 1984, 36).

Once the data have been standardized and a correlation matrix calculated, eigenvalues are determined from the correlation matrix. The sum of the eigenvalues,  $\lambda_i$ , will equal the number of variables, p. The proportion of the total "variance" explained by each component is  $\lambda_i/p$ . (Dillon and Goldstein, 1984: 36).

Interpreting principal components is clarified with the use of component loadings. The first column of the loadings matrix describes the interrelationship among variables (MOEs) for the first principal component. The *jth* column of the loadings matrix is associated with the *jth* largest principal component. Fidell and Tabachnick use, as a rule of thumb, loadings in excess of 0.3 as eligible for interpretation. It is further suggested that loadings in excess of 0.71 are excellent, 0.63 very good, 0.55 good, 0.45 fair, and 0.32 poor (411). Higher loadings indicate higher correlations with other loadings with a high value in that given column. The actual cutoff for interpretability of the loadings is a matter of research preference.

Several popular techniques exist to determine how many principal components to retain when using the correlation matrix. Kaiser's criterion suggests retaining those components associated with eigenvalues greater than one (Fidell and Tabachnick, 1983: 406). Cattell's scree test uses a graphical approach where each factor/component is plotted (as designated (1, 2, 3, etc.)) against the value of its respective eigenvalue. A

"scree line" is then applied to the graph to separate those components to retain (above line) or discard (below line) (Dillon and Goldstein, 1984: 48-49).

Once the decision is made on how many factors/components to retain, component scores may be generated to be used in later analyses. These scores can be used to replace the original responses. In PCA, these scores are exact; this makes this approach very appealing, since unique scores are a very attractive feature. With the common factor model, having unique scores is generally false and no exact solution for the factors is possible (Dillon and Goldstein, 1984: 50). Plotting the principal components scores against one another can provide insight to trends or groupings in the data set.

#### Factor Analysis (FA)

Factor Analysis follows the same procedures as PCA; however, fundamental differences exist between the two approaches. In PCA, unobservable factors are functions of its indicators (variables); in FA, indicators are a function of the unobserved factors. PCA is oriented around total variation; FA is oriented around common variation. Factor analysis in this research serves to clarify the results of principal components analysis. Factor analysis clarifies PCA results by rotating the axis system of the design space. The rotations usually performed are orthogonal. With an orthogonal rotation: the factors remain uncorrelated, the variance explained by a specific factor changes, and the total variance explained by the factors remains the same, but each factor's share changes (Fidell and Tabachnick, 1983: 395-396). The most popular method of rotation is the varianx rotation, which attempts to maximize variation of squared factor loadings within a factor (Dillon and Goldstein, 1984: 91). Simply put, the varianx rotation aims to make any large

correlations larger, and any small correlations smaller (Fidell and Tabachnick, 1983: 387). Such a rotation may or may not prove useful in clarifying the principal component loadings.

#### Summary

Applying response surface methodology to investigate the effects of changing force structure in THUNDER leads to the creation of metamodels for measures of effectiveness. Adequacy of these metamodels can be determined with test statistics and residual plots. A metamodel can gain purpose and credibility through validation efforts, which seek to determine the predictability of a model compared to new data. Data with known design settings can be applied to multivariate analysis. Using multivariate data analysis may serve to find relationships among measures of effectiveness. These relationships can then be reduced to more general terms, which provide for quicker, approximate results.

#### III. Methodology

#### Introduction

Chapter III covers the methodology of the research accomplished in this thesis. First, some data files of THUNDER were "competitively enhanced" so as to make the scenario more reasonable. The RSM design levels (minimum and maximum of each aircraft in the design space) were decided upon with input from the customer, HQ ACC/XP-SAS. Response surface methodology was used to create an experimental design and create metamodels for each of the outputs. Multivariate analysis was then performed using the methods of principal components analysis and factor analysis, discussed in Chapter II. The results from the methodology presented here are discussed in Chapter IV. <u>Input Variables</u>

The input variables for the experimental design were the primary tactical aircraft in the United States Air Force inventory. These aircraft included the A-10, F-15, F-16, F-111, and EF-111A. Only the number of each aircraft was modified in the research. These modifications were made in the *squadron.dat* file of THUNDER. An example of a *squadron.dat* file is found in Appendix A.

#### Output Variables

Five Measures of Effectiveness (MOE) were observed as part of this thesis effort. These MOEs included:

• The number of days needed to push the Iraqis back past the Forward Line of Troops (FLOT) set at day one (this MOE referred to as "Days needed to neutralize FLOT");

- Days needed to achieve air supremacy, defined as the time when the Red sortie rate is
   5% or less than the day one sortie rate;
- Number of air kills achieved by Blue forces of Red targets;
- Number of Blue aircraft lost, and
- The depth, in kilometers, of the Red forces' advancement into Blue territory. These measures were collected by the data report generated by THUNDER at the end of each experimental run.

#### **THUNDER Modifications**

In this research, an unclassified database was used with the scenario set in the Southwest Asia theater, similar to Operation Desert Shield/Desert Storm. This scenario, left unchanged, proved to be too unbalanced to show any importance of the variables. The war objectives were met in a matter of a couple of days, due to a weak Iraqi response, and thus resulting in an uninteresting scenario. Drastic, unrealistic changes of the allied force structure would have been needed to produce noticeable changes in output. Changes were made to both sides of the battlefield to make the wargame more "competitive."

HQ ACC/XP-SAS furnished a scenario where the Red forces "goals" were set further into Blue territory compared to the baseline scenario. These modifications influenced the movement of the FLOT. Several of the data files were modified to change the war objectives of the Iraqis, so as to "force the action" by the Iraqis on the allied forces.

The *squadron.dat* file was further modified by increasing the inventory of every Red aircraft squadron by 50 percent. The European Tornado squadrons were deactivated to reduce the size of the allied forces. The single squadrons of the F-117A stealth aircraft and the F-15E ground attack aircraft were also deactivated, since these aircraft have profiles of F-111 aircraft in the unclassified scenario. Finally, the three squadrons of the Navy EA-6B jammer aircraft were deactivated in order to increase any importance the EF-111A aircraft had to the simulation outputs.

All of these adjustments provided the stage for each 30 day THUNDER run. Each run was performed on a SUN Sparc-2 workstation, and took about 40 minutes to run the program, post-process the data, and generate a data report.

#### Linear Design with Two-Factor Interactions

The purpose of this thesis is to investigate HOW the number of each aircraft affect the five selected outputs. The initial goal was to create a model that would contain main effects and two-factor interactions. Given these criteria, the best choice for the experimental design was of Resolution V. With five MOEs under study, a half-fraction, 16 run design was selected. This design is written symbolically as  $2_V$ <sup>5-1</sup> (Box and Draper, 164). Table 3.1 is the uncoded design for the Resolution V design.

The lower bound for each aircraft (except for the EF-111A) represents a half squadron of aircraft, while the upper bound represents six squadrons of aircraft (Mehuron, 1995: 48). At first, the aircraft ranges look very large; however, such a large design space will generate greater ranges in the measures of effectiveness and possibly a highly irregular surface. Highly irregular surfaces are not modeled well by two level designs. Viewing the experimental design in terms of squadrons, the range is from 0.5 to 6; the EF-111A would be a binary variable. The Resolution V coded design used in experimentation is found in Appendix B.

Run	A-10	<b>F-15</b>	F-16	F-111	EF-111A
1	12	12	12	12	24
2	144	12	12	12	0
3	12	144	12	12	0
4	144	144	12	12	24
5	12	12	162	12	24
6	144	12	162	12	0
7	12	144	162	12	0
8	144	144	162	12	24
9	12	12	12	144	0
10	144	12	12	144	24
11	12	144	12	144	24
12	144	144	12	144	0
13	12	12	162	144	24
14	144	12	162	144	0
15	12	144	162	144	0
16	144	144	162	144	24
Center	78	78	87	78	12

 Table 3.1. Uncoded RSM Design

After performing the regression analysis, various statistics were evaluated to determine the adequacy of the linear and two-way interaction model. Any metamodels not having a strong indication as adequate only as a linear and two-factor metamodel were considered candidates for adding quadratic terms.

#### Use of a Face Centered Central Composite Design

Chapter II discusses the measures taken to adjust the experimental design for finding any significant quadratic terms. The experimental design for finding quadratic metamodels in this research consisted of the sixteen original design runs, three center point replications, and ten runs to find the "star," or "axial" points.

The distance from the center of the design to the axial points could not realistically be set so as to promote rotatability. A coded value of  $\pm 2.38$  would have been necessary; however, the uncoded low value corresponding to this length resulted in a negative number of all aircraft in the experimental design. With this being unrealistic, ensuring the metamodels provided a uniform distribution of information was not guaranteed (Box and Draper, 1987: 488).

Table 3.2 displays the settings for the additional runs augmented to the original sixteen run design. Note the three center point replications correspond to runs 17-19, while the axial points correspond to runs 20-29.

Run	A-10	F-15	F-16	<b>F-111</b>	EF-111A
17	78	78	87	78	12
18	78	78	87	78	12
19	78	78	87	78	12
20	144	78	87	78	12
21	12	78	87	78	12
22	78	144	87	78	12
23	78	12	87	78	12
24	78	78	162	78	12
25	78	78	12	78	12
26	78	78	87	144	12
27	78	78	87	12	12
28	78	78	87	78	24
29	78	78	87	78	0

Table 3.2. Additional "Face Centered CCD" Runs to Augment Original Design

With this design, regression analysis generated a second-order metamodel only if twofactor interactions or quadratic terms were significant.

Once the quadratic models were calculated, any improvements were noted with the use of the validation data set. The validation results were calculated with both the quadratic metamodel and the linear/two-factor model. Predictive error measurements were then compared.

#### Multivariate Analysis

Multivariate Analysis was performed on the 16 x 5 matrix of THUNDER output. Two similar methods of analysis were used: Principal Components Analysis (PCA) and Factor Analysis (FA).

#### Principal Components Analysis

The PCA approach used in this thesis utilized the sample correlation matrix, R, to extract principal components, since the population covariance matrix,  $\Sigma$ , was not known. The matrix R was also selected for analysis due to the difference in units between each of the MOEs (Fidell and Tabachnick, 1983: 19). Once these components were extracted, they were examined to determine how many to retain.

Principal Component Scores were then calculated to have a new means of representing the data. The scores of the principal components were then plotted one against another to gain insight on any possible trends or groupings.

#### Factor Analysis

The FA method used in this thesis was accomplishing an orthogonal rotation of the results of the PCA. The varimax rotation was used to change the axis system of the

components to clarify any correlations within the data. The number of factors to retain were then assessed, and from this correlations between the MOEs were evaluated.

Factor Scores were then calculated to see if any of the insight determined in the principal components analysis could be clarified. The scores of the retained factors were plotted one against the other. Plotting the factor scores proved to be helpful in explaining any trends or groups.

#### Summary

Initial investigation with THUNDER revealed modifications to the simulation were necessary to create a more realistic scenario. Response surface methodology provided the method of collecting data points and the framework for generating metamodels. Principal components analysis and factor analysis presented a way in which relationships between inputs and outputs were seen in a much clearer manner. Creating principal components scores and factor scores provided a means to generate plots in which trends and groupings were much easier to extract. Finding these relationships between the inputs and outputs presented results that could be used to gain new information and insight.

#### IV. Results

#### **Output Results**

Each THUNDER run was based on a sequence of random numbers. THUNDER has ten different random number "seeds" which generate different sequences. Different seeds were used for each run of the campaign model.

The sixteen THUNDER runs of the initial  $2v^{5-1}$  design and their results appear in Table 4.1. Initially, the number of blue aircraft lost was measured by percent of total force for an experimental run; however, using this measure created a situation where the variance of the response was a function of the value of the response. A fundamental assumption of regression is that the variance of the response is constant throughout the design region. Using the total number of aircraft lost for each run eliminated this problem (Forsythe, 3-6).

#### Linear and Two-Factor Interactions Metamodels

A multiple regression analysis was performed with each measure of effectiveness, using the statistics software *Statistix v4.1*. After each regression was performed, the statistical measures discussed in Chapter II were computed to evaluate model adequacy. The most significant terms were then chosen, and a subsequent regression was performed with these variables. The following paragraphs discuss the evaluation of each response surface generated.

Appendix C contains the complete regression results for the metamodels of the most significant terms. The results of these regressions also appear in Table 4.2

	# of	# of	# of	# of	# of	Neut FLOT	Air Suprem	Air Kills	Blue AC lost	Depth Adv
Run	A-10	F-15	F-16	F-111	EF-111A	(days)	(qa)s)	(number of)	(fo under of)	(kilometers)
1	12	12	12	12	24	14.5	19	5612	91	64
2	144	12	12	12	0	13	19	8334	120	58
3	12	144	12	12	0	15	16	4819	101	65
4	144	144	12	12	24	14	18	9058	106	58
S	12	12	162	12	0	14	15	9228	155	56
9	144	12	162	12	24	12.5	19	12260	135	52
7	12	144	162	12	24	13	17	9798	87	52
8	144	144	162	12	0	12	14	12568	118	51
6	12	12	12	144	0	15.5	20	5182	95	65
10	144	12	12	144	24	13.5	16	8961	120	59
11	12	144	12	144	24	13.5	15	6326	96	58
12	144	144	12	144	0	13.5	14	8969	124	59
13	12	12	162	144	24	13.5	20	10408	113	54
14	144	12	162	144	0	12.5	15	14067	132	52
15	12	144	162	144	0	13.5	14	9375	108	55
16	144	144	162	144	24	12.5	15	12486	146	48

Table 4.1. Uncoded Design Matrix and Output Results for Linear and Two-Factor Interactions Design

•
Prediction	Days to Neutralize	Days to Achieve	# of Air	Number of	Depth of Enemy
Variable	FLOT	Air Supremacy	Kills	Blue AC Lost	Advance
Intercept	13.5	16.625	9215.69	115.438	56.625
A-10	-0.5625		1622.19	9.6875	-2
F-15	-0.125	-1.25		-4.6875	-0.875
F-16	-0.5625	-0.5	2058.06	8.8125	-4.125
F-111		-0.5	256.063		-1
EF-111A	-0.125	0.75	147.937	-3.6875	
A-10, F-15	0.1875			3.0625	
A-10, F-16					
A-10, F-111		-0.75		4.0625	
A-10, EF-111A	0.3125		-294.563	5.3125	0.625
F-15, F-16			-176.188	-4.8125	
F-15, F-111	-0.125		-141.937	6.4375	
F-15, EF-111A					-0.75
F-16, F-111					
F-16, EF-111A	0.3125	0.875	-183.688		
F-111, EF-111A				5.6875	
Adjusted R-sq	0.9306	0.7627	0.9931	0.9446	0.9489
F test statistic	29.71	9.04	270.86	26.57	47.47
MSE	0.0625	1.16667	52619.9	21.5625	1.33333
Std Error	0.25	1.08	229.39	4.644	1.155
Max Predictive Std Deviation	0.348	1.504	319.4	6.46	1.61

## Table 4.2 Response Surface Analysis: Significant Terms Observed (Linear and Two-Factor Interactions)

# MOE #1: Days Needed to Neutralize FLOT (Neut FLOT)

The A-10, F-15, F-16, and EF-111A were the aircraft found at a 90% significance level to have a linear effect on the days needed to move the Iraqis back into their territory completely. The primary mission of the A-10, and one of many missions of the F-16, was close air support (CAS). The significance of the F-15 variable indicated the battle for air superiority did influence the ground war. The F-111 contributed through an interaction with the F-15. The EF-111A presence did contribute significantly to achieving the objectives.

Four interaction terms appeared in the final metamodel. Since the objective of MOE #1 is to minimize the number of days needed, negative signs on these terms were

expected. However, this was not the case, and a better understanding of why some of the interactions were positive was needed.

Analysis of interaction terms is best seen visually with an *interaction plot*. This type of plot takes into consideration the possible combinations (high and low levels) and uses the average output from each combination to describe graphically the interaction over the design region. One of the interaction terms of particular interest in this MOE was the term involving the A-10 and F-15--a combination of a ground attack aircraft with an air superiority aircraft. The interaction plot of this term appears in Figure 4.1.





When the A-10 is set at the coded high level, the end result appeared to change minimally in changing the number of F-15s. This change seen in Figure 4.1 is within the error of the metamodel. With the A-10 set at the coded low level, a noticeable difference appeared between having many or few F-15s. This difference could possibly suggest either the importance of having air superiority aircraft flying to support ground operations, or the competition for resources. In a battle environment where aircraft are competing for resources, an optimum balance exists for aircraft to do each of their jobs effectively, receive appropriate maintenance and support, and achieve the MOE objectives quickly and decisively. The interaction apparently indicates a balance of the aircraft is needed to do the best job at meeting objectives. The interaction term acts as an "adjustment factor" to the linear effects for these shortcomings.

The F-15 and F-111, however, had similar roles in that their mission concerns were not on the ground in Blue territory. Figure 4.2 shows the interaction plot for these terms.

Interaction Plot: F-15 & F-111



Figure 4.2. Interaction Plot of F-15 and F-111 for MOE #1 (Optimum: Minimize Days)

This interaction plot does show the importance of the F-111, despite the fact it was not included as a linear term in the final metamodel. With the F-111 set at the low coded level, the number of F-15s present appeared to not make a significant difference in the result. When the F-111 was coded to the high level, a significant difference is seen between having few or many F-15s. With the F-15 coded to the low level, a much better outcome was observed compared to the F-15 at the high level. This difference of almost two days may suggest a competition for resources, or the importance of the mission of '

deep strike interdiction. The F-15 (only an air superiority fighter) may contribute little to the deep strike environment.

## MOE #2: Days Needed to Achieve Air Supremacy

The F-15 was the primary air superiority aircraft among the five aircraft in this study; therefore, this aircraft was expected to have the most influence on this prediction function. This aircraft did have the most importance. Every aircraft did contribute in the metamodel, either having a linear effect and/or an interaction effect with another aircraft.

One might immediately notice that the EF-111A had a linear effect that is detrimental to the mission of achieving air supremacy. One possible explanation of this is found in the mission of the EF-111A. The EF-111A was "produced for missions that include barrier standoff jamming, degradation of radars during CAS operations, and closein jamming and direct support for deep strike missions." During Operation Desert Storm, EF-111A area jamming was crucial to maintaining air supremacy (Mehuron, 140). From its list of missions, the EF-111A apparently is important for air supremacy *maintenance*, not *achievement*. Using this jammer aircraft to support achieving air supremacy appeared to lower force mix effectiveness in accomplishing air supremacy in a minimal time.

Consulting a THUNDER expert on this "quirk" in the metamodel provided some useful information. Expert advice indicated the jammer role should not hinder the accomplishment of air supremacy. Using a flight of, instead of zero, aircraft as the coded low level may have been a better idea for the experimental design. Recently, THUNDER experts indicated having trouble modeling measures of effectiveness that are measured in time (Logan, 1996: interview). THUNDER apparently measures time in an abnormal

manner. With a range of only six days in this output, this unusual time measuring may be clouded (Logan, 1996: interview).

The EF-111A and F-16 provided an interaction effect in achieving air supremacy. Its interaction plot is found in Figure 4.3. This interaction plot demonstrates part of the difficulty in explaining the presence of the EF-111A. With the F-16 set at the low coded level, the presence of the EF-111A did appear to significantly contribute to gaining air supremacy whether actively flying in the scenario or not. With the F-16 set at the high



Figure 4.3. Interaction Plot of F-16 and EF-111A for MOE #2 (Optimum: Minimize Days)

coded level, three additional days are needed to achieve air supremacy objectives with EF-111As flying. Observing sortie rates for the two plot points under the F-16 coded high level, many more sorties were flown for CAS with the EF-111As at the coded low level. This suggests the importance of close air support, as well as a competition for resources. Between these aircraft, competition for resources appears to be a significant factor to gaining air supremacy.

Another interesting interaction was that of the A-10 and F-111. The A-10 did not have a linear effect on achieving air supremacy, as this aircraft performed CAS missions. The plot of this interaction is found in Figure 4.4. With the A-10 at the coded low level, adding F-111s did not improve the days needed to achieve this MOE; in fact, adding F-111s made matters worse. With the F-111s not flying to perform the deep strike mission, no aircraft behind enemy lines were being destroyed on the ground. These aircraft became eligible to participate in the air war, and thus more airborne targets



Figure 4.4. Interaction Plot of A-10 and F-111 for MOE #2 (Optimum: Minimize Days)

for the F-15 and F-16. When the A-10 was at the coded high level, increasing the number of F-111s improved mission accomplishment. A-10s in mass appeared to able to attack those targets aimed at Blue aircraft--such as surface-to-air missiles. Those aircraft performing the air supremacy mission were better able to function without additional threats from the ground. Clearly, these two aircraft complemented each other in achieving air supremacy.

#### MOE #3: Number of Air Kills

Air Kills are those Red targets destroyed by Blue aircraft. The majority of these targets are on the ground, and thus ground attack aircraft were expected to be the major role players. The A-10, F-16, and F-111 performed these missions and did make contributions to the prediction function. The EF-111A's role of jamming was seen as a linear term and an interaction with the F-16, supporting the earlier statements describing the EF-111A's role in CAS missions.

Each of the two-factor interactions in this metamodel served to account for the finite number of targets and multiple aircraft capable of destroying those targets. These interactions appeared to be adjustment factors for the linear effects. The EF-111A did not destroy targets, per se, but rather provided a better environment for target destruction. The interaction plot of Figure 4.5 demonstrates how its presence contributes



Figure 4.5. Interaction Plot of A-10 and EF-111A for MOE #3 (Optimum: Maximize Kills)

to the A-10 mission. With the A-10 set at the coded low level, more air kills are seen with the EF-111A in greater number. At the A-10 high level, the principal of mass becomes

evident, as the EF-111A presence becomes less noticeable. Some targets were destroyed with the jammer aircraft present, others were not.

The interaction term of the F-15 and F-16 described the multi-role aspect of the F-16, as less F-15s involved in the war meant a greater demand for the Fighting Falcon to fly air-to-air combat missions. The interaction term of the F-15 and F-111 indicated that while the F-111 accomplished its deep strike missions, the presence of the F-15 hindered the ability to score deep strike kills. A demand for resources and overlapping missions in the same airspace were possible factors that lowered the overall effectiveness of the F-111 to score deep strike kills. The comments from a THUNDER expert examining this interpretation found this explanation to be reasonable (Logan, 1996: interview).

## MOE #4: Number of Blue Aircraft Lost

The number and type aircraft lost depends on the lethality of the mission to be performed, as well as how well equipped the aircraft is for that mission. In the metamodel created for number of Blue aircraft lost, those aircraft with the more dangerous missions played a major role in calculating this measure of effectiveness.

The A-10 and F-16 with their CAS missions had highly significant linear effects. Having more of these aircraft meant more possible CAS missions to be flown, and thus more opportunities for the enemy to score a ground-to-air kill. The EF-111A's jamming mission can be accomplished out of the range of enemy fire, and thus its linear effect appeared as negative. The presence of the F-15 in the metamodel was favorable to the Blue forces, as the F-15 most likely kept the skies clear of enemy aircraft, as well as staying clear of receiving anti-aircraft fire. The F-15 improved survivability of other aircraft; an example of this is seen in an interaction plot with the F-16 (Figure 4.6).



Figure 4.6. Interaction Plot of F-15 and F-16 for MOE #4 (Optimum: Minimize Aircraft Lost)

With the F-16 set at the coded low level, the change from coded low to high F-15 is not evident. However, at the F-16 coded high level, the F-15's presence appears to preserve around twenty aircraft. Flying F-15s in higher numbers appears to make the battlefield environment safer for all other aircraft. The THUNDER expert interviewed agreed with this assessment (Logan, 1996: interview).

The jamming mission was also seen as important through an interaction plot with the F-111, which appears in Figure 4.7. With the F-111 coded to the low level, the presence of the EF-111A appears to significantly lower Blue aircraft losses. Setting the F-111 at the coded high level saw more aircraft lost and a less significant effect of the EF-111A's presence. The role of the EF-111A as an escort jammer displays itself well in this interaction; escort jamming was cited as important by the THUNDER expert consulted (Logan, 1996: interview).



Figure 4.7. Interaction Plot of F-111 and EF-111A for MOE #4 (Optimum: Minimize Aircraft Lost)

## MOE #5: Depth of Enemy Advance

An overview of the entire metamodel for determining the depth of the Red forces' advance into Blue territory shows all aircraft having a contributing positive effect to the Blue forces. The F-16 had the most significant linear influence, most likely due to its multi-role mission status.

Only two two-factor interactions were present. The interaction plot of the A-10 and EF-111A is found in Figure 4.8. With this plot, it is clearly seen that having the maximum number of EF-111As is better for the low design level of the A-10, and less important for the high level. The plot indicates having EF-111As present enhances the aircraft force mix. Without EF-111As flying, Red forces appear to advance further on average. Having EF-111As flying provides a favorable effect to the objective. The EF-111A interacting with the F-15 also had a favorable effect to the objective.





The interaction plot for The F-15 and EF-111A appears in Figure 4.6. The

interaction plot indicates a complementary relationship between these two aircraft





Interaction Plot: F-15 & EF-111A **Depth of Enemy Advance** 

Figure 4.9. Interaction Plot of F-15 and EF-111A for MOE #5 (Optimum: Minimize Kilometers)

in the mission of minimizing the depth of the enemy advance. With the F-15 set at the coded low level, having EF-111As present decreased the Red advance by about a half kilometer. Having the F-15 set at the coded high level, the addition of the EF-111A squadron aided in reducing the Red advance by three kilometers. With six squadrons of. F-15s in the force mix, adding EF-111As did little to improve this measure of effectiveness. The F-15 appeared to need support from the EF-111A to have an effect on minimizing the depth of the Red forces' advance; or, the importance of the EF-111A is seen by the interaction plot. In either case, the THUNDER expert consulted agreed with the importance of the EF-111A in this objective (Logan, 1996: interview).

#### Metamodels with Quadratic Terms

The linear and two-factor design was augmented with additional runs to create a design for finding quadratic terms of each aircraft. Each MOE was tested for the presence of quadratic terms; only two MOEs proved to have quadratic terms of a 90% level of significance. Appendix D contains the complete regression output results from *Statistix*, with residual plots included. The coefficients and significant statistics are presented in Table 4.3.

With both metamodels, the results obtained were not much different than those of the linear and two-factor models. The terms most important for number of air kills remained the same, with the addition of the F-15 quadratic term. The A-10/EF-111A interaction term did not remain a part of the depth of enemy advance metamodel with the addition of F-15 and F-16 quadratic terms included. Neither metamodel measured up to the linear/two-factor models in favorable test statistics; however, the quadratic metamodels' test statistics still were reasonable for an adequate metamodel. Validation will determine which is the better predictor of the pairs of metamodels. Validation also proves useful in bringing credibility to the multivariate statistics results.

Predictor	Number of	Depth of
Variable	Air Kills	Red Advance
Intercept	9015.45	56.3905
A-10	1605.94	-2.0000
F-15		-0.66667
F-16	2059.94	-4.27778
F-111	238.833	-0.66667
EF-111A	107.167	-0.94444
A-10, F-15		
A-10, F-16		
A-10, F-111		
A-10, EF-111A	-294.563	
F-15, F-16	-176.188	
F-15, F-111	-141.937	
F-15, EF-111A		-0.75
F-16, F-111		
F-16, EF-111A	-183.688	
F-111, EF-111A		
A-10, A-10		
F-15, F-15	229.157	-2.14793
F-16, F-16		2.35207
F-111, F-111		
EF-111A, EF-111A		
Adjusted R-sq.	0.9866	0.8677
F test statistic	230.10	23.96
MSE	61395.3	2.4152
Standard Error	247.78	1.554
Max Predictive	1100	2.178
Standard Deviation		

# Table 4.3 Response Surface Analysis: Significant Terms Observed(Quadratic, Linear, and Two-Factor Interactions)

## Principal Components Analysis

The results from this analysis consisted of determining the true dimensionality of the data, the number of components or factors to retain, and an analysis of those components or factors. The component scores and factor scores were examined for any possible explanation of what is happening with interrelationships among the variables; insight was gained by investigating these scores.

To select the correct number of components to retain, Kaiser's criterion and Cattell's scree test was used. Kaiser's criterion is a rule of thumb in which any components or factors associated with an eigenvalue greater than one should be retained. An eigenvalue less than one would explain less variance than one of the original variables. Cattell's scree test is a graphical approach compared to the rubble at the bottom of a cliff. Any components or factors above the "rubble" should be retained (Dillon and Goldstein, 1984: 48-50).

The data matrix used for the principal components analysis was the 16 x 5 matrix of the THUNDER output results. A new measure of effectiveness, remaining Red inventory, was used instead of number of air kills in the multivariate analysis (reasons for this change are discussed later). The calculations for the principal components were made using Mathcad PLUS 5.0 and are found in Appendix E. The eigenvalues that determine the amount of variance explained by each principal component were extracted from the sample correlation matrix. The calculated eigenvalues, difference between each and the next largest, proportion of total variance explained, and cumulative variance explained by the principal components are cataloged in Table 4.4.

Component	1	2	3	4	5
Eigenvalue	3.3449	0.8213	0.6071	0.1532	0.0735
Difference	2.5236	0.2142	0.4538	0.0797	
Proportion	0.6690	0.1643	0.1214	0.0306	0.0147
Cumulative	0.6690	0.8332	0.9547	0.9853	1.0000

 Table 4.4: Eigenvalues with Relationships Among Them

Using Kaiser's criterion, only the first principal component was kept; however, the second largest eigenvalue was not too far from the cutoff. Figure 4.10 is the scree plot of the principal components. The scree plot has a large gap between the first and second



Figure 4.10. Scree Plot of Principal Components

principal components, thus supporting the selection of only one principal component. The retained principal component explained 66.9% of the variance. A modified loadings matrix (loadings modified to read from largest to smallest, left to right) from Appendix E is shown in Table 4.5. Note that the top row of the matrix contains the corresponding eigenvalue to that principal component. Each column corresponds to a principal component. The entries in the first numerical column suggest some very

<u>E-vals</u>	3.34490	0.8213	0.60708	0.15323	0.07351
Nt FLOT	0.92191	-0.17493	0.27395	0.20421	-0.05222
Air Sup	0.50518	0.84396	0.17965	-0.01517	-0.00468
Red EQ	0.94020	-0.16779	-0.01875	-0.13539	-0.26304
AC lost	-0.71817	-0.10401	0.68335	-0.05492	-0.05859
Dpth Ad	0.91653	-0.19860	0.18011	-0.10119	0.27903
_	PC #1	PC #2	PC #3	PC #4	PC #5

Table 4.5. Loadings Matrix, L, for Principal Components

strong correlations between the MOEs in the first principal component. Days needed to neutralize FLOT, remaining red inventory, and depth of enemy advance are very highly correlated. These high correlations appear to indicate better equipped Iraqis penetrate further into Saudi Arabia, and as a result, more time is needed to push them back into their own territory. (The initial PCA, using number of air kills instead of remaining red inventory, produced number of air kills very oppositely correlated with days to neutralize FLOT and depth of enemy advance. Since the correlations are at almost equal levels, a new MOE was used to avoid a "canceling out" of the effects.) Number of blue aircraft lost showed itself significant in the first principal component, having an opposite response to the other three significant correlations. Blue aircraft lost was also significant in the third largest principal component, with an opposite sign. The correlation in the largest principal component indicated fewer aircraft were lost as the Iraqi forces were more successful in achieving the objectives of the other three MOEs. The further the Iraqis advanced, the fewer the number of Blue aircraft lost. While the presence of this high opposite correlation might indicate an overrun of airfields, consider principal components two and three. These components fail Kaiser's criterion for retention; however, having eigenvalues close to one suggests a rotation of the axis system may clarify this. Principal component three (labeled "PC #3" below the appropriate column), indicates an independent, opposite correlation from the same MOE in PC #1. This apparent contradiction was clarified with a rotation of the axis system, which is discussed later in this chapter.

Days to air supremacy was left as an independent indicator in PC #2. Column two of the loadings matrix in Table 4.6 corresponds to the second largest principal component, and the second entry in the column locates where this MOE is highly correlated to nothing else in the column. Days to air supremacy, therefore, continued to be examined as an independent measure.

Principal component 1 can be used to create a linear combination of all the outputs that explains 66.9% of the variance. The meaning of this new variable was examined with principal components scores. Principal components scores were generated and the scores from the two largest principal components were plotted against each other. These scores were found from the calculations in Appendix E. The plot of principal components scores appears in Figure 4.11. The three center point replications included in the quadratic metamodel experimental design were "scored" using the results of the sixteen run study, and are included in the principal component score plots (as triangles) to see how these results fared against the others.

The plot of Figure 4.11 lists aircraft with selected points. These aircraft were set at a high level for that particular experimental run. Notice that the far left of the plot consists of points with only one aircraft set at the high level. At the far right is the point with all aircraft set at the high level. In between these regions are the various combinations of other aircraft. Not observing the EF-111A high level (present due to the coding scheme of the experimental design), the runs with three aircraft high are more to the right, while the runs with two aircraft high are to the left. The principal component scores for the first principal component appear to indicate the best force mix for meeting ground war objectives. A lower score indicates a better force mix; on the plot, a point more to the right.

If any evidence is to not support this conclusion, the A-10 at the coded high level all alone, as well as the F-16 at the coded high level alone in the middle of the plot would suggest these aircraft alone are better than some combinations. The fact that the stronger



Figure 4.11. Principal Components Scores with Associated High Aircraft Levels (Optimal: to the Right)

MOEs within the component are more oriented to the *ground*, and not a balance of air and ground, contribute to the higher scores for the CAS aircraft. The plot overall suggests the A-10 is a very important aircraft to the force mix. The F-16 is also important, as it is a multi-role aircraft.

Using the "spread" of the center points in the plot can be used as a rough rule of thumb to distinguish points and groups. Any points separated by a distance greater than the largest distance between center points may have distinguishing characteristics. Using this rule, the far left of the plot has a group of three points, while the far right has a group of four points. The rest of the points form a cluster in the center of the plot. Each of these groups could be seen as, from left to right, "below average" force mixes, "average" force mixes, and "optimal" force mixes. Again, the force mixes to the right appear to be best suited for achieving ground war objectives.

## Factor Analysis

A varimax rotation of the axis system was performed in an effort to clarify the loadings in Table 4.5. Appendix F contains the SAS output (note the first page is simply the principal components results--the factor analysis starting point). The loadings matrix resulting from rotation appears in Table 4.6.

<u>E-vals</u>	2.46566	1.17091	1.04928	0.21594	0.09821
Nt FLOT	0.94378	-0.17896	0.18532	0.07734	-0.19218
Air Sup	0.16624	-0.13691	0.97600	0.03218	0.00150
Red EQ	0.78655	-0.39841	0.13677	0.45125	-0.01675
AC Lost	-0.27956	0.94554	-0.15225	-0.06750	-0.00849
Dpth Adv	0.92222	-0.25955	0.14308	-0.02714	0.24683
_	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5

Table 4.6. Loadings Matrix after Varimax Rotation

(Note the factors now appear left to right as most important to least important.) The loadings matrix now shows the data set to clearly be three dimensional. The three highly positively correlated MOEs from the principal components analysis--days needed to neutralize FLOT, red inventory remaining, and depth of enemy advance--were again highly correlated. After rotation, the consideration of Blue aircraft lost in the first principal component was removed. This first factor better indicated a "ground war index": a successful war for the Blue forces constituted a low index. A high index indicated the Red forces were more successful in achieving their objectives. Blue aircraft lost and days to air supremacy remained independent. Using Kaiser's criterion, these factors are retained. Along with Kaiser's criterion, a scree plot of the factors also supported keeping three factors, as is seen in Figure 4.12. With three factors to retain, scores of these factors proved to be the most insightful.

Scree Plot of Factors



Figure 4.12. Scree Plot of Factors

Factor scores were computed and are found in Appendix E. Three plots were created: Factor 1 versus Factor 2, Factor 1 versus Factor 3, and Factor 2 versus Factor 3. Again, these plots were generated to gain insight as to the meaning of the Factor Scores.

The plot of Factor 1 versus Factor 2, seen in Figure 4.13, shows the "ground objectives index" versus the "Blue attrition index." The factor scores in the Ground Objectives Index had a similarity to the principal components scores in that they appeared to weigh one side of the plot with individual aircraft, while the combinations of the most aircraft weighted the other side. To better understand the scores, the Ground Objectives Index was exactly that--concerned with those war objectives dealing with the ground. The lower factor scores (to the right of the plot) for the Ground Objectives Index had a higher frequency of the two CAS aircraft: the A-10 and F-16. The two aircraft not involved with CAS--the F-15 and F-111--were found as part of higher scores more often



Factor Scores: Ground Objectives Index vs. Blue Attrition Index

Figure 4.13. Factor Score Plot for Factors 1 and 2, with High Aircraft Levels Listed (Optimal: Up, Right)

than not (left of the plot). The center point scores were toward the center of the plot, and showed a wide "spread" in the ground objectives index. Because of the "spread" in center point scores, the plot indicates no distinct groupings; however, the index scores appeared to indicate how good a force mix was for meeting ground war objectives.

Blue aircraft lost, or the "Blue Attrition Index," was an independent factor significant after rotation, and its meaning can be observed in both plots in which it is included. Moving from left to right in the plot of Blue Attrition Index versus Air Lethality Index, found in Figure 4.14, the CAS aircraft appeared to be with points corresponding to higher scores, while the air-to-air and deep strike aircraft had lower scores. From this, higher factor scores for blue aircraft lost suggested the primary aircraft used were under



Factor Scores: Blue Attrition Index vs. Air Lethality Index

Figure 4.14. Factor Score Plot for Factors 2 and 3, with High Aircraft Levels Listed (Optimal: Up, Right)

the CAS mission; lower scores involved those non-CAS missions. The center point scores for the Blue attrition index suggested the missions accomplished for that force mix were relatively conservative; CAS missions did not dominate these experimental runs.

A lower Air Lethality Index meant a force mix which would produce fewer days to achieve air supremacy. Observing Figure 4.14, the upper points predominantly consist of the F-15 and F-16, while the lower points consist of ground attack aircraft. A closer look at this plot suggests two groups, divided approximately with the zero of the Air Lethality Index axis. The upper group appeared to be those force mixes oriented to achieving air supremacy. The lower group appeared to be those force mix combinations not suited to achieving air supremacy in a timely manner. Plotting the center point replications indicates the points in the extreme upper and lower regions of the plot are those force mixes with significant differences in achieving air supremacy quickly.

An expert who uses THUNDER daily weighed in on the results of the multivariate analysis, and found them very favorable. The analysis performed here would prove most interesting with the classified database and more variables to correlate (Logan, 1996: interview).

## **Conclusions**

Using principal components analysis and factor analysis, the data outputs were one dimensional before rotating the axis system, and three dimensional afterwards. The variable generated from principal components analysis demonstrated a measure of the principle of mass. The Ground Objectives Index indicated the best force mix consisted of the A-10, F-15, and F-16 set at the coded high levels. The Blue Attrition Index prescribed a force mix of the F-15, F-16, and F-111 at the coded high levels to produce the fewest number of aircraft lost. The Air Lethality Index dictated the optimal force mix of the F-15, F-16, and EF-111A.

With sixteen runs used in this analysis, a validation of some sort would provide confidence and credibility in these results. Data points collected to provide validation to the RSM results of the research were also used to provide support of the conclusions made in this multivariate analysis.

### V. Validation of Metamodels and Multivariate Analysis

## **Introduction**

In Chapter II, some methods of validating a statistical model are explained. Validation of the metamodels generated in this thesis was accomplished with the collection of new data. THUNDER output results from within the design space were collected and compared to the outputs of the metamodels with the same aircraft settings. These comparisons were then used to measure the predictive ability of the metamodels. The closeness of metamodel prediction to actual THUNDER output showed how successful and useful the metamodels could be to a potential user.

The validation experimental runs were also used with the multivariate analysis. Instead of beginning a new study with a data set of sixteen new runs, these runs were augmented to the original data set, and an analysis of 32 runs was accomplished. The multivariate analysis of this larger data set hoped to clarify and/or solidify any deductions made from the original sixteen runs.

### Experimental Design for Collecting Validation Data

The strategy for collecting validation data consisted of finding observations within the original design region. The metamodels generated were best suited for the design points from which they were built. Those areas between the design points are where future predictions will be made; rarely, if ever, will a prediction be made using exact aircraft levels from one of the experimental design runs.

A half fraction factorial design was used to systematically collect observations inside the design region. The validation design coding scheme, simply put, was the

original design, which used -1 and +1 levels, modified such that the levels are -0.5 and +0.5, respectively. The uncoded design and the THUNDER output results are found in Table 5.1.

## **Results**

The ability of the metamodels to predict outcomes with different aircraft force mixes was measured with the Mean Square Prediction Error (MSPR), discussed in Chapter II, and the Mean Absolute Percentage Error, MAPE. This predictive measure is found using

$$MAPE = \frac{100}{n} \times \sum_{i=1}^{n} \frac{|Y_i - \hat{Y}_i|}{|Y_i|} , \qquad (4)$$

where  $Y_i$  is the actual observation of the *i*th validation run,  $\hat{Y}_i$  is the predicted value by the metamodel for the *i*th validation run, and *n* is the number of runs.

Appendix G presents the validation results for finding MSPR and MAPE using Microsoft Excel 5.0. Table 5.2 catalogs the results of the MSPR for each MOE and compares it with the MSE of each *linear/two-factor* metamodel. Recall that if the MSPR and MSE are fairly close to one another, the metamodel is not seriously biased and gives an appropriate indication of the predictive ability of the model. If the MSPR is much larger than the MSE, MSPR should be used to gage how well the metamodel will predict in the future (Neter, Wasserman, and Kutner, 1990: 466). Table 5.2 also shows the values for the MAPE of each linear/two-factor metamodel.

	# of	# of	# of	# of	# of	Neut FLOT	Air Suprem	Air Kills	Blue AC lost	Depth Adv
Run	A-10	F-15	F-16	F-111	EF-111A	(days)	(days)	(number of)	(number of)	(kilometers)
1	45	45	50	45	18	14.5	19	7530	111	62
2	111	45	50	45	6	14	15	10217	114	56
3	45	111	50	45	6	14.5	13	6639	100	57
4	111	111	50	45	18	14	13	8717	114	58
S	45	45	125	45	6	13.5	21	8530	125	56
9	111	45	125	45	18	13	15	11202	120	54
7	45	111	125	45	18	13.5	14	9305	93	55
×	111	111	125	45	6	13	15	11147	125	53
6	45	45	50	111	6	14.5	15	7615	<del>7</del> 6	57
10	111	45	50	111	18	13.5	18	8987	131	55
11	45	111	50	111	18	14.5	15	7756	100	57
12	111	111	50	111	6	13.5	14	9410	100	53
13	45	45	125	111	18	13.5	21	8943	117	55
14	111	45	125	111	6	13	21	10514	146	53
15	45	111	125	111	6	14	14	10132	111	57
16	111	111	125	111	18	15	15	11057	129	54

Table 5.1. Uncoded Design and Output Results for Validation Experimental Design

MOE	MSE	MSPR	MAPE
Days to Neutralize FLOT	0.0625	0.1232	1.78 %
Days to Air Supremacy	1.1667	8.68	15.75 %
Number of Air Kills	52619.9	297944.6	4.39 %
Blue Aircraft Lost	21.563	99.75	7.20 %
Depth of Enemy Advance	1.3333	3.6763	2.73 %

 

 Table 5.2. Comparison of MSE and MSPR, MAPE Results for Validation Data (Linear/Two-Factor Metamodel)

The MSPR of each measure of effectiveness was at least two times larger than the respective MSE. The MSPR appeared to be a measure how well the metamodel will predict in the future; however, for the first and last MOEs, the difference may be small enough to consider the predictive ability of the metamodels to be unbiased. The MAPE indicated these metamodels may not be as bad as the MSPR portrayed. Only the number of days to air supremacy had a MAPE above 10 percent. Such a significantly higher value for this measure compared to the other four may be due to the fact that out of the five MOEs, this one had the most subjectivity associated with it. Air Supremacy was roughly defined in this research as the point in time when the Red forces' aircraft sortie rate dropped to five percent of the day one sortie rate. The values recorded were the result of examining data reports and finding the first day of many when the sortie rate appeared to stabilize at a constant rate. The MAPE for days to air supremacy would possibly reduce with more distinct, defined criteria for this MOE.

The MSPR and MAPE were also found for the design points--points from which the metamodel was built. These results appear in Table 5.3. (Calculations for MSPR and MAPE for both validation data set and design data set are found in Appendix G).

MOE	MSE	MSPR	MAPE
Days to Neutralize FLOT	0.0625	0.15985	2.396 %
Days to Air Supremacy	1.16667	1.519531	5.893 %
Number of Air Kills	52619.9	19935.5	1.301 %
Blue Aircraft Lost	21.5625	7.8125	1.998 %
<b>Depth of Enemy Advance</b>	1.33333	2.011719	2.128 %

 Table 5.3. Comparison of MSE and MSPR, MAPE Results for Design Data

 (Linear/Two-Factor Metamodel)

The MSPR results showed the metamodel was a better predictor for the design points than for the validation points. Number of Air Kills and Blue aircraft lost have a smaller MSPR than MSE. This was due to the small differences in prediction and actual values. A trend was seen in the MAPEs, in comparison to the validation MAPEs. Days to Air Supremacy was again seen having the highest MAPE, which was due to the subjectivity of the measure as discussed earlier. The rest of the MAPEs were well under 10 percent. All of the MSPRs for the design data were not significantly larger than the MSE and were thus "not seriously biased" in giving an indication of the predictive ability of the metamodels. The amount larger than the MSE was relative to the size of the MSE; while "Number of Air Kills" had a high MSE, its MSPR was 5.7 times larger.

#### Comparison of Linear/Two-Factor and Quadratic Metamodels

Table 5.4 compares the MSPR of the Linear/Two-Factor metamodels and the quadratic metamodels. Regarding MOE #3, Number of Air Kills, the MSPR for both the validation and design points was larger than for the linear/two-factor metamodel. This difference indicates the linear/two-factor metamodel was less biased than the quadratic metamodel, and thus a better predictor with respect to this predictive measure. The same

can be said for the validation design points of MOE #5; however the difference is less than

0.5.

MOE	MSE	Linear/Two-Way MSPR	Polynomial MSPR
MOE #3: Val Pts	52619.9	297944.6	342473.9
MOE #3 : Des Pts	52619.9	19935.5	26052
MOE #5: Val Pts	1.3333	3.6763	4.1045
MOE #5: Des Pts	1.3333	2.0117	1.1529

## Table 5.4. Comparison of MSPR for Linear/Two-Factor and Quadratic Metamodels

The design points revealed an MSPR that was less than for the design points. The two metamodels appeared to be almost inseparable in predictive ability with respect to MSPR.

Table 5.5 compares the MAPEs of both metamodels:

Table 5.5.	<b>Comparison of MAPE for Linear/Two-Factor</b>
	and Quadratic Metamodels

MOE	Linear/Two-Way MAPE	Polynomial MAPE
MOE #3: Val Pts	4.385 %	4.8595 %
MOE #3 : Des Pts	1.301 %	1.3175 %
MOE #5: Val Pts	2.727 %	2.9030 %
MOE #5: Des Pts	2.128 %	1.4343 %

The differences in MAPEs for the two metamodels was less than 0.5 percent. Even for the MAPEs of MOE #5, the differences were less than one percent. In general, the quadratic metamodels did not do any better at predicting than the linear/two-factor metamodels. Even if the quadratic metamodels had been better, a significantly better predictive ability would have needed to be seen to justify the additional thirteen runs.

How much confidence put into the metamodels generated depends on the one who uses it extensively in any decision making process. The comparison of prediction measurements over the design space and validation space indicate a difference of less than ten percent for each respective MAPE. The decision maker must decide whether or not he or she is willing to have up to a ten percent error in the approximations.

## Multivariate Analysis with Both Data Sets

Both the original data set of outputs and validation set of outputs were combined and a principal components analysis performed. Appendix H contains the complete calculations of this analysis.

The underlying dimensionality of the combined output set showed itself to have the same dimensionality as the design output data set. The correlations within each principal component were very similar to what was calculated with the original sixteen runs. The same correlations were seen, and at about the same degree of correlation.

The initial hypothesis that the first principal component reflected the ability of achieving ground objectives was seen in much clearer in a plot of the principal components scores, seen in Figure 5.1. (Those labels with a "(V)" indicate the run was a validation run. Those points which are triangles are center point replications.) The smallest values for the first principal component indicated better force mixes for achieving ground objectives. The absolute lowest first principal component score corresponded to all aircraft at the coded high level. The highest score corresponded to the experimental run where the F-111 deep strike aircraft was the only aircraft flying at the coded high level. This aircraft does not actively participate in ground war efforts on the allied side of the

FLOT. The next highest score corresponded to only the F-15 air superiority fighter flying at the coded high level. After the points referring to the original design runs, plotted scores corresponding to the validation runs with similar aircraft levels (for example, the





validation run with the F-111 as the only aircraft at the coded high level) appeared next.

Three center point replications were scored and plotted as with the original data set, and are indicated as triangles on the plot. Their relatively close scores indicated a small variability in the scores of principal component one. This close variability led to three distinct regions on the components plot. The center region of many points indicated force mixes which were very similar in ability to address ground war objectives. To the right of this region, these aircraft force mixes appear to be above average to optimum.

(Within this region, the validation scores were higher than the original analysis scores.) To the left, aircraft combinations appeared to be less effective in the ground war. (Within this region, the validation scores were lower than the original design scores.) The "ground objectives index" appeared to indicate a smaller score means a better aircraft force mix for addressing ground war objectives.

After rotating the loadings matrix (SAS output of this found in Appendix I), the Ground Objectives Index appeared to have this quality of grouping aircraft mixes in a more distinct manner. All aircraft force mixes, except for two, fell into one group in the center of the plot of Ground Objectives Index versus Blue Attrition Index, found in Figure 5.2. The low score outlier consisted of the force mix of the A-10, F-15, and F-16. This appeared to indicate that having all of these aircraft alone set at the coded high level, dedicating all resources to them, will result in the most decisive achievement of MOEs pertaining to the ground war. The other extreme point was the run corresponding to the F-111 coded at the high level, suggesting this force mix was the least effective in achieving ground war objectives.

The variability in the center point replications indicated these outlier end points were not extremely different from the respective edges of the central cluster of plotted points. Because of this variability, the Ground Objectives Index appeared to rank order the various force mixes, from most to least effective. This clarified the initial results with the principal components scores. The plot of Figure 5.2 also clarified the meaning of the Blue Attrition Index.

Factor scores for the Blue Attrition Index appeared to indicate a high score meant more aircraft lost in combat. The highest factor score consisted of the experimental run where only the F-16 flew in high numbers; the lowest factor score consisted of the experimental run where the F-15, F-16 and EF-111A flew in high numbers. Referencing Table 4.2, the run with only the F-16 flying in high numbers lost 155 aircraft--the most of



#### Validation Factor Scores: Ground Objectives Index vs. Blue Attrition Index

Figure 5.2. Validation Factor Scores: Ground Objectives Index versus Blue Attrition Index (Optimal: Up, Right)

any run. Similarly, the run with only the F-15, F-16, and EF-111A flying in high numbers lost 87 aircraft--the least of any run. These points appeared as outliers from the central cluster of points in the factor score plot of Figure 5.2.

A somewhat small variability in the center point replications indicated these outliers were distinct from the central region of points. Flying only the F-16 to perform its multi-role missions of CAS, air superiority, and others resulted in exposing this aircraft to a multitude of dangerous combat situations. Its ability to perform some missions better than others enters into the picture, since the achievement of mission objectives means using every capable resource. These factors affect the high loss of aircraft with only the F-16.

The low loss of Blue aircraft was seen with the dominant presence of air superiority aircraft and jammers. The aircraft of these missions were exposed to little or no low altitude attack; thus making an aircraft loss in these missions due to air-to-air engagements. These losses would be low, due to the superiority of allied forces pilots. Runs with these aircraft entering the force mix in relatively high numbers, compared to the rest, composed the bottom ridge of the central region of points.

Along the upper ridge of the central region of points, those runs with CASoriented force mixes dominated. Points from both the original data set and the validation set followed this pattern; the original data were the more distinctive cases. The Blue Attrition Index appeared to indicate a rank order of force mixes, with the lower scores corresponding to those with the least losses.

Two distinct groups, as opposed to a rank order, appeared in the Air Lethality Index. The factor score plot found in Figure 5.3 clearly shows how the factor scores had separated the outputs from each experimental run into two groups. The scores along the bottom of the lower group matched up with those aircraft force mixes more oriented around close air support--such as the A-10, F-16, and F-111; the F-15 did not appear among these force mixes. In the upper group, the upper ridge of the group was indicative of force mixes with the F-15 and F-16--both used in air superiority missions. Taking these indications into account, it appeared that the group with negative factor scores were the

better force mixes for achieving air supremacy, while the other group of positive scores was not as effective in achieving these objectives.



Figure 5.3. Validation Factor Scores: Ground Objectives Index versus Air Lethality Index (Optimum: Up, Right)

## Summary

The use of a validation set provided some credibility for the results obtained from the original design. The additional points proved most useful for clarifying the principal components analysis ground objectives variable. The Ground Objectives Index and the Blue Attrition Index indicated the same optimum force mixes as previous. The Air lethality index again indicated two different groups of force mixes. The addition of even more runs would add credibility to the results found with adding the validation run outputs.

# VI. Summary, Recommendations for Follow-On Efforts, and Conclusions

#### Summary

The research of this thesis investigated the effects of changing force structure on THUNDER output. Modifications of the force structure consisted of the United States Air Force primary tactical aircraft. Each aircraft amount was limited to a half squadron (or none for the jammer aircraft) or six squadrons (or one squadron for the jammer aircraft). These different limits were incorporated into an experimental design, from which a response surface for a measure of effectiveness was generated. The metamodels created were found to be adequate to predict measures of effectiveness within the range of each aircraft.

Principal components analysis and factor analysis presented a relationship among those effectiveness measures relating to the ground war. Achieving the ground war objectives most efficiently depended upon the force mix used. The number of Blue aircraft lost appeared to be minimized with the increased use of air superiority aircraft. Minimizing the number of days to achieve air supremacy appeared to follow suit, as two different classes of force mixes emerged from the analysis. Those measures dealing with the air war were weighted towards the air superiority aircraft; the ground war was weighted towards the CAS aircraft. Allocating resources towards a balance of this dichotomy would prove essential in achieving victory in a large scale campaign.

## Recommendations for Follow-On Efforts

The results of this research proved most interesting, considering the size of the experiment, number of variables, and number of outputs observed. The research
presented may indicate new directions for finding insight as to how THUNDER models a large-scale campaign and interaction among inputs and outputs.

An unclassified database was used in this research effort. A similar research effort using a classified database would prove useful in seeing if the classified parameters change the conclusions from this research. Performing a research effort like the one presented in this thesis with a classified database would also serve as another validation tool.

The EF-111A Raven, at the time of this writing, is scheduled for deactivation by the USAF inventory. The experimental design observed the EF-111A's presence with the absence of the US Navy's EA-6B Prowler. The EF-111A proved to be significant in all of the metamodels produced. An interesting investigation would be to deactivate the Ravens and activate all the Prowlers, and then create new metamodels to see how the Prowler fits into the new metamodels. Then, compare the different metamodels to see which jammer had the greatest influence. A fundamental difference between the Air Force and Navy jammer is that the EF-111A is supersonic; the EA-6B is not. These metamodel comparisons could provide insight to the importance of speed in an airborne jammer, if that were a factor in the EF-111A's demise.

Observing the validation method for the multivariate analysis indicates more data means better results and insight. While only five measures of effectiveness and a grand total of 32 runs were presented in the multivariate research, more interesting conclusions could be made with twenty or more MOEs and two hundred or more output runs. Such an effort would demand good bookkeeping to document the parameters of each run, if they are not part of an experimental design. Knowing the dominant factors of each run

6-2

would allow the runs to be weighed appropriately. This research could be accomplished in the background of several other THUNDER studies over a period of months. Using a classified database would bring more credibility to the results; unfortunately, the classified database would mean a classified multivariate analysis.

### **Conclusion**

The research presented in this thesis has shown that reasonably good metamodels can be produced from a Resolution V, sixteen run experimental design. The range for number of each aircraft was relatively large; however, the large design space did not prove to cause the creation of highly irregular response surfaces. Multivariate Analysis showed a relationship among different measures of effectiveness and the potential to create an "index" for use in quickly deciphering scenario results. This multivariate analysis, along with response surface methodology, has proved to be extremely useful in analyzing the results of changing force structure within THUNDER.

## <u>APPENDIX A</u>

The following is the text to the *squadron.dat* file used in THUNDER. Note that the only values changed are found under "AUTH.QTY."

```
SQUADRONS.305
```

NUMBER.OF.MISSION.CLASSES: 9 AIR.SUPERIORITY DEEP.STRIKE GROUND.SUPPORT JAMMER MULTI.ROLE RECCE WEASEL AWACS JSTARS NUMBER.OF.SORTIE.PROFILES: 17 1001 "A-10" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 5.00 1.00 4.00 END.PROFILE 1002 "F-16" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 3.60 4.50 2.50 3.50 6.00 END. PROFILE 1003 "RF-4" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 2.50 3.00 6.00 1.50 2.00 END.PROFILE 1004 "F-111" DAY.IN.THEATER..AUTH.QTY.SORT/DAY.AC.MAX.SORT/DAY 1.00 2.00 2.50 6.00 1.20 1.50 END.PROFILE 1005 "F-15" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 3.00 3.50 6.00 2.20 2.50 END.PROFILE 1006 "AV-8B" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 4.00 5.00 END.PROFILE 1007 "F/A-18" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 3.60 4.00 6.00 2.50 3.50 END.PROFILE 1008 "A-6" DAY. IN. THEATER . . AUTH. QTY. SORT/DAY . . AC . MAX . SORT/DAY

2.00 2.50 1.00 1.50 1.20 6.00 END.PROFILE 1009 "F-14" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 3.00 3.50 2.50 2.20 6.00 END.PROFILE 1010 "E-3" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY .67 1.50 1.00 END.PROFILE 1011 "E-8" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY .67 1.50 1.00 END.PROFILE 2001 "MIG-23" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 3.00 3.00 1.00 1.20 6.00 1.20 END.PROFILE 2002 "MIRAGE F-1" DAY. IN. THEATER . . AUTH. QTY. SORT/DAY. . AC. MAX. SORT/DAY 1.00 4.00 4.00 6.00 2.70 2.70 END.PROFILE 2003 "MIG-21" DAY. IN. THEATER. . AUTH. QTY. SORT/DAY. . AC. MAX. SORT/DAY 3.00 1.00 3.00 6.00 1.20 1.20 END.PROFILE 2004 "MIG-29" DAY. IN. THEATER . . AUTH. QTY. SORT/DAY. . AC. MAX. SORT/DAY 4.00 4.00 1.00 2.70 2.70 6.00 END.PROFILE 2005 "SU-25" DAY.IN.THEATER..AUTH.QTY.SORT/DAY..AC.MAX.SORT/DAY 1.00 2.20 2.20 6.00 .80 .80 END.PROFILE 2006 "MAINSTAY" DAY. IN. THEATER . . AUTH. QTY. SORT/DAY . . AC . MAX. SORT/DAY 1.00 .67 1.50 END.PROFILE NUMBER.OF.SQUADRONS: 61 11401 "F14 USN 1" SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID 1 1102 1009 20 1009 1009 MOB.ID..DISP.AB.ID..MISSION.CLASS 1002 AIR.SUPERIORITY 1013 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA 100 100 100 100 100 0 0 0 0 0 0 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC...AEW..SREC..RESV 0 0 0 0 0 0 0 100 0 0 100 ORDERS

```
END.ORDERS
```

```
100 100 100
      100 100 100 100 0 100
                                                100
   100
  .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC...AEW..SREC..RESV
                          0 0 100 0 0
                                                 0 100
  100 100 100 100
                     0
 ORDERS
 END.ORDERS
19603 "EA6B USN 3"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  1 1103 1008 0 1099 1008
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  1015 1002
                JAMMER
  ...DCA...ODCA...HVAA...BARC...FSWP....RCA...STI....CAS....BAI....INT....OCA
    0 0 0 0 0 0 0 0 0
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC...AEW..SREC..RESV
   0 0 0 0 100 100 0 0 0 0 100
 ORDERS
 END.ORDERS
10604 "A6E USMC 1"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  1 1102 1008 25 1008 1008
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  1002 1017 DEEP.STRIKE
 ...DCA...ODCA...HVAA...BARC...FSWP....RCA...STI....CAS....BAI....INT....OCA
   0 0 0 0 0 0 100 100 100 100 100
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
  100
      0 0 0 0 0 0 0
                                             0 0
                                                    100
 ORDERS
 END.ORDERS
11804 "FA18 USMC 1"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  1 1102 1007 48
                                  1007
                                            1007
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  1002
        1017
                MULTI, ROLE
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
  .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
  100 100 100 100 0 0 0 100 0 0 100
 ORDERS
 END.ORDERS
10804 "AV8B USMC 1"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  1 1102
            1006 60
                               1006
                                           1006
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  1002 1017 GROUND.SUPPORT
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
    0 0 0 0 0 100 100 100 100 100
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
  100 0 0 0 0
                          0 0 0 0
                                            0 0
                                                    100
 ORDERS
 END.ORDERS
11001 "A10 1"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  1 1104 1001 26 1001 1001
 MOB.ID..DISP.AB.ID..MISSION.CLASS
```

A-7

END.ORDERS

```
2032
                 AIR.SUPERIORITY
   2029
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
                     0
                          0
                             0 10
                                       0 0 0
  100 0 0 10
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
   0 0 0 0 0 0 0 0 0
                                                     100
 ORDERS
 END.ORDERS
22103 "MIG21 3"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
   2 2101 2003 38 2003 2003
 MOB.ID..DISP.AB.ID..MISSION.CLASS
   2032 2029 AIR.SUPERIORITY
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
  100 0 0 10 0 0 10 0 0 0
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
   0 0 0 0 0 0 0 0 0 0 100
 ORDERS
 END.ORDERS
22104 "MIG21 4"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  2 2101 2003 38 2003 2003
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  2004 2009
                AIR.SUPERIORITY
 ...DCA...ODCA...HVAA...BARC...FSWP....RCA...STI....CAS....BAI....INT...OCA
  100 0 0 10 0
                          0 0 10 0
                                             0 0
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC...AEW..SREC..RESV
            0 0 0 0 0
                                   0 0 0 100
   0
       0
 ORDERS
 END.ORDERS
22105 "MIG21 5"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  2 2101 2003 38
                                  2003
                                            2003
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  2019 2020 AIR.SUPERIORITY
 ...DCA...ODCA...HVAA...BARC...FSWP....RCA...STI....CAS...BAI....INT....OCA
      0 0 10 0 0 10 0 0 0
  100
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
   0 0 0 0 0 0 0 0 0 0 100
 ORDERS
 END.ORDERS
22106 "MIG21 6"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
       2101 2003 38
  2
                                 2003 2003
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  2020 2019 AIR.SUPERIORITY
 ...DCA..ODCA...HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
  100 0 0 10 0 0 10 0 0
                                                0
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
       0
   0
            0 0 0
                          0
                              0 0 0 0 100
 ORDERS
 END.ORDERS
20101 "MIRAGE F1 1"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
```

END.ORDERS

```
22304 "MIG23 4"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
  2 2101 2001 38 2001 2001
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  2021 2024
              MULTI.ROLE
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
  .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC..AEW..SREC..RESV
  100 100 100 100 0 0 0 100 0 0 100
 ORDERS
 END.ORDERS
20000 "MAINSTAY"
 SIDE..SUP.CMD.ID..TYPE.AC.ID..AUTH.QTY..SERVE.KIT.ID..SORT.PROF.ID
 2 2101 2006 6 2006 2006
 MOB.ID..DISP.AB.ID..MISSION.CLASS
  2014 2013
               AWACS
 ..DCA..ODCA..HVAA..BARC..FSWP...RCA...STI...CAS...BAI...INT...OCA
   0 0 0 0 0 0 0 0 0
 .DSED..SSUP..CSUP..ESUP..SJAM..CJAM..EJAM..EAIR..RECC...AEW..SREC..RESV
   0 0 0 0 0 0 0 0 100 0 100
 ORDERS
 END.ORDERS
```

END.SQUADRONS

END.ORDERS

**APPENDIX B** 

The following is the coded design for the linear and two-way interaction model.

F111*EF	1-	1	1	-1-	-1	<b>.</b>	4	1	-1	ч	Ч	Ч Ч	Ч	<b>!</b> -	- 1	ч
F16*EF	<b>!</b>	ы	ч	-1	Ļ	ч	ч	-1	Ч	<b>.</b>	-1	ы	1		-	н
F16*F111	ч	1	ы	гı	Ļ	4	-1	-1	Ļ	<b>-</b>	<b>1</b> -	Г. -	ч	г	Ч	г
<u>F15*EF</u>	- 1	ч	۲٩ י	ч	1	- 1	г	Ч Ч	ы	<b>1</b> -	ч	<b>-</b>	-	ч	H '	щ
F15*F111	<b>,</b>	Ч	Ļ	<del>г</del> '	1	ы	-1	4	<b>1</b>	7	ч	ч	-1	4	-1	Ч
F15*F16	1	Ч	Ļ	<b>r</b> -	-1	۲.	ы	н	ы	ы	-1	4	-1	Ļ	ы	1
A10*EF	4	Ļ	г	Ч	ч		4	н -	Ч	ч	ŗ,	1-	۲ ۱	- 1	1	н
<u>A10*F111</u>	ч	<b>1</b> -	Ч	4	1	-1	1	Ļ ,	r4 1	Ч	-1	H	ч -	ч	-1	Ч
A10*F16	1	-1	1	-1	<b>1</b>	Ч	4	Ч	н	<b>1</b> -	н	н '	-1	-1	-1	ч
A10*F15	1	1	.1	1	Ļ	1-	-1	1	1	-1	-1	1	4	-1	<del>г</del> -	Ч
<u>EF-111A</u>	ч	-1	-1	ri	<b>!</b> -	H	ч	-1	-1	1	1	н -	1	Ļ	н -	щ
F-111	н '	-1	-1	년 1	1-	1-	4	1	Ч	Ч	Ч	ы	Ч	ч	ы	н
F-16	Ļ		4	-1	Ч	ч	ч	Ч	ŗ	7	7	ŗ	Ч	Ч	Н	1
<u>F-15</u>	- 1	-1	гł	ч	Ļ	Ļ.	Ч	ы	н -	н -	г	Ч	-1	- 1	T	ч
<u>A-10</u>	н -	ы	<b>1</b> .	ч	۲.	ы	н 1	ч	н -	Ч	۲. ۱	Ч	년	1	н -	Ч
RUN #	ч	7	m	4	ß	9	7	ø	6	10	11	12	13	14	15	16

**B-**]

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# APPENDIX C

The following tables are the complete results from performing regression analysis with only the most significant (90% and above) terms included. Residual plots for each regression are also presented.

#### STATISTIX 4.1

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF DAYS TO NEUTRALIZE FLOT

PREDICTOR							
VARIABLES	COEFFI	CIENT	STD ERROR	STUDENT'S 7	C :	P	VIF
CONSTANT	13.	5000	0.06250	216.00	0.0	000	
A10	-0.5	6250	0.06250	-9.00	0.0	000	1.0
F15	-0.1	.2500	0.06250	-2.00	0.0	805	1.0
F16	-0.5	6250	0.06250	-9.00	0.0	000	1.0
EF111	-0.1	.2500	0.06250	-2.00	0.0	805	1.0
A10F15	0.1	.8750	0.06250	3.00	0.0	171	1.0
A10EF	0.3	1250	0.06250	5.00	0.0	011	1.0
F15F111	-0.1	.2500	0.06250	-2.00	0.0	805	1.0
R-SQUARED		0.9630	RESIDUAL	MEAN SQUARE	(MSE)	0.0	6250
ADJUSTED I	R-SQUARED	0.9306	STANDARD	ERROR OF EST	TIMATE	0.2	5000
SOURCE	DF	SS	MS	F	P		
REGRESSIO	N 7	13.0000	1.8571	4 29.71	0.0000		
RESIDUAL	8	0.50000	0.0625	0			
TOTAL	15	13.5000					

CASES INCLUDED 16 MISSING CASES 0



UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF DAYS TO AIR SUPREMACY

PREDICTOR	000000	OT THE				<b>、</b>	1710
VARIABLES	COEFFI	CIENT	STD ERROR	SIUDENI'S	I P		VIF
CONCTANT		6250	0 27003	61 57			
CONSTANT	10.	6230	0.27003	4.57	0.00	110	1 0
F15	-1.2	5000	0.27003	-4.63	0.00	112	1.0
F16	-0.5	0000	0.27003	-1.85	0.09	171	1.0
F111	-0.5	0000	0.27003	-1.85	0.09	971	1.0
EF111	0.7	5000	0.27003	2.78	0.02	15	1.0
A10F111	-0.7	5000	0.27003	-2.78	0.02	15	1.0
F16EF	0.8	7500	0.27003	3.24	0.01	.02	1.0
R-SQUARED		0.8576	RESIDUAL	MEAN SQUARE	(MSE)	1.16	667
ADJUSTED R-S	QUARED	0.7627	STANDARD	ERROR OF EST	TIMATE	1.08	012
SOURCE	DF	SS	MS	F	P		
REGRESSION	6	63.2500	10.541	7 9.04	0.0022		
RESIDUAL	9	10.5000	1.1666	7			
TOTAL	15	73.7500	)				
CASES INCLUI	DED 16	MISSING	CASES 0				



Residual Plot of Days to Air Supremacy

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF NUMBER OF AIR KILLS

PREDICTOR							
VARIABLES	COEFF	ICIENT	STD ERROR	STUDENT'S	Т	P	VIF
CONSTANT	923	15.69	57.3476	160.70	0.0	1000	
A10	162	22.19	57.3476	28.29	0.0	000	1.0
F16	205	58.06	57.3476	35.89	0.0	000	1.0
F111	256	5.063	57.3476	4.47	0.0	029	1.0
EF111	14'	7.937	57.3476	2.58	0.0	365	1.0
A10EF	-294	4.563	57.3476	-5.14	0.0	013	1.0
F15F16	-176	5.188	57.3476	-3.07	0.0	180	1.0
F15F111	-14:	L.937	57.3476	-2.48	0.0	425	1.0
F16EF	-183	3.688	57.3476	-3.20	0.0	150	1.0
R-SOUARED		0.9968	RESIDUAL	MEAN SQUARI	E (MSE)	526	19.9
ADJUSTED R-S	QUARED	0.9931	STANDARD	ERROR OF ES	STIMATE	229	.390
SOURCE	DF	SS	MS	F	P		
PEOPESSION	 8	1 1408+08		7 270 86	0.0000		
DECTDUAL	7	2 6935105	52610	۵ ۵	0.0000		
RESIDUAL		3.883E+03	52619.	5			
TOTAL	15	1.144E+08					
CASES INCLUD	ED 16	MISSING	CASES 0				



#### Residual Plot of Number of Air Kills

C-3

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF BLUE AIRCRAFT LOST

PREDICTOR						
VARIABLES	COEFFI	CIENT	STD ERROR	STUDENT'S T	P	VIF
CONSTANT	115	.438	1.16089	99.44	0.000	U
A10	9.6	8750	1.16089	8.34	0.000	4 1.0
F15	-4.6	8750	1.16089	-4.04	0.009	9 1.0
F16	8.8	1250	1.16089	7.59	0.000	6 1.0
EF111	-3.6	8750	1.16089	-3.18	0.024	6 1.0
A10F15	3.0	6250	1.16089	2.64	0.046	1 1.0
A10F111	4.0	6250	1.16089	3.50	0.017	3 1.0
A10EF	5.3	1250	1.16089	4.58	0.006	0 1.0
F15F16	-4.8	1250	1.16089	-4.15	0.008	9 1.0
F15F111	6.4	3750	1.16089	5.55	0.002	6 1.0
F111EF	5.6	8750	1.16089	4.90	0.004	5 1.0
R-SQUARED		0.9815	RESIDUAI	MEAN SQUARE	(MSE)	21.5625
ADJUSTED R	-SQUARED	0.9446	STANDARI	ERROR OF EST	IMATE	4.64354
SOURCE	DF	SS	MS	F	P	
REGRESSION	10	5730.13	573.01	.3 26.57	0.0010	
RESIDUAL	5	107.812	21.562	25		
TOTAL	15	5837.94	Ŀ			

CASES INCLUDED 16 MISSING CASES 0



**C-4** 

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF DEPTH OF ENEMY ADVANCE

PREDICTOR VARIABLES	COEFFI	CIENT	STD	ERROR	STUDENI	''S T	P	VIF
CONSTANT	56.	6250	Ο.	28868	196.1	.5	0.0000	
A10	-2.0	0000	Ο.	28868	-6.9	3	0.0001	1.0
F15	-0.8	7500	Ο.	28868	-3.0	13	0.0142	1.0
F16	-4.1	2500	Ο.	28868	-14.2	9	0.0000	1.0
EF111	-1.0	0000	Ο.	28868	-3.4	6	0.0071	1.0
F15EF	-0.7	5000	Ο.	28868	-2.6	0	0.0288	1.0
A10EF	0.6	2500	0.	28868	2.1	.7	0.0586	1.0
R-SQUARED		0.9694		RESIDUAL	MEAN SQU	JARE (MS	E) 1	.33333
ADJUSTED R-	SQUARED	0.9489		STANDARD	ERROR OF	ESTIMA	TE 1	.15470
SOURCE	DF	SS		MS	F		P	
REGRESSION	6	379.750	)	63.291	7 47.4	.7 0.0	000	
RESIDUAL	9	12.0000	)	1.3333	3			
TOTAL	15	391.750	)					
CASES INCLU	DED 16	MISSING	CASE	ES O				



**C-5** 

# **APPENDIX D**

The following tables and plots are the quadratic polynomial regression results for MOE #3, Air Kills, and MOE #5, Depth of Enemy Advance--keeping only those terms having a 90% level of significance.

STATISTIX 4.1

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF NUMBER OF AIR KILLS

PREDICTOR							
VARIABLES	COEFF	ICIENT	STD ERROR	STUDENT'S	т	P	VIF
CONSTANT	90	15.45	74.7087	120.67	Ο.	0000	
A10	16	05.94 -	58.4025	27.50	Ο.	0000	1.0
F16	20	59.94	58.4025	35.27	ο.	0000	1.0
F111	23	8.833	58.4025	4.09	Ο.	0006	1.0
EF111	10	7.167	58.4025	1.83	Ο.	0822	1.0
AlOEF	-29	4.563	61.9452	-4.76	Ο.	0001	1.0
F15F16	-17	6.188	61.9452	-2.84	Ο.	0104	1.0
F15F111	-14	1.937	61.9452	-2.29	Ο.	0335	1.0
F16EF	-18	3.688	61.9452	-2.97	Ο.	0079	1.0
F15F15	22	9.157	94.8274	2.42	0.	0259	1.0
R-SQUARED		0.9909	RESIDUAL	MEAN SOUARE	(MSE)	613	953
ADJUSTED R-SQ	UARED	0.9866	STANDARD	ERROR OF ES	TIMATE	247	.781
SOURCE	DF	SS	MS	F	P		
REGRESSION	 9	1.271E+08		 7 230 10			
RESIDUAL	19	1.167E+06	61395	200.10	0.0000		
TOTAL	28	1.283E+08	02000.	-			
CASES INCLUDE	D 29	MISSING	CASES 0				



D-2

UNWEIGHTED LEAST SQUARES LINEAR REGRESSION OF DEPTH OF ENEMY ADVANCE

PREDICTOR						
VARIABLES	COEFFI	CIENT	STD ERROR	STUDENT'S	т р	VIF
CONSTANT	56.	3905	0.49290	114.41	0.000	C
A10	-2.0	0000	0.36630	-5.46	0.000	0 1.0
F15	-0.6	6667	0.36630	-1.82	0.0838	3 1.0
F16	-4.2	7778	0.36630	-11.68	0.000	1.0
F111	-0.6	6667	0.36630	-1.82	0.0838	3 1.0
EF111	-0.9	4444	0.36630	-2.58	0.0179	€ 1.0
F15EF	-0.7	5000	0.38852	-1.93	0.0679	€ 1.0
F15F15	-2.1	4793	0.84108	-2.55	0.0189	9 2.0
F16F16	2.3	5207	0.84108	2.80	0.0113	L 2.0
R-SQUARED		0.9055	RESIDUAL	MEAN SQUARE	(MSE)	2.41520
ADJUSTED R-S	SQUARED	0.8677	STANDARD	ERROR OF ES	TIMATE :	L.55409
SOURCE	DF	SS	MS	F	Р	
REGRESSION	8	462.937	57.867	2 23.96	0.0000	
RESIDUAL	20	48.3041	2.4152	0		
TOTAL	28	511.241				
CASES INCLUI	DED 29	MISSING	CASES 0			

**D-3** 

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# **<u>APPENDIX E</u>** Principal Components Analysis using Mathcad PLUS 5.0

						i := 0	15	5
	14.5	19	35522	91	64		1	]
	13	19	33683	120	58	COLUMN 1: Days Needed to Neutralize FLOT	1	
	15	16	35829	101	65	Days recall to recuraize relor	1	
	14	18	33405	106	58	COLUMN 2:	1	
	14	15	34078	155	56	Days to Air Supremacy	1	
	12.5	19	32288	135	52	COLUMN 3:	1	
	13	17	33964	87	52	Red Inventory Remaining at War's end	1	
37	12	14	31854	118	51	COLUMN 4:	1	
<b>X</b> :=	15.5	20	35793	95 <sup>.</sup>	65	Number of Blue Aircraft Lost one :=	1	
	13.5	16	33178	120	59	COLUMN 5:	1	
	13.5	15	35129	96	58	Depth (in km) of Red Advance	1	
	13.5	14	33049	124	59		1	
	13.5	20	33462	113	54		1	:
	12.5	15	31493	132	52		1	
	13.5	14	33896	108	55		1	
	12.5	15	32072	146	48		1	

Finding the means to each measure of effectiveness (means to each vector of the data set):

$\mathbf{v}_i \coloneqq \mathbf{X}_{i,0}$	$Xbar_{i,0} := mean(v)$
$\mathbf{w}_i := \mathbf{X}_{i, 1}$	$Xbar_{i,1} := mean(w)$
g <sub>i</sub> := X <sub>i,2</sub>	$Xbar_{i,2} = mean(g)$
$\mathbf{h}_{\mathbf{i}} \coloneqq \mathbf{X}_{\mathbf{i},3}$	$Xbar_{i,3} := mean(h)$
$m_i := X_{i,4}$	Xbar <sub>i.4</sub> := mean(m)

Define "Dhalf" as the diagonal matrix	$\left[\frac{1}{0.9486833}\right]$	0	0	0	0
with elements 1/standard deviation:	0	$\frac{1}{2.21735578}$	0	0	0
Dhalf:=	0	0	1 1372.90466	0	0
	0	0	0	1 19.7280469	0
	0	0	0	0	1 5.11044682

Sample Covariance Matrix is:

r

$$\mathbf{S} := \mathbf{X}^{\mathrm{T}} \cdot \mathbf{X} - \frac{1}{16} \cdot \left( \mathbf{X}^{\mathrm{T}} \cdot \operatorname{one} \right) \cdot \left( \operatorname{one}^{\mathrm{T}} \cdot \mathbf{X} \right) \qquad \qquad \mathbf{C} := \frac{1}{15} \cdot \mathbf{S}$$

$$\mathbf{S} = \begin{bmatrix} 13.5 & 11.5 & 1.71 \cdot 10^{4} & -130.5 & 65 \\ 11.5 & 73.75 & 1.52 \cdot 10^{4} & -214.38 & 55.75 \\ 1.71 \cdot 10^{4} & 1.52 \cdot 10^{4} & 2.83 \cdot 10^{7} & -2.63 \cdot 10^{5} & 8.76 \cdot 10^{4} \\ -130.5 & -214.38 & -2.63 \cdot 10^{5} & 5.84 \cdot 10^{3} & -794.38 \\ 65 & 55.75 & 8.76 \cdot 10^{4} & -794.38 & 391.75 \end{bmatrix}$$

$$C = \begin{bmatrix} 0.9 & 0.767 & 1.142 \cdot 10^3 & -8.7 & 4.333 \\ 0.767 & 4.917 & 1.015 \cdot 10^3 & -14.292 & 3.717 \\ 1.142 \cdot 10^3 & 1.015 \cdot 10^3 & 1.885 \cdot 10^6 & -1.754 \cdot 10^4 & 5.837 \cdot 10^3 \\ -8.7 & -14.292 & -1.754 \cdot 10^4 & 389.196 & -52.958 \\ 4.333 & 3.717 & 5.837 \cdot 10^3 & -52.958 & 26.117 \end{bmatrix}$$

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Here, we choose to use the correlation matrix, R, because each vector uses different units:

$$\mathbf{R} \coloneqq \mathbf{DhalfC} \cdot \mathbf{Dhalf}$$

$$\mathbf{R} \coloneqq \begin{bmatrix} 1 & 0.364 & 0.877 & -0.465 & 0.894 \\ 0.364 & 1 & 0.333 & -0.327 & 0.328 \\ 0.877 & 0.333 & 1 & -0.648 & 0.832 \\ -0.465 & -0.327 & -0.648 & 1 & -0.525 \\ 0.894 & 0.328 & 0.832 & -0.525 & 1 \end{bmatrix}$$

Eigenvalues taken from Correlation matrix, R: evals = eigenvals(R)  $evals = \begin{bmatrix} 3.3449 \\ 0.60708 \\ 0.07352 \\ 0.82128 \\ 0.15323 \end{bmatrix}$ 

$$\frac{3.345}{5} = 0.669 \qquad \qquad \frac{3.345 + 0.82128}{5} = 0.833$$

66.9% of variance explained by first principal component. (83.3% of variance explained by first two principal components.)



Ar := eigenvecs(R)Xd := X - Xbar $L := Ar \cdot \Lambda half$ 

The matrix of eigenvectors is:

$$Ar = \begin{bmatrix} 0.504 & 0.352 & 0.753 & -0.193 & -0.133 \\ 0.276 & 0.231 & -0.056 & 0.931 & -0.012 \\ 0.514 & -0.024 & -0.499 & -0.185 & -0.672 \\ -0.393 & 0.877 & -0.203 & -0.115 & -0.15 \\ 0.501 & 0.231 & -0.373 & -0.219 & 0.713 \end{bmatrix}$$

Principal Component Loadings are found in the matrix L:

eigenvals(R)<sup>T</sup> =  $(3.34489892 \ 0.60707727 \ 0.07351713 \ 0.82127912 \ 0.15322755)$ 

r

	PC1	PC2	РС3	PC4	PC5	
	0.92191	0.27395	0.20421	-0.17493	-0.05222	D
	0.50518	0.17965	-0.01517	0.84396	-0.00468	D
L =	0.9402	-0.01875	-0.13539	-0.16779	-0.26304	E
	-0.71817	0.68335	-0.05492	-0.10401	-0.05859	В D
	0.91653	0.18011	-0.10119	-0.1986	0.27903	

Days to Neutralize FLOT Days to Air Supremacy Ending Red Inventory Blue Aircraft Lost Depth of Enemy Advance

Largest principal component correlates days to neutralize FLOT, depth of enemy advance, ending Red inventory, and blue aircraft lost. The first three have an opposite effect to Blue aircraft lost.

Second largest principal component has a high correlation value for Air Supremacy all alone.

Principal Component Scores, Y, calculated as: Y := Xd DhalfAr

Principal Component Scores:	[	2.731	-0.168	-0.228	0.37	0.153
	0.0	0.08	0.326	-0.609	1.012	0.208
		2.637	0.19	-0.043	-1.134	0.013
		0.661	-0.024	0.455	0.507	0.315
		-0.632	2.731 $-0.168$ $-0.228$ $0.37$ $0.08$ $0.326$ $-0.609$ $1.012$ $2.637$ $0.19$ $-0.043$ $-1.134$ $0.661$ $-0.024$ $0.455$ $0.507$ $-0.632$ $1.74$ $-0.072$ $-1.043$ $-1.595$ $0.561$ $-0.215$ $1.472$ $0.004$ $-1.625$ $0.116$ $0.583$ $-2.406$ $-0.938$ $-0.08$ $-0.326$ $3.507$ $0.525$ $0.328$ $0.484$ $0.119$ $0.254$ $-0.026$ $-0.325$ $0.866$ $-0.997$ $-0.391$ $-0.825$ $0.496$ $0.226$ $0.03$ $-1.171$ $0.134$ $0.127$ $0.207$ $1.572$ $2.332$ $0.026$ $0.206$ $-0.084$	-0.649		
· · · · ·	Y =	-1.595	0.561	-0.215	1.472	0.01
		0.004 -1.625 0.116 0.5 -2.406 -0.938 -0.08 -0.3	0.583	-0.506		
			-0.326	0.309		
		3.507	0.525	0.328	0.484	-0.016
-		-0.119	0.254	-0.026	-0.325	0.54
		0.866	-0.997	-0.391	-0.825	-0.367
		-0.496	0.226	0.03	-1.171	0.584
	- - -	0.134	0.127	0.207	1.572	-0.265
		-2.332	0.026	0.206	-0.084	0.443
		-0.253	-0.681	0.179	-1.02	-0.267
		-2.786	0.457	0.144	-0.072	-0.504

Add center point replications as additional points for Principal Component Scores: j := 0..2

(The means used are of the original data set)

$$C := \begin{pmatrix} 14 & 17 & 33726 & 127 & 57 \\ 13 & 16 & 33586 & 123 & 54 \\ 13.5 & 15 & 33813 & 122 & 56 \end{pmatrix}$$

$$Cbar_{j,0} := mean(v)$$

$$Cbar_{j,3} := mean(m)$$

$$Cbar_{j,4} := mean(m)$$

$$Cb$$

NOTE: Center Point Replications are labeled as "x" on plot.

## PrincipalComponent Score Plots:



Principal Component 1 ("Ground War Index")

## Factor Scores: After varimax rotation, the loadings matrix appears as

	Fl	F2	F3	F4	F5	
	0.94378	-0.17896	0.18532	0.07734	-0.19218	
	0.16624	-0.13691	0.97600	0.03218	0.00150	Days to Neutralize FLOT Days to Air Supremacy
<b>F</b> :=	0.78655	-0.39841	0.13677	0.45125	-0.01675	Ending Red Inventory
	-0.27956	0.94554	- 0.15225	-0.06750	- 0.00849	Blue Aircraft Lost Depth of Enemy Advance
	0.92222	-0.25955	0.14308	-0.02714	0.24683	

eigenvalues:= (2.465658 1.170908 1.049284 0.215936 0.098214)

j := 0..2

To standardize the data set, use:

 $Xs := Xd \cdot Dhalf$ 

Fhat :=  $\mathbf{Xs} \cdot \mathbf{R}^{-1} \cdot \mathbf{F}$ 

Calculating factor scores, use:

Factor scores appear as:

[	0.957	-0.865	0.8	0.352	0.935
	-0.333	0.405	1.185	0.682	2.148
	1.746	-0.335	-0.645	0.351	0.177
	0.29	-0.446	0.575	-1.535	-0.965
	0.865	2.372	-0.611	1.405	-0.725
Fhat =	-1.093	0.968	1.414	0.127	0.63
	-1.204	-1.809	0.096	0.911	-1.026
_	-1.371	-0.471	-1.026	-0.618	0.695
	1.735	-0.423	1.219	-0.375	-1.034
	0.359	0.235	-0.282	-1.094	0.832
	-0.007	-1.067	-0.958	1.745	0.74
	0.557	0.343	-1.219	-1.271	0.729
	-0.544	-0.032	1.648	0.049	-1.032
	-0.813	0.457	-0.497	-1.542	-0.031
	-0.069	-0.614	-1.296	0.305	-0.893
	-1.077	1.281	-0.403	0.509	-1.179

Center Points Factor Scores:

$Cs := Cd \cdot Dhalf$	(Note again the means used are		
	from the original data set)		

Fhat2 := 
$$\mathbf{Cs} \cdot \mathbf{R}^{-1} \cdot \mathbf{F}$$

$$Fhat2 = \begin{pmatrix} 0.5 & 0.779 & 0.205 & -0.185 & -0.89 \\ -0.488 & 0.308 & -0.198 & 1.06 & 0.296 \\ 0.129 & 0.304 & -0.746 & 0.497 & -0.17 \end{pmatrix}$$

NOTE: Center Point Replications labeled as squares on plots.

Factor Score Plots:



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Factor 2 (Blue Aircraft Lost)

**APPENDIX F** Factor Analysis Varimax Rotation (SAS Output)

FACTOR ANALYSIS OF THUNDER OUTPUT

Means and Standard Deviations from 16 observations

	NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
Mean	13.5	16.625	33668.4375	115.4375	56.625
Std Dev	0.9486833	2.21735578	1372.90466	19.7280469	5.11044682

Initial Factor Method: Principal Components

Prior Communality Estimates: ONE

Eigenvalues of the Correlation Matrix: Total = 5 Average = 1

	1	2	3	4	5
Eigenvalue	3.3449	0.8213	0.6071	0.1532	0.0735
Difference	2.5236	0.2142	0.4538	0.0797	
Proportion	0.6690	0.1643	0.1214	0.0306	0.0147
Cumulative	0.6690	0.8332	0.9547	0.9853	1.0000

5 factors will be retained by the NFACTOR criterion.

Factor Pattern

	FACTOR1	FACTOR2	FACTOR3	
NEUTRAL	0.92191	-0.17493	0.27395	days to neutralize FLOT
AIRSUPRM	0.50518	0.84396	0.17965	days to air supremacy
REDINVEN	0.94020	-0.16779	-0.01875	remaining red inventory
ATTRIT	-0.71817	-0.10401	0.68335	percent blue aircraft lost
DEA	0.91653	-0.19860	0.18011	depth of enemy advance

FACTOR4 FACTOR5

NEUTRAL	0.05222	-0.20421	days to neutralize FLOT
AIRSUPRM	0.00468	0.01517	days to air supremacy
REDINVEN	0.26304	0.13539	remaining red inventory
ATTRIT	0.05859	0.05492	percent blue aircraft lost
DEA	-0.27903	0.10119	depth of enemy advance

Variance explained by each factor

FACTOR1 FACTOR2 FACTOR3 FACTOR4 FACTOR5 3.344899 0.821279 0.607077 0.153228 0.073517

Final Communality Estimates: Total = 5.000000

NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
1.000000	1.000000	1.000000	1.000000	1.000000
### Rotation Method: Varimax

Orthogonal Transformation Matrix

	1	2	3	4	5
1	0.81903	-0.45612	0.30882	0.16007	0.01201
2	-0.37849	-0.07816	0.92023	-0.06049	-0.01271
3	0.40972	0.87836	0.23929	-0.05354	-0.02209
4	-0.10932	0.08511	0.00898	0.82558	-0.54693
5	-0.07815	0.08419	0.02174	0.53504	0.83670

Rotated Factor Pattern

NEUTRAL	0.94378	-0.17896	0.18532	days to neutralize FLOT
AIRSUPRM	0.16624	-0.13691	0.97600	days to air supremacy
REDINVEN	0.78655	-0.39841	0.13677	remaining red inventory
ATTRIT	-0.27956	0.94554	-0.15225	percent blue aircraft lost
DEA	0.92222	-0.25955	0.14308	depth of enemy advance

### FACTOR4 FACTOR5

FACTOR1 FACTOR2 FACTOR3

NEUTRAL	0.07734	-0.19218	days to neutralize FLOT
AIRSUPRM	0.03218	0.00150	days to air supremacy
REDINVEN	0.45125	-0.01675	remaining red inventory
ATTRIT	-0.06750	-0.00849	percent blue aircraft lost
DEA	-0.02714	0.24683	depth of enemy advance

### Variance explained by each factor

FACTOR1	FACTOR2	<b>FACTOR3</b>	FACTOR4	FACTOR5
2.465658	1.170908	1.049284	0.215936	0.098214

Final Communality Estimates: Total = 5.000000

NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
1.000000	1.000000	1.000000	1.000000	1.000000

### **APPENDIX G**

MSPR and MAPE Calculations using Microsoft Excel 5.0

### **VALIDATION RUNS**

MOE # 1: Days Needed to Neutralize FLOT

MOE # 1: Days Needed to Neutralize FLOT

**DESIGN RUNS** 

### MAPE calc 0.0811639 0.0312945 0.0125082 0.0324484 0.0144049 0.0196078 0.0044643 0.0044643 0.0044248 0.0224475 0.0469012 0.0235027 0.02419980.0327381 0.0137581 0.0149724 Diff Sq 0.1936 0.1936 0.1936 1.1236 0.0036 0.0036 0.0036 0.3136 0.0361 0.0361 0.0361 0.0361 0.0961 0.0961 0.0961 0.0961 2.39563 % 0.15985 Difference -0.44 -0.19 -0.06 -0.44 -0.06 0.19 0.19 0.19 1.06 -0.56 0.44 0.31 0.06 0.31 -0.31 0.31 Metamodel Output MAPE =14.06 13.44 15.19 13.56 12.69 13.19 MSPR =13.81 13.06 15.81 13.44 13.44 13.56 11.94 13.19 13.81 12.81 Thunder Output 14.5 12.5 13.5 12.5 12.5 15.5 13.5 13.5 13.5 13.5 14 13 12 13 15 14 Run # 6 01 14 15 16 12 13 $\infty$ 11 6 4 0.04 0.0014815 0.0084615 0.0103448 0.0392857 0.0103704 0.0007692 0.0103704 0.0115385 0.0055172 0.0551724 0.0007407 0.0148148 0.0414286 0.0015385 **MAPE** calc 0.0328571 Diff Sq 0.2116 0.0225 0.3025 0.0196 0.3364 0.0196 0.0225 0.0064 0.0004 1E-04 1E-04 0.0121 0.3364 0.0004 0.64 0.04 1.779321 % 0.123163 Difference 0.58 0.46 -0.14 0.15 0.55 -0.01 0.14 0.15 0.08 0.02 -0.01 0.8 -0.2 0.11 0.58 0.02 Metamodel Output 13.92 13.54 14.35 13.45 13.64 13.01 13.36 12.85 12.89 14.42 13.48 MAPE =13.51 MSPR =13.7 13.7 13.42 12.98 Thunder Output 14.5 14.5 13.5 13.5 14.5 13.5 14.5 13.5 13.5 13 13 14 14 13 14 Run # 10 12 13 14 15 16 11 9 ∞ 6 ŝ 4 Ś 5

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MOE # 2: Days Needed to Achieve Air Supremacy

MSFK = MAPE =				%	6.074479	MAPE =		
- duby					0 670063	NCDD -		
15.25	15	16	0.0606667	0.8281	-0.91	15.91	15	16
13.5	14	15	0.0778571	1.1881	-1.09	15.09	14	15
14.5	15	14	0.24	25.4016	5.04	15.96	21	14
19.25	20	13	0.2219048	21.7156	4.66	16.34	21	13
14.75	14	12	0.1178571	2.7225	-1.65	15.65	14	12
16	15	11	0.0893333	1.7956	-1.34	16.34	15	11
17	16	10	0.0433333	0.6084	0.78	17.22	18	10
18.75	20	6	0.152	5.1984	-2.28	17.28	15	6
17.75	14	×	0.0393333	0.3481	-0.59	15.59	15	8
16.25	17	7	0.1721429	5.8081	-2.41	16.41	14	7
20.25	19	9	0.202	9.1809	-3.03	18.03	15	9
15.5	15	S	0.2161905	20.6116	4.54	16.46	21	Ś
17	18	4	0.2953846	14.7456	-3.84	16.84	13	4
15.75	16	ę	0.3384615	19.36	-4.4	17.4	13	e
19.75	19	2	0.1853333	7.7284	-2.78	17.78	15	7
18	19	1	0.0673684	1.6384	1.28	17.72	19	1
Outpu	Output	<u>Run #</u>	<b>MAPE calc</b>	<u>Diff Sq</u>	Difference	Output	Output	<u>Run #</u>
Metamo	Thunder					Metamodel	Thunder	

### **DESIGN RUNS**

MOE # 2: Days Needed to Achieve Air Supremacy

	Thunder	Metamodel			
<u>Run #</u>	Output	Output	Difference	Diff Sq	MAPE calc
1	19	18	1	1	0.0526316
2	19	19.75	-0.75	0.5625	0.0394737
ŝ	16	15.75	0.25	0.0625	0.015625
4	18	17	1	1	0.0555556
Ś	15	15.5	-0.5	0.25	0.0333333
9	19	20.25	-1.25	1.5625	0.0657895
7	17	16.25	0.75	0.5625	0.0441176
8	14	17.75	-3.75	14.0625	0.2678571
6	20	18.75	1.25	1.5625	0.0625
10	16	17	-1	1	0.0625
11	15	16	-1	1	0.0666667
12	14	14.75	-0.75	0.5625	0.0535714
13	20	19.25	0.75	0.5625	0.0375
14	15	14.5	0.5	0.25	0.0333333
15	14	13.5	0.5	0.25	0.0357143
16	15	15.25	-0.25	0.0625	0.0166667
		- dasw	1 610621		
			100010.1		
		MAPE =	5.892724	%	

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### MOE # 3: Number of Air Kills

### MOE # 3: Number of Air Kills

**DESIGN RUNS** 

	<b>MAPE</b> calc	0.0044547	0.0197984	0.0315418	0.0197615	0.0061769	0.0068515	0.018167	0.0233132	0.0098418	0.0087044	0.0199178	0.0071357	0.0073982	0.0189806	0.0046933	0.0014416		
	Diff Sq	625	27225	23104	32041	3249	7056	31684	85849	2601	6084	15876	4096	5929	71289	1936	324		%
	<b>Difference</b>	25	165	-152	179	57	-84	178	293	51	-78	-126	-64	-17	267	44	-18	10035 5	1.301115
Metamodel	Output	5587	8169	4971	8879	9171	12344	9620	12275	5131	9039	6452	9033	10485	13800	9331	12504	MSPR =	MAPE =
Thunder	Output	5612	8334	4819	9058	9228	12260	9798	12568	5182	8961	6326	8969	10408	14067	9375	12486		
	<u>Run #</u>	1	2	e.	4	5	9	7	×	6	10	11	12	13	14	15	16		
	<b>MAPE</b> calc	0.0205843	0.1427033	0.0527188	0.033383	0.0817116	0.0266024	0.0113917	0.0150713	0.0392646	0.0211416	0.0048994	0.0327311	0.0683216	0.0770401	0.0728385	0.0012662		
	Diff Sq	24025	2125764	122500	84681	485809	88804	11236	28224	89401	36100	1444	94864	373321	656100	544644	196		%
	Difference	155	1458	-350	-291	-697	298	-106	168	299	-190	38	308	-611	-810	738	-14	797944 K	4.385436
Metamodel	Output	7375	8759	6869	9008	9227	10904	9411	10979	7316	6177	7718	9102	9554	11324	9394	11071	MSPR =	MAPE =
Thunder	Output	7530	10217	6639	8717	8530	11202	9305	11147	7615	8987	7756	9410	8943	10514	10132	11057		
	<u>Run #</u>	1	2	e	4	S	9	٢	8	6	10	11	12	13	14	15	16		

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MOE # 4: Number of Blue Aircraft Lost

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	Thunder	Metamodel				
Run #	Output	Output	Difference	Diff Sq	<b>MAPE</b> calc	Run
I	111	106	ŝ	25	0.045045	1
7	114	119	ŝ.	25	0.0438596	2
n	100	115	-15	225	0.15	e
4	114	111	ŝ	6	0.0263158	4
Ś	125	127	-2	4	0.016	5
9	120	126	φ	36	0.05	9
٢	93	106	-13	169	0.1397849	7
×	125	121	4	16	0.032	8
6	94	107	-13	169	0.1382979	6
10	131	117	14	196	0.1068702	10
11	100	103	e.	6	0.03	11
12	100	117	-17	289	0.17	12
13	117	119	-2	4	0.017094	13
14	146	126	20	400	0.1369863	14
15	111	113	-2	4	0.018018	15
16	129	125	4	16	0.0310078	16
	·	MSPR =	99.75			
		MAPE =	7.195498	%		

### **DESIGN RUNS**

•

MOE # 4: Number of Blue Aircraft Lost

	<b>MAPE</b> calc	0.0549451	0	0.049505	0.009434	0.0193548	0.0296296	0.0229885	0.0423729	0.0210526	0.0166667	0.03125	0.0080645	0	0.0075758	0	0.0068493		
	Diff Sq	25	0	25	1	6	16	4	25	4	4	6	1	0	1	0	1		%
	Difference	ŝ	0	ŝ	1	ę	4	2	Ś	2	2	ę	1	0	1	0	1	7.8125	1.998054
Metamodel	Output	. 96	120	106	105	152	139	85	113	93	118	93	123	113	131	108	145	MSPR =	MAPE =
Thunder	Output	16	120	101	106	155	135	87	118	95	120	96	124	113	132	108	146		
	<u>Run #</u>	1	7	ę	4	S	9	7	×	6	10	11	12	13	14	15	16		

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MOE # 5: Depth of Enemy Advance

### DESIGN RUNS

MOE # 5: Depth of Enemy Advance

	nce Diff Sq MAPE calc	5 0.5625 0.0117188	5 1.5625 0.0215517	0.5625 0.0115385	5 0.5625 0.012931	5 0.0625 0.0044643	5 3.0625 0.0336538	5 1.5625 0.0240385	0.25 0.0098039	6.25 0.0384615	1 0.0169492	2.25 0.0258621	4 0.0338983	0.25 0.0092593	9 0.0576923	1 0.0181818	0.25 0.0104167	219	
model	iput Differe	.75 -0.7	-1.2	.25 0.75	.75 -0.7	.25 -0.2	.75 -1.7	.25 -1.2	.5 0.5	5 2.5	0 -1	.5 -1.5	7 2	5 -0.5	9 3	4 1	.5 -0.5	<b>ξ = 2.01</b>	
under Metai	utput Out	64 64	58 59.	65 64.	58 58	56 56	52 53.	52 53.	51 50	65 62	59 6	58 59	59 5	54 54	52 4	55 55	48 48	MSPF	
μL	Run# O	1	2	e	4	Ś	9	7	8	6	10	11	12	13	14	15	16		
	<b>MAPE</b> calc	0.0220968	0.0401786	0.0626316	0.0053448	0.0078571	0.0151852	0.0045455	0.0118868	0.0450877	0.0534545	0.0242105	0.0707547	0.008	0.0024528	0.0361404	0.0264815		
	Diff Sq	1.8769	5.0625	12.7449	0.0961	0.1936	0.6724	0.0625	0.3969	6.6049	8.6436	1.9044	14.0625	0.1936	0.0169	4.2436	2.0449		
	<b>Difference</b>	1.37	-2.25	-3.57	0.31	-0.44	-0.82	-0.25	-0.63	-2.57	-2.94	-1.38	-3.75	-0.44	-0.13	2.06	1.43	3.676263	
Metamodel	Output	60.63	58.25	60.57	57.69	56.44	54.82	55.25	53.63	59.57	57.94	58.38	56.75	55.44	53.13	54.94	52.57	MSPR =	
Thunder	Output	62	56	57	58	56	54	55	53	57	55	57	53	55	53	57	54		
	<u>Run #</u>	1	7	ŝ	4	S	9	٢	×	6	10	11	12	13	14	15	16		

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POLYNOMIAL METAMODELS

MOE # 3: Number of Air Kills

	Thunder	Metamodel					Thunder	Metamodel
Run#	Output	Output	Difference	Diff Sq	<b>MAPE</b> calc	<u>Run #</u>	Output	Output
1	7530	7228	302	91204	0.0401062	I	5612	5607
7	10217	8636	1581	2499561	0.1547421	2	8334	8237
ę	6639	7041	-402	161604	0.0605513	ŝ	4819	5073
4	8717	8844	-127	16129	0.0145692	4	9058	8866
ŝ	8530	9123	-593	351649	0.0695193	ŝ	9228	9276
9	11202	10743	459	210681	0.0409748	9	12260	12335
٢	9305	9266	39	1521	0.0041913	7	9798	9644
8	11147	10857	290	84100	0.026016	×	12568	13008
6	7615	7192	423	178929	0.0555483	6	5182	5198
10	8987	8996	6-	81	0.0010014	10	8961	8991
11	7756	7553	203	41209	0.0261733	11	6326	6437
12	9410	8962	448	200704	0.0476089	12	8969	9067
13	8943	9594	-651	423801	0.0727944	13	10408	10474
14	10514	11186	-672	451584	0.0639148	14	14067	13839
15	10132	9272	860	739600	0.0848796	15	9375	9401
16	11057	10892	165	27225	0.0149227	16	12486	12460
	·	MSPR =	342473.9					MSPR =
		MAPE =	4.85946	%				MAPE =

0.0211967 0.0052016 0.0061175 0.0157175 0.0350095 0.0030876 0.0033478

9409 64516 36864 2304 5625 5625 5625 193600 12321 900 12321 9604 4356 51984 676

-254 192 -48 -48 -75 -15 -15 -30 -30 -30 -26 -26 2228 26

0.0175466 0.0109265 0.0063413 0.0162081

0.0027733 0.0020823

> 26052 1.317466 %

**DESIGN RUNS** 

MOE # 3: Number of Air Kills

**MAPE calc** 

Diff Sq 25

Difference

5 97

0.0008909 0.0116391 0.052708

> 9-9 U

POLYNOMIAL METAMODELS

# MOE # 5: Depth of Enemy Advance

	Difference	-0.01	-24	0.43	0.82	0.16	0.54	-0.62	-1.01	1.93	0.32	-1.84	-0.23	-0.12	1.49	0.32	0.71	1 157860	1 434763 9
Metamodel	Output	64.01	60.4	64.57	57.18	55.84	51.46	52.62	52.01	63.07	58.68	59.84	59.23	54.12	50.51	54.68	47.29	MSPR =	MAPF =
Thunder	Output	64	58	65	58	56	52	52	51	65	59	58	59	54	52	55	48		
	Run #	1	2	ę	4	Ś	9	7	8	6	10	11	12	13	14	15	16		
	<b>MAPE</b> calc	0.0335484	0.0444643	0.0561404	0.0193103	0.0042857	0.0061111	0.0067273	0.0179245	0.0494737	0.0409091	0.0212281	0.0854717	0.0001818	0.0107547	0.0301754	0.0377778		
	Diff Sq	4.3264	6.2001	10.24	1.2544	0.0576	0.1089	0.1369	0.9025	7.9524	5.0625	1.4641	20.5209	1E-04	0.3249	2.9584	4.1616		0
	<b>Difference</b>	2.08	-2.49	-3.2	1.12	-0.24	0.33	0.37	-0.95	-2.82	-2.25	-1.21	-4.53	-0.01	-0.57	1.72	2.04	4.104481	2.903027 9
Metamodel	Output	59.92	58.49	60.2	56.88	56.24	53.67	54.63	53.95	59.82	57.25	58.21	57.53	55.01	53.57	55.28	51.96	MSPR =	MAPE =
Thunder	Output	62	56	57	58	56	54	55	53	57	55	57	53	55	53	57	54		,,
	<u>Run #</u>	٦	7	e	4	S	9	7	×	6	10	11	12	13	14	15	16		

**DESIGN RUNS** 

MOE # 5: Depth of Enemy Advance

0.0066154 0.0141379

0.1849 0.6724 0.0256 0.2916

0.0028571

**MAPE calc** 0.0001563 0.0413793

Diff Sq

0.0001

5.76

0.0103846 0.0119231 0.0198039

0.3844 1.0201 3.7249

0.0296923

0.0054237 0.0317241

0.1024

3.3856 0.0529

0.0038983 0.0022222 0.0286538

0.0144

2.2201

0.0058182 0.0147917

0.1024 0.5041

1.434263 %

MAPE =

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	S 5.0
--	-------

:	14.5	19	35522	91	64		1		[ 14.5	19	34530	111	62	
<b>X</b> :=	13	19	33683	120	58		1		14	15	33092	114	56	
	15	16	35829	101	65		1		14.5	13	35117	100	57	
	14	18	33405	106	58		1		14	13	33578	114	58	
	14	15	34078	155	56		1		13.5	21	34222	125	56	
	12.5	19	32288	135	52	one :=	1		13	15	32335	120	54	
	13	17	33964	87	52		1		13.5	14	33780	93	55	
	12	14	31854	118	51		1	Viral	13	15	32656	125	53	
	15.5	20	35793	95	65		one :=	Une	1	2xvai	14.5	15	34500	94
	13.5	16	33178	120	59			1		13.5	18	33433	131	55
	13.5	15	35129	96	58		1		14.5	15	34467	100	57	
	13.5	14	33049	124	59		1		13.5	14	33351	100	53	
	13.5	20	33462	113	54		1		13.5	21	33921	117	55	
	12.5	15	31493	132	52		1		13	21	32985	146	53	
	13.5	14	33896	108	55		1		14	14	33572	111	57	
	12.5	15	32072	146	48		1		13	15	32582	129	54	

m := 0...15

One := stack(one, one)

### Means of each Measure of Effectiveness

n := 0..4

$Xbar_{m,0} := 13.609375$	Days to Neutralize FLOT
Xbar <sub>m, 1</sub> := 16.375	Days to Air Supremacy
Xbar <sub>m,2</sub> := 33650.5	Ending Red Inventory
Xbar <sub>m, 3</sub> := 114.90625	Blue Aircraft Lost
$Xbar_{m,4} := 56.1875$	Depth of Enemy Advance

Define the complete data set as T: T := stack(X, Xval) Tbar := stack(Xbar, Xbar)

$$\mathbf{R} := \mathbf{DhalfC} \cdot \mathbf{Dhalf}$$
$$\mathbf{R} = \begin{bmatrix} 1 & 0.068 & 0.855 & -0.526 & 0.84 \\ 0.068 & 1 & 0.197 & 0.122 & 0.187 \\ 0.855 & 0.197 & 1 & -0.623 & 0.791 \\ -0.526 & 0.122 & -0.623 & 1 & -0.47 \\ 0.84 & 0.187 & 0.791 & -0.47 & 1 \end{bmatrix}$$

evals := eigenvals(R)  
evals = 
$$\begin{array}{c} 3.09548\\ 0.52026\\ 0.11004\\ 1.08653\\ 0.18768 \end{array}$$

 $\frac{3.09548}{5} = 0.619 \qquad \frac{3.09548 + 1.08653}{5} = 0.836$ 

61.9% of variance explained by first principal component.(83.6% of variance explained by first two principal components.)

Matrix of Eigenvectors is:

$$\mathbf{Ar} = \begin{bmatrix} 0.528 & 0.348 & 0.719 & -0.022 & -0.288 \\ 0.09 & -0.374 & 0.154 & 0.91 & 0.027 \\ 0.537 & -0.028 & -0.611 & 0.056 & -0.578 \\ -0.402 & 0.784 & -0.156 & 0.394 & -0.209 \\ 0.513 & 0.351 & -0.25 & 0.114 & 0.734 \end{bmatrix}$$

Principal Component Loadings:

 $eigenval(\mathbf{R})^{T} = (3.09547891 \ 0.52026387 \ 0.11004288 \ 1.08653182 \ 0.18768255)$ PC1 PC2PC3 PC4 PC50.92958 0.25092 0.2384 -0.02313 -0.1247 Days to Neutralize FLOT 0.15828 -0.2696 0.05095 0.94844 0.01159 Days to Air Supremacy **Ending Red Inventory** L = 0.94466 - 0.02026 - 0.20270.05788 -0.25054 Blue Aircraft Lost -0.70727 0.56566 -0.05162 0.41102 -0.09055 Depth of Enemy Advance 0.90205 0.25346 -0.08281 0.11907 0.31785

Largest principal component correlates days to neutralize FLOT, depth of enemy advance, ending red inventory, and blue aircraft lost. The first three have an opposite effect to Blue attrition.

Second largest principal component has a high correlation value for air supremacy all alone.

(principal component scores calculated later)

### Factor Loadings Matrix from varimax rotation needed to calculate Factor Scores:

rotated matrix		FI	<i>F2</i>	F <b>3</b>	F4	F5	
		0.94685	-0.24782	0.01426	0.20443	0.00781	
		0.06222	0.06471	0.99402	0.05361	0.03156	
	<b>F</b> :=	0.75261	-0.38507	0.15004	0.19940	0.47225	
		-0.28380	0.94483	0.08733	-0.11664	-0.07426	
		0.68118	-0.21256	0.11942	0.68455	0.08917	

eigenvalues = (2.011374 1.151772 1.032674 0.566637 0.237542)

To standardize the data set, use: Ts := Td Dhalf

Principal Component Scores, Y, calculated as: Y = Td DhalfAr

Factor scores calculated using: Fhat :=  $Ts R^{-1} \cdot F$ 

Principal Component Scores:

Factor Scores:

	3.186 -0.432 -0.336 0.688 0.468	0.505 -1.13 0.961 1.777 0.808
	-0.187 -0.264 -0.582 1.13 0.512	-1.143 0.153 0.986 1.551 1.041
	3.464 0.772 -0.381 -0.128 0.156	1.496 -0.079 -0.364 1.678 1.138
	0.648 -0.304 0.56 0.407 0.449	0.306 -0.631 0.709 0.286 -1.819
	-0.541 2.183 -0.312 0.434 -0.906	1.458 3.031 -0.848 -0.627 1.502
Y =	-2.338 -0.302 -0.025 1.245 0.124	$\mathbf{Fhat} = \begin{bmatrix} -1.284 & 0.707 & 1.095 & -0.218 & -0.247 \end{bmatrix}$
	-0.13 -2.022 -0.178 -0.506 -0.374	-1.126 -2.192 0.501 -1.336 1.014
	-2.797 -0.644 -0.33 -0.976 0.504	-2.361 -0.386 -0.794 0.431 0.073
	4.067 0.132 0.396 1.153 0.106	2.219 -0.649 1.323 0.724 -0.681
	-0.07 0.503 -0.087 0.044 0.747	-0.405 0.374 -0.219 1.68 -0.596
	1.276 -0.586 -0.946 -0.798 -0.18	-0.561 -0.978 -0.572 0.659 2.836
	-0.297 0.984 -0.173 -0.588 0.745	-0.332 0.752 -1.055 1.853 -0.459
	-0.278 -0.861 0.379 1.186 -0.208	-0.053 -0.465 1.552 -1.085 -0.691
	-2.796 0.17 0.2 -0.299 0.535	-1.384 0.606 -0.468 0.273 -1.406
	-0.032 -0.127 -0.242 -1.03 -0.251	-0.162 -0.365 -0.917 -0.347 0.87
	-3.365 0.438 0.007 -0.064 -0.686	-0.698 1.555 -0.514 -1.813 0.281
	1.974 0.329 0.159 1.04 0.371	0.968 0.057 0.934 1.128 -0.582
	-0.059 0.333 0.606 -0.559 0.11	0.632 -0.005 -0.508 -0.382 -1.76
	1.652 0.248 -0.112 -1.481 -0.799	1.338 -0.428 -1.375 -1.082 1.226
	0.367 0.794 0.089 -1.193 0.208	0.497 0.252 -1.4 0.569 -0.522
	0.107 -0.3 -0.217 1.917 -0.368	0.033 0.502 1.787 -0.396 1.052
	-1.506 0.002 0.176 -0.488 0.429	-0.856 0.05 -0.476 0.278 -1.085
	0.263 -0.81 -0.042 -1.38 -0.007	-0.442 -1.437 -0.808 -0.33 0.178
	-1.598 0.133 0.017 -0.386 0.013	-0.642 0.421 -0.509 -0.293 -0.257
	1.564 -0.305 0.405 -0.933 -0.382	1.162 -1.064 -0.477 -1.037 -0.501
	-0.654 0.347 0.047 0.911 -0.246	0.185 0.944 0.594 -0.444 0.056
	1.407 -0.03 0.369 -0.797 -0.438	1.267 -0.648 -0.515 -1.02 -0.387
	-0.37 -0.658 0.259 -1.299 -0.241	-0.163 -1.075 -0.785 -1.16 -0.452
	0.018 -0.748 0.086 1.689 -0.3	-0.042 -0.139 1.882 -0.799 0.212
	-1.717 0.201 0.007 2.265 -0.352	-0.273 1.596 1.781 -0.756 0.212
	0.34 0.42 0.243 -0.933 0.071	0.532 -0.05 -0.949 0.02 -0.746
	-1.597 0.407 -0.042 -0.269 0.19	-0.672 0.722 -0.552 0.216 -0.306

Add center point replications as additional points for scores:

b := 0..2

$$\mathbf{C} := \begin{pmatrix} 14 & 17 & 33726 & 127 & 57 \\ 13 & 16 & 33586 & 123 & 54 \\ 13.5 & 15 & 33813 & 122 & 56 \end{pmatrix}$$

PC Scores for center points:

Cd := C - Cbar $Z := Cd \cdot DhalfAr$ 

$$Z = \begin{pmatrix} 0.146 & 0.706 & 0.195 & 0.519 & -0.173 \\ -0.932 & -0.04 & -0.483 & 0.002 & -0.252 \\ -0.235 & 0.457 & -0.326 & -0.324 & -0.181 \end{pmatrix}$$

j = 0..2

Center Point Factor Scores:

 $Cs := Cd \cdot Dhalf$ 

Fhat2 :=  $\mathbf{Cs} \cdot \mathbf{R}^{-1} \cdot \mathbf{F}$ 

$$Fhat2 = \begin{pmatrix} 0.815 & 0.923 & 0.159 & -0.202 & -0.366 \\ -0.697 & 0.399 & -0.168 & -0.153 & 1.43 \\ -0.019 & 0.579 & -0.618 & 0.112 & 0.964 \end{pmatrix}$$

### Principal Components Score Plot



PC1 ("Ground War Index")

Factor Score Plots:



Factor 1 ("Ground War Index")





Factor 2 (Blue Aircraft Lost)

**APPENDIX I** 

### Factor Analysis Varimax Rotation of Combined Design and Validation Outputs.

### FACTOR ANALYSIS OF THUNDER OUTPUT

### Means and Standard Deviations from 32 observations

	NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
Mean	13.609375	16.375	33650.5	114.90625	56.1875
Std Dev	0.78014034	2.53682555	1103.83019	17.1489854	3.93034103

### Initial Factor Method: Principal Components

### Prior Communality Estimates: ONE

Eigenvalues of the Correlation Matrix: Total = 5 Average = 1

	ĩ	2	3	4	5
Eigenvalue	3.0955	1.0865	0.5203	0.1877	0.1100
Difference	2.0089	0.5663	0.3326	0.0776	
Proportion	0.6191	0.2173	0.1041	0.0375	0.0220
Cumulative	0.6191	0.8364	0.9405	0.9780	1.0000

5 factors will be retained by the NFACTOR criterion.

### Factor Pattern

	FACTOR1	FACTOR2	FACTOR3	
NEUTRAL	0.92958	-0.02313	0.25092	days to neutralize FLOT
AIRSUPRM	0.15828	0.94844	-0.26960	days to air supremacy
REDINVEN	0.94466	0.05788	-0.02026	red inventory remaining
ATTRIT	-0.70727	0.41102	0.56566	number of blue aircraft lost
DEA	0.90205	0.11907	0.25346	depth of enemy advance

FACTOR4 FACTOR5

NEUTRAL	0.12470	-0.23840	days to neutralize FLOT
AIRSUPRM	-0.01159	-0.05095	days to air supremacy
REDINVEN	0.25054	0.20270	red inventory remaining
ATTRIT	0.09055	0.05162	percent blue aircraft lost
DEA	-0.31785	0.08281	depth of enemy advance

### Variance explained by each factor

FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5
3.095479	1.086532	0.520264	0.187683	0.110043

Final Communality Estimates: Total = 5.000000

٠	NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
	1.000000	1.000000	1.000000	1.000000	1.000000

### Rotation Method: Varimax

Orthogonal Transformation Matrix

	1	2	3	4	5
	0 70055	0 46645	0 11574	0 35112	0 19103
7	0.78055	-0.40045	0.113/4	0.033112	0.03422
2	0.04154	0.37537	0.92149	0.06330	-0.06827
3	0.41840	0.78566	-0.36094	0.26972	-0.08827
4	0.33941	0.13314	-0.01170	-0.81688	0.44681
5	-0.31426	0.08087	-0.08391	0.36003	0.87065

### Rotated Factor Pattern

FACTOR1 FACTOR2 FACTOR3

NEUTRAL	0.94685	-0.24782	0.01426	days to neutralize FLOT
AIRSUPRM	0.06222	0.06471	0.99402	days to air supremacy
REDINVEN	0.75261	-0.38507	0.15004	red inventory remaining
ATTRIT	-0.28380	0.94483	0.08733	percent blue aircraft lost
DEA	0.68118	-0.21256	0.11942	depth of enemy advance

### FACTOR4 FACTOR5

NEUTRAL	0.20443	0.00781	days to neutralize FLOT
AIRSUPRM	0.05361	0.03156	days to air supremacy
REDINVEN	0.19940	0.47225	red inventory remaining
ATTRIT	-0.11664	-0.07426	percent blue aircraft lost
DEA	0.68455	0.08917	depth of enemy advance

### Variance explained by each factor

FACTOR1 FACTOR2 FACTOR3 FACTOR4 FACTOR5 2.011374 1.151772 1.032674 0.566637 0.237542

Final Communality Estimates: Total = 5.000000

NEUTRAL	AIRSUPRM	REDINVEN	ATTRIT	DEA
1.000000	1.000000	1.000000	1.000000	1.000000

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Captain M. Ryan Farmer was born on 14 November 1968 at Tullahoma, Tennessee. He graduated among the top ten students in his class at Las Cruces High School, Las Cruces, New Mexico, in 1987. He received a Bachelor of Science degree in Applied Physics from the United States Air Force Academy at Colorado Springs, Colorado, in 1991. He was then assigned under casual status to the Department of Physics at the United States Air Force Academy from August to December of 1991. After elimination from Undergraduate Pilot Training in August 1992, he was assigned to the AETC Studies and Analysis Squadron as a Test Data Analyst until July 1994. Captain Farmer entered the School of Engineering at the Air Force Institute of Technology in August of 1994. Upon receiving a Master of Science degree from the institution, he became a member of the Forces Analysis Branch of the ACC Studies and Analysis Squadron.

Permanent address: 4309 Mission Bell Avenue

Las Cruces, NM 88010

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In today's reduction of a development of force structure. ' authority. Campaign models can THUNDER is a campaign model of changing the force structure w	America's national defense, ca The effects of drawdown are of a bring those high ranking offic l used frequently by the United rithin THUNDER require mod	mpaign level models are b significant interest to the cials the answers they see States Air Force and man ifying variables before exe	being used more in the ose at the highest levels of k with high confidence. ny of its contractors. The effects ecuting a new experimental run.	
Changes in such issues as force s Response Surface Metho	structure cannot be immediately odology (RSM) can be used to	y addressed. provide a quick answer to	effects of changing force	
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