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A VALIDATION STUDY OF THE KNOWLEDGE BASED LOGISTICS PLANNING SHELL USING SENSITIVITY ANALYSIS

by

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(1) Time to run demand generator,
(2) Time to run distribution planner, and
(3) Percentage fill of orders generated

are used as data for the study. The data is analyzed using graphical and non-parametric statistical techniques. The intuitiveness of the observed sensitivities based on their magnitude, direction and range are used to assess the validity of the data generated by this model. The results of the study suggested a fairly high level of validity of the model's output.

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A VALIDATION STUDY OF THE KNOWLEDGE BASED LOGISTICS PLANNING SHELL USING SENSITIVITY ANALYSIS

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EXECUTIVE SUMMARY

This thesis seeks to conduct a limited results-validation study of the Knowledge Based Logistics Planning Shell (KBLPS), using the method of sensitivity analysis. The results of the study suggested a fairly high level of validity of the KBLPS output.

The Knowledge Based Logistics Planning Shell is a deterministic logistics planning model. It uses artificial intelligence technology to help military logisticians quickly plan the allocation and transportation of ammunition and fuel in support of a particular course of action.

Three parameters of the model were selected for variation: *unit size*, or the size of the maneuver force to be supplied; *battle intensity*, which relates the intensity of the conflict to the quantity of supplies required by the maneuver force; and *consumer residual percentage*, which is a threshold for deciding which priorities to fill. These parameters are varied in the context of a 2 X 3 X 3 fixed factorial model, using two unit sizes, three levels of battle intensity, and three priority threshold values.

Measurements of three measures of effectiveness (MOEs) were the data for the study. The MOEs selected were:

1. Time to run the demand generator;
2. Time to run the distribution planner; and

3. Percentage fill of orders generated.

The study seeks to obtain answers to the following questions.

1. Is the model sensitive to changes in the values of the selected parameters?

2. Do changes in the selected parameters generate intuitive changes in the model's output?

3. Are there interaction effects among the parameters on the measures of effectiveness?

4. What values of input parameters yield the best supply distribution plan for given unit sizes, as measured by the percentage fill of orders generated?

The intuitiveness of the observed sensitivities based on their magnitude, direction, and range, are used to assess the validity of the KBLPS output. The magnitude of the sensitivity is based on computations related to Mann-Whitney and Kruskal-Wallis test statistics. The direction and range of the sensitivities are obtained from empirical response surface plots. Interaction effects among factors are identified using factor means plots. These are used to assist in interpreting the empirical response surfaces.

The results of this study are very encouraging with regard to the validity of the KBLPS output on the observed sensitivities. However, this study was limited in scope, and a more comprehensive study of this nature could prove useful in validating the full scope of data output from the model.

Most of the results on the magnitude of the sensitivities was intuitive. All the MOEs were highly sensitive to the change in unit size except for the percentage fill of orders generated in the fuel model. For the battle intensity and consumer residual percentage parameters, nine of twelve sensitivity values were considered to be intuitive in the ammunition model. All twelve magnitudes were intuitive in the fuel model. Fairly similar results were obtained for the direction and range of the sensitivities.

The KBLPS model indicated that the best fuel distribution plan, as indicated by the highest percentage fill of orders generated, was obtained with a consumer residual percentage setting of 70 percent. This result conflicts with the conventional wisdom of filling all highest priority requisitions first, i.e., using a 100 percent consumer residual percentage. The conventional wisdom prevailed in ammunition models where the percentage fill of orders generated was generally insensitive to variations in consumer residual percentage.

In the case of fuel distribution, other logistics models should be used to validate the result that a maximum percent fill of orders generated is associated with a consumer residual percentage of approximately seventy percent. Further, studies need to be conducted to see if maximizing percentage fill of orders generated improves overall unit operational efficiency. If the above is true, the concept of using a seventy percent consumer residual percentage for fuel should be tested in field exercises.

I. INTRODUCTION

The Knowledge Based Logistics Planning Shell (KBLPS), is a deterministic logistics planning model which uses artificial intelligence programs, and provides "rapid decision support capability" to logisticians [Ref. 1]. Of somewhat recent development, this model has not yet received all the testing which is needed to provide a full understanding and interpretation of its output. The work reported in this thesis is directed toward understanding this model.

This chapter begins by outlining the purpose of this study and identifies the research questions to be answered. The background of events leading up to this study are then discussed, followed by an overview of previous testing of the Knowledge Based Logistics Planning Shell. Current operational considerations related to KBLPS and the potential benefits of this study are summarized in the presentation of the motivation for the thesis. Finally, the organization of the thesis is presented.

A. PURPOSE OF THE THESIS

This thesis describes a limited results-validation study of the KBLPS model using sensitivity analysis. Three parameters of the model are selected for variation: *unit size*, or the size of the maneuver force to be supplied; *battle* *intensity*, which relates the intensity of the conflict to the quantity of supplies required by the maneuver force; and *consumer residual percentage*, which is a threshold for deciding which priorities to fill. These parameters are varied in the context of a 2 X 3 X 3 fixed-factor factorial model, using two unit sizes, three levels of battle intensity, and three priority threshold values.

1. Is the model sensitive to changes in the values of the selected parameters?

2. Do changes in the selected parameters generate intuitive changes in the model's output.

3. Are there interaction effects among the parameters on the measures of effectiveness?

4. What values of input parameters yield the best supply distribution plan for given unit sizes, as measured by the percentage fill of orders generated?

The first three research questions represent a sequential approach to understanding the sensitivities of this model. The fourth question is application-oriented. It seeks to identify the parameter settings that will yield the highest level of percentage fill of orders generated. Unit commanders usually have little control over the size of the force and the intensity of the battle for a given scenario. Thus for given combinations of unit size and battle intensity, the consumer residual percentage will be varied to obtain maximum values for the percentage fill of orders generated.

B. BACKGROUND TO THE THESIS

Operation Desert Shield, Desert Storm, and Desert Farewell demonstrated the size and complexity of logistics operations required to support a large combat force which was operating a great distance from the U.S. mainland. Logisticians operating at the division and corps level during the Saudi Arabian conflict noted that they felt constrained by the lack of a fast and efficient decision support system to analyze the many trade offs and interdependencies that were prevalent in the logistics operations. They desired the ability to foresee logistics constraints associated with the maneuver commander's decision making process. The Knowledge Based Logistics Planning Shell has been designed to solve this problem.

On battlefields which are characterized by continuous movement of forces, small staffs, and demands for greater flexibility in logistics support, many of today's logistical planning tools are potentially inadequate to support a rapid decision cycle for the maneuver commander [Ref. 1:p. 2]. The intended capability of the Knowledge Based Logistics Planning Shell to rapidly generate and analyze many alternative logistics plans gives the maneuver commander greater flexibility in analyzing different courses of action. This capability may enhance the maneuver commander's prospects for victory.

C. PREVIOUS TESTING OF THE KNOWLEDGE BASED LOGISTICS PLANNING SHELL (KBLPS)

Since the completion of the development of the KBLPS model in 1991, three types of tests have been conducted to evaluate the utility of this type of planning tool:

1. An operational field test at the headquarters of the XVIII Airborne Corps located at Fort Bragg which is ongoing [Ref. 1:p. 5];

2. A comparison of the attributes of this model with two other emerging logistics decision support systems conducted by the Training and Doctrine Analysis Command, Fort Lee [Ref. 2]; and

3. Parametric performance testing conducted by a contractor, Information Technology Solutions, Inc., located in Virginia [Ref. 3].

Within the XVIIIth Airborne Corps, the KBLPS model has been used in the planning and execution phases of several major exercises including Prairie Warrior and the Force Projection Logistics Exercise. It is also currently used by the logistics planning cell of this corps in the day to day evaluation of course of action, for planning the sustainment of ammunition as well as bulk fuel consumption and distribution [Ref. 1:p. 5]. Initial feedback from these logisticians has been very favorable.

The systems evaluated by the Training and Doctrine Command, along with KBLPS, were the Logistics Intra-theater Support Tool and the Distribution System Analyzes. These systems were evaluated to determine if they would assist the Combat Service Support Control System program in providing Combat Service Support commanders and staffs with automated sustainability and supportability analysis tools [Ref. 2:p. 1]. The study did not select one above the others, but concluded that each system was designed for very different uses [Ref. 2:p. 32]. The study noted that KBLPS was the only system that created plans while the other systems focused on comparing and analyzing plans that were already developed.

The parametric performance testing conducted on KBLPS by Information Technology Solutions encompassed a comprehensive series of univariate analyses. Parameters were varied individually and a determination made of the effect upon KBLPS performance [Ref. 3:p. 1]. The study found that the model was fully or partially sensitive to three of six parameters tested. The model was very sensitive to differing levels of consumer residual percentage for both ammunition and fuel. Ammunition and fuel showed differing sensitivities to the number of product types used in the models, and to the three different levels of battle intensity. The model was insensitive to the number of ammunition product types used. However, it was sensitive to the use of the Army's single fuel, JP8, versus the normal mix of JP4, diesel, and mogas. The model was sensitive to variations in battle intensity for ammunition use, but it was insensitive to variations in battle intensity for fuel use.

This thesis adopts a multivariate approach to parameter testing and represents a natural extension of the study conducted by Information Technology Solutions. Although the study reported here narrows the scope in that only three parameters are varied, interaction effects among these parameters are studied. Studying interaction effects can potentially shed light on the joint functional dependence of measures of effectiveness on the input parameters. For example, two input parameters acting together may impact a measure of effectiveness to a degree greater than the sum of the effects of each parameter acting singly. This is particularly important in light of the fact that one objective of the study is to determine the optimal settings of the experimental factors that maximize the percent fill or orders generated.

D. MOTIVATION FOR THE THESIS

The model currently provides logistics planning data for only fuel and ammunition. However, there are plans to expand its scope to include other classes of supply, expand the domain representation to theater level, add software which will generate briefing graphics, and ultimately incorporate the model into the Combat Service Support Control System. An important precursor to this proposed expansion is an understanding of the model's sensitivity to key parameters. That is the focus of this thesis.

The results of this analysis may provide the Army Research Laboratory, proponent agency for KBLPS, with insight to fine tune the current model. It may also guide them in expanding the model's scope to include other classes of supply and expanding the model's domain from corps-level to theater-level analysis.

This analysis may provide an immediate benefit to logisticians who currently use the model. An understanding of the effects of key underlying parameters may reduce the quantity of "what happens if" analyses which need to be conducted in consideration of uncertain battle events.

In summary, the results of this study can have a two-fold effect. It may guide decision-making associated with the expansion of KBLPS and secondly, may allow current users the following benefits:

- Improvement in supportability recommendations to commanders from a logistical perspective;
- Improvement in the speed of logistics recommendations and planning; and
- Analytical tool for doctrinal developers.

E. ORGANIZATION OF THE THESIS

The next chapter offers a general description of the structure and working of the KBLPS model, with emphasis on its unique features. Fixed parameter settings selected for the study, and a description of the simulated test environment are given in Chapter III.

Chapter IV discusses the measures of effectiveness selected for assessing the performance of the model; the parameters selected for variation; and the methods used for analyzing the model.

Chapter V presents an analysis of the data collected. This analysis is structured by the selected measures of effectiveness. The final chapter presents conclusions which can be logically drawn from the results of the experiment. These conclusions are framed within the context of the research questions. Recommendations are then provided to include both proposals for action and the manner in which they can be implemented.

II. THE MODEL

The Knowledge Based Logistics Planning Shell (KBLPS) is a knowledge based decision support system. It uses artificial intelligence tools to help military logisticians plan the allocation and transportation of ammunition and fuel for a particular course of action. The logistician enters a description of the situation using standard and familiar symbols and terminology, and then KBLPS uses its base of stored knowledge to produce a logistics plan for the modeled action. The KBLPS model was developed by the Army Research Laboratory, in collaboration with industry (Carnegie Group, Inc.), and academia (Carnegie Mellon University). The model was implemented in 1991.

This chapter describes the structure and working of the KBLPS model, its components, and its unique features. Key assumptions for the model use and limitations in model applications are also reviewed.

A. DESCRIPTION OF THE MODEL AND ITS USE

In the KBLPS model, the input process is visually oriented, allowing the logistician to focus on the problem without having to specify the details of the operating system. Using standard military symbols on full-color maps, along with graphical input forms and spreadsheets, the user builds a new model or modifies an existing one by specifying the units that comprise the force. The user then enters into KBLPS details about the units along with supply routes and other information about the situation such as: mission (offensive or defensive); projected battle intensity (light, medium or heavy); and criteria governing the way in which the supplies will be distributed. The KBLPS model understands much of the doctrinal laydown and hierarchial structure of a force, along with details about standard units. This saves the user the effort of manually entering a lot of information about the system.

The model first calculates the ammunition and fuel needs for all the units, then it works out a plan to meet those needs. Using doctrinal knowledge and information in the model, it works out the consumption over the specified timeframe for each handled item on a unit-by-unit basis. With the specific needs known, KBLPS then uses the artificial intelligence technology called "Constraint Directed Search" to allocate the supplies and schedule the truck convoys to move through the distribution network. Even if KBLPS cannot find a workable solution, it still works toward a partial solution, pointing out the unmet needs [Ref. 4:pp. 2.1-2.2].

B. COMPONENTS OF THE KNOWLEDGE BASED LOGISTICS PLANNING SHELL

The KBLPS model has several major areas of functionality that work together to solve the planning problem. These include the Graphical User Interface; the Knowledge Base; and the Distribution Planner and are shown in Figure 1.

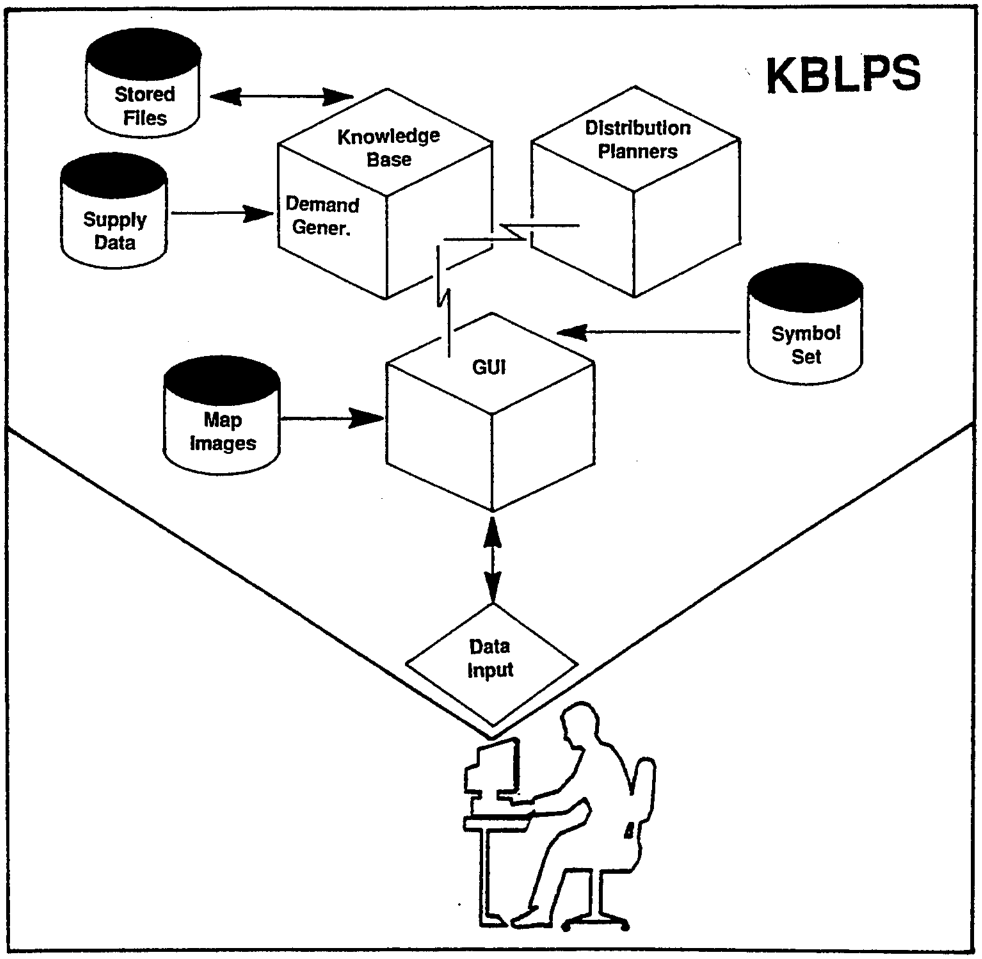

Figure 1. Knowledge Based Logistics Planning Shell Architecture.

The **Graphical User Interface** (GUI) accepts user input and represents the planning problem to be solved in a graphical manner. It allows the user to change the characteristics of the algorithm in ways that match the nature of the problem or the commander's direction. The Graphical User Interface consists of an extensive set of model building and plan analysis interfaces. It also contains digital terrain maps of selected areas of operation [Ref. 4:p. 2.3].

The **Knowledge Base** stores and manages information, from the user and the data libraries, about the problem being solved. It is the core of KBLPS that serves the other modules with information about the current scenario. It contains an object-oriented representation of the army corps-level planning domain. Combat Service Support information contained in the Knowledge Base is currently limited to a XVIIIth Airborne Corps scenario for modeling ammunition and fuel requirements.

A major function within the Knowledge Base process is the Demand Generator. It is invoked by the Graphical User Interface. The Demand Generator calculates unit demand and stockage objectives, creates orders, and stores the results in the Knowledge Base. When the demand and orders have been generated, the user can request that a distribution plan be generated [Ref. 4:p. 2.3].

The **Distribution Planner** uses information in the Knowledge Base to decide when, where, and how to move specific quantities of supplies. Using a Constrained-Directed Search, the distribution planner algorithm plans stockage and multiple shipment movements based on required delivery dates, shipment priority, and resource availability for ammunition and fuel [Ref. 4:p. 2.3].

C. UNIQUE FEATURES OF THE MODEL

The KBLPS model is unique in the way it handles time, the satisfaction of demand, and variations in demand. Unlike most logistics models, KBLPS does not simulate time. It represents time as a member of a set of resources or constraints. For example, the distribution planner represents time as one of seven resources, and produces plans which are feasible with respect to all the resources which it considers. These seven resources are:

1. Time;
2. Inventory;
3. Material handling equipment;
4. Trucks;
5. Main supply route capacity;
6. Helicopters; and
7. Hoseline for fuel [Ref. 4:p. 5.2].

Most other current logistics models simulate time using dynamic discrete event-step time processes that model the passage of time by placing events on a calendar, and then processing them at the appropriate time. Examples of such models are the Logistics Intra-Theater Support Tool and the Distribution System Analyzer [Ref. 2:p. 5].

Because the KBLPS model is constrained in its distribution planning by the order's due time, late deliveries are not considered by the model. Demand is considered satisfied when appropriate quantities of ammunition or fuel are allocated to a given user-unit order, and are available at the appropriate destination supply point on or before the stated time that the order was due. In the Army, late deliveries would be considered and the orders filled late would be considered as satisfied demands. Late deliveries are included in stochastic models.

The KBLPS algorithms do not deal with randomness. Items typically represented stochastically in other systems, such as the probability of demand for a particular product type by a particular category of unit, are spread over time as part of the initial KBLPS algorithmic step. The basis of the algorithmic approach is first to identify which resources are most heavily in demand relative to their availability at specific times within the planning horizon, and then to plan for those resources so as to optimize the efficiency of their distribution. Stochastic models, such as the Distribution System Analyzer, use selected probability distributions to represent variables which fluctuate naturally. Deterministic models, such as the Logistics Intra-theater Support Tool, use expected values to deal with such demand variations [Ref. 2:p. 5]. The KBLPS model does not use expected values of demand.

D. EXPERT SYSTEMS

The KBLPS model is the first logistics model to use expert system technology. Expert systems are currently the most emphasized area in the field of artificial intelligence, and represent the leading edge of commercialization in computer sciences [Ref. 5:p. 1]. Prof. E. Feigenbaum of Stanford University, a pioneer in the field of artificial intelligence, defines an expert system as: "an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution." The knowledge necessary to perform at such a level, plus the inference procedures used, can be thought of as a model of the expertise of the best practitioners of the field.

The knowledge of an expert system consists of facts and heuristics. The facts constitute a body of information that is widely shared, publicly available, and generally agreed upon by experts in the field. The heuristics are mostly private, little-discussed rules of good judgment that characterize expert-level decision making in the field. The performance level of an expert system is primarily a function of the size and quality of the knowledge base that it possesses.

An expert system consists of:

1. A knowledge base of domain facts and heuristics associated with the problem;

2. An inference procedure for utilizing the knowledge base in the solution of the problem; and

3. A working memory—"global database"—for keeping track of the problem status, the input data for the particular problem, and the relevant history of what has been done [Ref. 5:pp. 2-3].

A human "domain expert" usually collaborates in the development of the knowledge base. In the case of KBLPS, the chief domain expert was Dr. B. Don Sullivan of Cameron University, who is a logistician and retired Army colonel. In addition to solving problems, a developed system can be used to help instruct personnel in developing their own expertise.

An expert system differs from more conventional computer programs in several important aspects. In an expert system, there is a clear separation of general knowledge about the problem and the methods for applying the general knowledge to the problem. In a conventional computer program, knowledge pertinent to the problem and methods for utilizing the knowledge are all intermixed, making it difficult to change the program.

Expert systems offer some significant advantages over more conventional programs.

1. Expert systems can increase productivity by replicating the expertise of scarce human experts.

2. Expert systems provide a "corporate memory" for the knowledge held by a procession of human experts over the years or for the knowledge possessed separately by a number of cooperating human experts at one time.

3. Expert systems, by virtue of the generality of their knowledge representations, promise increased efficiency in developing future systems because of the potential for reusing knowledge from existing systems.

4. In contrast with humans, expert systems are good at handling the myriad of details of complex, fast changing situations, such as often occur on the battlefield.

5. In contrast with other computational approaches that are formal and algorithmic, expert systems are more robust:

they are designed to deal with problems exhibiting uncertainty, ambiguity, inaccuracy, and missing data.

Unfortunately, there are disadvantages to expert systems as well.

1. They are expensive to build.
2. They cannot be left alone to run autonomously for long periods because they require human interaction.
3. Expert systems are only as good as the human experts were: expert systems can not learn to improve their performance on their own [Ref. 5:pp. 21-28].

E. ASSUMPTIONS AND LIMITATIONS OF THE MODEL

There are a number of assumptions and limitations that have an impact on the operational situations for which KBLPS may be used. In particular, the KBLPS model requires that the logistician be an essential part of the system, and therefore assumes that his knowledge and skills are adequate.

Perfect communications and intelligence are assumed in the model in that there is no time delay in the transfer of information and all unit locations are assumed known. The loss of material in transit is assumed to be zero.

The user may modify existing objects and types of objects, but does not have the ability to create new types of objects. KBLPS has a domain library that contains domain-specific types of Army objects, including combat units, combat support units, and combat service support units.

In this chapter we have familiarized ourselves with the features and use of the KBLPS model. We will now proceed to review the manner in which the model was prepared for the experiment.

III. PREPARATION OF THE KBLPS MODEL FOR THE STUDY

Using any large model such as KBLPS requires a considerable amount of preparation. Not only must computing resources be made available and their suitability established, but initial values for the many model parameters must be determined and placed in the scenario.

This chapter provides a review of the computer hardware used in the study. It also identifies and describes system parameters which were set to constant values for the conduct of the study.

A. COMPUTER USED IN THE STUDY

All testing was conducted on a stand alone SUN SPARC 10 workstation that was configured as follows:

1. Random Access Memory (RAM) with 64 megabytes capacity;
2. Central Processing Unit (CPU) with 40 megahertz speed; and
3. External hard disk storage space of 1.97 gigabytes.

The 3.9 version of the KBLPS software was used for the study with a Sun OS version 4.1.3 operating system.

B. CONSTANT PARAMETER VALUES ESTABLISHED FOR THE STUDY

Several parameter values were established and kept constant during the study. These constant parameter settings are discussed below.

1. Days of Supply Requirements

The stockage objectives for each supply point are expressed in days of supply, and are determined by the expected demand of the units supported by a particular supply point. There are three types of fuel supply points: the General Supply Point; the Division Supply Point; and the Forward Supply Point. Likewise, there are three types of ammunition supply points: the Corps Supply Area; the Ammunition Supply Point; and the Ammunition Transfer Point. The stockage objectives for the fuel and ammunition supply points are presented in Tables 1 and 2 respectively.

TABLE 1. STOCKAGE OBJECTIVES FOR FUEL SUPPLY POINTS

Type of Supply Point	Days of Supply
General Supply Point	3 Days
Division Supply Point	2 Days
Forward Supply Point	1 Day

TABLE 2. STOCKAGE OBJECTIVES FOR AMMUNITION SUPPLY POINTS

Type of Supply Point	Days of Supply
Corps Supply Point	7 Days
Ammunition Supply Point	5 Days
Ammunition Transfer Point	1 Day

It should be noted that the days-of-supply measure also indicate the frequency with which supplies will be delivered to each type of supply point. An allocation of 2 days of supply to each Division Supply Point, for example, means that each Division Supply Point will be supplied with fuel every two days and will receive a quantity of fuel equal to twice the estimated daily demand for the division.

2. Initial Inventory in Days of Supply

Prior to the start of regularly scheduled deliveries of supplies, each supply point will be loaded with an initial inventory. This initial inventory serves as safety stock. In the event a scheduled delivery is delayed, this safety stock will allow the supply point to remain operational, temporarily. This safety stock is continually rotated since issues from the supply points are made on a First-In, First-Out basis. The initial inventory values fuel and ammunition supply points are shown in Tables 3 and 4 respectively.

TABLE 3. INITIAL INVENTORY FOR FUEL SUPPLY POINTS

Type of Supply Point	Initial Inventory
General Supply Point	3 Days of Supply
Division Supply Point	1 Day of Supply
Forward Supply Point	.5 Days of Supply

TABLE 4. INITIAL INVENTORY FOR AMMUNITION SUPPLY POINTS

Type of Supply Point	Initial Inventory
Corps Supply Area	5 Days of Supply
Ammunition Supply Point	1 Day of Supply
Ammunition Transfer Point	0 Days of Supply

3. OPTEMPO Planning and Consumption Factors

Planning factors for supply usage vary based on terrain and climate conditions. This study reflects the operations of the XVIII Airborne Corps in Desert Storm. Hence, Southwest Asia planning and consumption factors were selected for the study.

4. Planning Horizon

The system's default planning horizon of 5 days was used for this study.

5. Unit Effectiveness

For this study, all units were exercised at 100 percent effectiveness.

Having prepared the KBLPS model for the experiment, we will now consider the methodology that will guide us in the conduct of this experiment.

IV. METHODOLOGY

This chapter first presents criteria for selecting measures of effectiveness, then applies them in the process of selecting measures of effectiveness for this study. Next, a set of possible parameters for variation is identified. Through a process of elimination using data from related studies and information from army logistics field manuals, three parameters are selected for variation. Finally, the experimental design and analytical methods are covered.

A. SELECTION OF MEASURES OF EFFECTIVENESS

A measure of effectiveness of a system is a variable that evaluates the capability of the system to accomplish its assigned missions under a given set of conditions. Three of these were selected to evaluate the KBLPS model. They are:

1. CPU time to run demand generator;
2. CPU time to run distribution planner; and
3. Percentage fill of orders generated.

Before discussing each measure of effectiveness, some general guidelines used in developing these MOEs are reviewed.

1. Criteria for Selecting Measures of Effectiveness (MOEs)

Consideration was given to the following criteria in selecting these MOEs.

- **Relevance**: Each MOE should be directly related to the missions of the system and to the design and other artificial issues that have been identified. It should not be overly broad and should not involve terms that do not affect the issues of the test.

  The concept of relevance was considered not only with reference to the mission of KBLPS, but also with reference to the bigger picture of the sustainment planning process. The sustainment planning process, as taught at the Army's Command and General Staff College has five phases. These are:

1. Capture the battlefield situation and proposed course of action;

2. Estimate the ammunition and fuel requirements;

3. Plan the logistics support concept and distribution plan;

4. Analyze logistics supportability; and

5. Advise the commander.

The three MOEs selected represent stages two, three, and four of this process.

- **Completeness**: All the selected input variables should appear as some sort of input to a MOE and might cause a change in the value of the MOE as it is varied.

- **Precise Definition**: The MOE definition should be adequate so that there is no possibility of misunderstanding what is meant by the MOE. It should be possible for an independent researcher to replicate the MOE results.

- **Meaningful**: The MOE should be expressed in terms that are meaningful to both tester and decision maker, and in such a way that its meaning is not in doubt after the passage of time and examination by other testers and decision makers.

- **Quantifiable**: The MOE and its input variables should be quantifiably measurable to preclude any subjectivity in the results [Ref. 6:pp. 54-55].

2. MOE-1: CPU Time To Run Demand Generator

The first MOE is the time to run the demand generator. It measures the time required for KBLPS to perform the estimation portion of the logistics staff planning process. A major goal of KBLPS is to significantly improve the speed of logistics planning. Logistics planning is currently conducted manually at most division and corps level commands. Since planning time is usually limited, this often constrains the planning effort to a very high level analysis. At division and especially at corps, detailed manual planning can be accomplished only if the lead time is very long or if a significant number of staff planners are committed to the effort. Otherwise, the analysis may be at a high level, and may border on being cursory. KBLPS is designed to generate detailed planning data rapidly, to facilitate detailed estimation in the logistics staff planning process.

In an attempt to select a precise and meaningful MOE, consideration was given to measuring either CPU time or elapsed time. Central Processing Unit time is mainly a function of the speed of the microprocessor. Elapsed time is dependent on both micro-processor speed and available Random Access Memory (RAM).

The CPU can only process that data which is available in RAM. All the data necessary to complete a process such as the Demand Generator cannot fit in RAM all at once. Consequently, periodically during the execution of a process the

CPU must stop working on the data that is in RAM because it needs other data. Some of the data in RAM must be moved out to be stored on hard disk to make room for the data needed. Then the data needed must be moved into RAM. While data is being moved in and out of RAM, the CPU is not working on the process. How much data swapping occurs is a function of how much RAM is available, how much data the process needs, and the speed of data transfer out to the hard disk and back into RAM. The CPU time was selected for measure because it is impacted by fewer variables than elapsed time and is thus more easily compared across different computer systems.

The CPU time was measured in minutes and seconds. A small shell program written by Information Technology Solutions was used to accurately capture these times.

3. MOE-2: CPU Time To Run Distribution Planner

The second MOE is the CPU time to run the Distribution Planner, and measures the time required to accomplish the KBLPS task of developing a distribution plan for a particular course of action. Distribution planning is step three of the sustainment planning process. It is also the most challenging and critical aspect of the process.

The CPU time elapsed was selected as a precise and meaningful method of measuring the MOE. The rationale for selecting CPU time elapsed was the same as for the first MOE.

4. MOE-3: Percentage Fill Of Orders Generated

A major factor in deciding whether a particular course of action should be selected is the extent to which it can be supported logistically. The third MOE measures the logistics supportability of a particular course of action (COA) on the basis of percentage fill of orders generated. Logistics supportability is the fourth step of the logistics planning process.

The third MOE is the ratio of the numbers of orders that can be distributed with available asset during the mission-period, to the number of orders generated for the mission by the demand generator. Since the distribution of orders is based on the priority of the orders, this ratio is meaningful in terms of both absolute number of orders filled and the priority of orders filled. For example, a seventy percent percentage fill of orders generated also implies that the high priority requisitions for the mission were filled and that a high percentage of the low priority requisitions were unfilled.

C. SELECTION OF PARAMETERS TO BE VARIED

The KBLPS model requires that a large number of parameter values be specified before each run. Five of these parameters were considered for selection to be varied: unit size, battle intensity, consumer minimum residual percentage; the number of specific products (types of ammunition, types of POL) available to the model; and stockage minimum residual percentage.

Three parameters were finally selected based on the results of a parameter test conducted on the KBLPS model by Information Technology Solutions Incorporated [Ref. 3:pp. 2-15]. These test results indicated that unit size, battle intensity, and consumer minimum residual percentage had a marked impact on the values of the MOEs selected. The number of specific products (types of ammunition or fuel), and the stockage minimum residual percentage were shown to have lower levels of impact on the values of the MOEs selected.

The significance of the three MOEs selected from the above referenced study were then further researched using Army logistics field manuals.

1. Unit Size Parameter

According to FM 701-58 [Ref. 7], the purpose of logistics planning is to support the maneuver commander and the operational requirements generated by the maneuver force. The size of the maneuver force required for the mission is a key factor in determining the mission support requirements. As the force increases in size, we experience not only an increase in numbers of soldiers and weapons system, but more significantly an increase in the structural complexity of the force and an expansion in the diversity of requirements. The complexities noted suggest that the time required for planning logistic support for varying force sizes is not linear and thus the time required and the ability of KBLPS to plan logistic support for various force sizes is a critical factor. The significance of this factor is supported by the desire of the KBLPS developers to expand the model's domain from corps level to theater level analysis.

2. Battle Intensity Parameter

The projected battle intensity is intimately related to the tactics of the battle. Each tactical mission has a logistical component that must be satisfied if the tactical mission is to be accomplished. The evaluation of a tactical plan or COA from a logistical perspective is a necessary and required function of the Military Decision Making Process. This evaluation function is specifically organized and called for in the staff estimates process outlined in FM 101-5, Staff Organization and Operations [Ref. 8] and the G-4 Battle Book published by the Command and General Staff College [Ref. 9]. This process results in formulation of the logistics estimate which has as its purpose an assessment of the supportability of the tactical COA.

The Deputy Chief of Staff for Operations or G3 as the primary staff officer with lead responsibility for tactical planning, will normally identify three or more tactical COAs which should be considered by the staff in conducting their staff estimates.

Because logistical planners tend to plan with discrete factors and numbers which vary with the nature of the battle; e.g., rounds fired, gallons consumed, etc., the more detailed the definition of the battle, the more definitive can be the derived requirements on which the logistical planning is based. Thus, a battle intensity parameter is crucial to refining the logistical support requirement beyond the level of the size of the force.

KBLPS allows for three levels of intensity (light, medium, and heavy) in the attack and defensive modes. The battle intensity parameter will be utilized in the light, medium, and heavy attack modes.

3. Consumer Residual Percentage Parameter

The Consumer Minimum and Residual threshold is the minimum percent fill of a priority level before KBLPS will fill the priority below it.

The priority of a requisition is a function of two main factors: the Force Activity Designator and the Urgency of Need. The Force Activity Designator classifies units according to their level of mission importance while the Urgency of Need addresses the impact on the units mission if the requisition is not filled. While high priority requisitions obviously need to be filled first, there needs to be some guiding policy on what level of fill of the higher priorities is considered acceptable before lower level priorities are filled. This policy is defined by the Consumer Minimum and Residual threshold.

The Consumer Minimum and Residual threshold has far reaching impacts in the process of logistics planning. This planning is often conducted in a constrained environment since requirements for combat service support more often than not exceed capabilities. Consequently, available combat service support resources are normally highly contended. The impact of consumer minimum residual percentage is best defined within the context of the high-level goals for logistics planning described in FM 701-58 [Ref. 7]. These are:

- Force-Level Planning;
- Supply Planning; and
- Transportation Planning.

Force-level logistics planning is concerned with total force support, with synchronization of the logistics support plan to the maneuver plan. Manipulation of the Consumer Residual Percentage can minimize the effects of identified shortfalls. However, decreasing the Consumer Residual Percentage from 100 percent will usually increase the time needed to complete the force level planning phase because of distribution planning complications.

Supply Planning is concerned with supply support to the force. The goal is to provide adequate amounts of supplies by type, time, and location to meet customers needs. The challenge is defining the term "adequate." Specification of the Consumer Residual Percentage defines the meaning of adequate in each scenario.

Transportation Planning is concerned with transportation support to the force and the effective control and employment of assets. The goal is to allocate transportation assets to maximize their utilization. As the Consumer Residual Percentage is decreased from 100 percent, the net effect is to decrease the size of each product delivery to a unit and increase the number of deliveries which usually results in decreasing the efficiency of transportation asset utilization.

D. DESIGN OF EXPERIMENT AND ANALYTICAL METHODS

This section is divided into three areas. First, the experimental design used to generate data for analysis is reviewed. Next, the various methods used to establish levels of sensitivity of the MOEs to parameters are described. Finally, a method for finding the level of consumer residual percentage that will generate the highest level of percentage fill of orders generated, for given levels of battle intensity and unit size, is outlined.

1. Data Generation

A 2 x 3 x 3 fixed factorial design was selected to generate data for analysis. This design was influenced by the fact that the two division model on the KBLPS test system used was not operational. Thus, the unit size factor was exercised over two levels. The battle intensity and consumer residual percentage factors were exercised over three levels to facilitate the generation of response surface curves for these factors.

Each class of supply generated 18 sets of data. The nomenclature and symbols used to describe the data are presented in Table 5. A matrix of the data generated is presented in Table 6.

TABLE 5. DATA NOMENCLATURE AND SYMBOLS

DATA NOMENCLATURE	SYMBOL
Unit Size	U_i
Battle Intensity	I_i
Consumer Residual Percentage	R_i
Level	i=1,2,3
Time to Run Consumption Generator	CT_n
Time to Run Distribution Planner	DT_n
Percentage Fill of Orders Generated	PF_n
Data Set	n=1...18

TABLE 6. DATA GENERATION MATRIX

n						
1	U_1	I_1	R_1	CTn	DTn	PFn
2	"	I_1	R_2	"	"	"
3	"	I_1	R_3	"	"	"
4	"	I_2	R_1	"	"	"
5	"	I_2	R_2	"	"	"
6	"	I_2	R_3	"	"	"
7	"	I_3	R_1	"	"	"
8	"	I_3	R_2	"	"	"
9	"	I_3	R_3	"	"	"
10	U_2	I_1	R_1	"	"	"
11	"	I_1	R_2	"	"	"
12	"	I_1	R_3	"	"	"
13	"	I_2	R_1	"	"	"
14	"	I_2	R_2	"	"	"
15	"	I_2	R_3	"	"	"
16	"	I_3	R_1	"	"	"
17	"	I_3	R_2	"	"	"
18	"	I_3	R_3	"	"	"

2. Statistical Considerations

The times to run the demand generator and distribution planner are stochastic in nature and lend themselves to statistical analysis. They represent the CPU times that elapsed for each process. Although CPU time is mainly a function of the microprocessor speed, it is impacted by the random transfer of data between the RAM and hard disk, making it stochastic in nature. The percentage fill of orders generated is a direct output of this deterministic model, and is therefore not stochastic. No random variables are generated internally in KBLPS. If the model is run repeatedly for a fixed set of input values, the output values will be identical.

The lack of randomness in the data on the percentage fill of orders generated, precludes the use of confidence intervals and hypothesis test with this data. Nonetheless, if we are careful about interpretation, some numerical measures usually associated with statistical analysis can be useful in interpreting our results. For example, simple averages or average sums of squares can provide useful information. The fitting of a linear or nonlinear function to the results using least squares may also be done, with the optimized sum of squares understood to be only a measure of fit.

3. Sensitivity Analysis

Sensitivity analysis of a model offers an analytical method for determining those parameters of the dynamic system which have the greatest influence on the system's performance. Sensitivity analysis was conducted using two methods. First, formal nonparametric hypothesis testing of the data was conducted using the Mann-Whitney and Kruskal-Wallis Tests. For the percentage fill of orders generated, these tests were used purely as quantitative measures and not as statistical measures to facilitate hypothesis testing. Secondly, empirical response surface three dimensional plots were used to present a graphical perspective and provide information on the range over which sensitivities exist. Factor means plots were also generated. These were used to assist in the interpretation of the sensitivity analysis results.

a. Hypothesis Testing

(1) Mann-Whitney test of medians was selected to test for the sensitivity of each MOE to the two levels of unit size used in the experiment. The MOE data associated with each of the two levels of unit size are considered as samples from two independent populations. The objective of the test is to detect differences in the populations based on their means.

The Mann-Whitney test uses the intuitive approach to a two-sample problem of combining both samples into a single ordered sample, then assigns ranks to the sample values from the smallest to the largest, without regard to which population each value came from. The test statistic is the sum of the ranks assigned to the values from one of the populations. If the sum is too small or too large, there is some indication that the values from that population tend to be smaller or larger as the case may be, than the values from the other population. Hence, the null hypothesis of no difference between the populations may be rejected if the ranks associated with one sample tend to be larger than those of the other sample.

Ranks may be considered preferable to the actual data for several reasons. First, if the numbers assigned to the observations have no meaning by themselves but attain meaning only in an ordinal comparison with the other observations, the numbers contain no more information than the ranks contain. Such is the nature of ordinal data. Second, even if the numbers have meaning but the distribution function is not normal, the probability theory is usually highly complicated when the test statistic is based on the actual data. The probability theory of statistics based on ranks is relatively simple and does not depend on the distribution in many cases. A third reason for preferring ranks is that the asymptotic relative efficiency of the Mann-Whitney test is never too bad when compared with the two-sample t test, the usual parametric counterpart. However, the contrary is not true; the asymptotic relative efficiency of the t test compared to the Mann-Whitney test may be as small as zero, i.e., infinitely bad. Thus, the Mann-Whitney test is a safer test to use [Ref. 10:pp. 215-216].

Let X_1, X_2, ..., Y_n denote the sample of size n from population 1. Let Y_1, Y_2, ..., Y_n denote the sample of size m from population 2. Assign the ranks 1 to n + m. Let $R(X_i)$ and $R\ (Y_j)$ denote the rank assigned to X_i and Y_j for all i and j. Let $N = n + m$.

The hypotheses are stated in terms of X and Y.

$$H_o: \; E(X) = E(Y)$$

$$H_a: \; E(X) \neq E(Y)$$

H_o is equivalent to stating that both the two-brigade and corps data have the same means. This is a two-tailed test. The hypothesis is rejected if the test statistic is less than the $\alpha/2$ Mann-Whitney quantile or greater than the $1 - \alpha/2$ quantile. H_o is accepted if the test statistic is between or equal to one of the two quantiles [Ref. 10:pp. 217-218]. Alpha (α) is the probability of a type one error. Typical values for α are 0.05 and 0.1. In this thesis an α of 0.1 is used.

(2) The Kruskal-Wallis test was selected to analyze the sensitivity of the measures of effectiveness to the battle intensity parameter and the consumer residual percentage parameter. These parameters were exercised over three levels. The Kruskal-Wallis test is an extension of the Mann-Whitney test to accommodate K samples, $K \geq 2$. The objective is to test the null hypothesis that all the populations are identical against the alternative that some of the populations tend to furnish greater observed values than other populations.

Consideration was given to the median test in selecting a test method for this section. However, the median test was deemed a less powerful test than the Kruskal-Wallis test because it uses less information contained in the observations than the Kruskal-Wallis test. The median test statistic is dependent only on the knowledge of whether the observations were below or above the grand median. The Kruskal-Wallis test statistic, on the other hand, is a function of the ranks of the observations in the combined sample.

The data consists of three random samples each representing one level of the associated parameter. The i^{th} random sample of size n_i is denoted by X_{i1}, X_{i2}, ... X_{in}. Let N denote the total number of observations. Then

$$N=\sum_{i=1}^{3} n_i .$$

A rank of 1 is assigned to the smallest of the totality of N observations, rank 2 to the second smallest, and so on to the largest of all N observations, which receives rank N. Let $R(X_{ij})$ represent the rank assigned to X_{ij}. Let R_i be the sum of the ranks assigned to the ith sample. Then

$$R_i=\sum_{j=1}^{3} R(X_{ij}) .$$

The hypotheses are as follows:

H_o: All three population distribution functions are identical; and

H_a: At least one of the populations tends to yield larger observations than at least one of the other populations.

The test statistic T is defined as:

$$T = \frac{1}{S^2}\left(\sum_{i=1}^{3} \frac{R_i^2}{n_i} - \frac{N(N+1)^2}{4}\right),$$

where N and R_i are defined as above and

$$S^2 = \frac{1}{N-1}\left(\sum R(X_{ij})^2 - N\frac{(N+1)^2}{4}\right).$$

The null hypotheses, H_o, at the selected α of .1 is rejected if T exceeds the 1-α quantile of the Kruskal-Wallis Test Statistic [Ref. 10:pp. 229-231].

b. Empirical Response Surface Plots

Empirical response surface plots were used to depict any joint functional dependence of the measures of effectiveness on the input parameters. They were also useful in providing information on the ranges over which MOEs were sensitive to the battle intensity and consumer residual percentage parameters.

The plots were organized by the size of the model. Each MOE was then compared with battle intensity and consumer residual percentage for the two-brigade and corps sized models.

A logarithmic transformation was used on the consumer residual percentage data to compensate for the fact that the data range is bounded. The actual KBLPs factors of .35, .65 and 1.0 which represent the low, medium, and high battle intensity settings were used in developing these plots [Ref. 4:p. 423].

c. Factor-Means Plots

The combined effect of two factors can be easily studied using a factor-means plot. The interaction is an additive effect due to the particular combination of two levels of different factors. For example, certain combinations of levels of battle intensity and level of consumer residual percentage may impact the time to run the demand generator in excess of the sum of the effects of the two levels involved. Conversely, a particular combination may reduce the percentage fill of orders generated to a lower level than expected.

Geometrically, the absence of interactions yields parallel lines when the means of the response variable are graphed for various combinations of levels of the factors. Interactions are indicated by deviations from parallelism [Ref. 11:p. 398].

4. Optimization Using Response Surface Analysis

One of the goals of this thesis is to determine the values of input parameters that will yield the best supply distribution plan, for the two-brigade and corps sized models, as measured by the percentage fill of orders requested. Unit size and battle intensity are usually scenario dependent and not within the absolute control of the unit commander. Thus, the commander's flexibility lies primarily in adjusting the consumer residual percentage to impact the effectiveness of his supply distribution plan. The optimization method described below is contingent on the percentage fill of orders generated, the third MOE, being sensitive to both battle intensity and consumer residual percentage, and the presence of a global maximum point on the response surface. If, for example, the third MOE was sensitive only to the consumer residual percentage parameter, the associated maxima, if present, could simply be read from the plot.

The first step is to identify a mathematical equation that accurately describes the empirical response surface. The model fitting capability of the AGSS statistical program will be used for this thesis. If a second order polynomial was found to provide the best fit, the associated equation would be

$$\hat{Y} = \hat{\beta}_o + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \hat{\beta}_3 X_1^2 + \hat{\beta}_4 X_1 X_2 + \hat{\beta}_5 X_2^2,$$

where

$\hat{Y}$	=	estimate of MOE-3,
X_1	=	battle intensity parameter,
X_2	=	consumer residual percentage parameters, and
$\hat{\beta}_o \ldots \hat{\beta}$	=	estimated coefficients.

Since the commander's flexibility lies primarily in adjusting the consumer residual percentage, we would take the partial derivative of $\hat{Y}$ with respect to the consumer residual percentage parameter giving,

$$\hat{Y}^1 = \hat{\beta}_2 + \hat{\beta}_4 X_1 + 2\hat{\beta}_5 X_2.$$

By substituting for each value of battle intensity X_1, and setting the first derivative equation equal to zero in each case, we can solve for the value of the consumer residual percentage that maximizes the third MOE under each of these conditions.

In summary, this chapter has established the measures of effectiveness for evaluating the model; identified the parameters of the model that will be varied during the experiment; and outlined the manner in which the experiment will be conducted. The data gathered from the experiment is presented in Appendix A and B. This data is now analyzed in the following chapter.

V. ANALYSIS OF DATA

This chapter presents an analysis of the data collected. The analysis is structured by MOE. The three MOEs are analyzed from the perspective of model validation. The analysis examines the realism of the sensitivities produced by the model.

The bases of the sensitivity analysis will be four-fold:

1. The direction of the sensitivity, positive or negative;
2. The magnitude of the sensitivity;
3. The range over which the sensitivity exists; and
4. The effect of factor interactions on the characteristics of the sensitivity observed.

Sensitivity to changes in unit size for each measure of effectiveness are analyzed, then effects of variations in battle intensity and consumer residual percent-age within each unit size are examined. For ease of interpretation, the test statistic values will be classified as low, medium or high sensitivity, based on the significance levels (Table 7).

TABLE 7. CLASSIFICATION OF SENSITIVITY RESULTS BASED ON SIGNIFICANCE LEVELS

Significance Level	Sensitivity Level
>.25	Low
.1 to .25	Medium
<.1	High

A. MOE-1: TIME TO RUN DEMAND GENERATOR

The time to run the demand generator (MOE-1) is analyzed first for the ammunition data, then for the fuel data.

1. Ammunition

When ammunition was considered, the time to run the demand generator showed a strong positive response to changing the unit size from a two-brigade to a corps-sized model (Table 8). The Mann-Whitney test indicated a high level of sensitivity to the change in unit size (Table 9). The test

TABLE 8. MOE-1 AMMUNITION DATA SORTED BY UNIT SIZE (MOE-1 = CPU time in Minutes to run the Demand Generator)

2BDE	.233	.267	.283	.217	.283	.267	.317	.250	.283
Corps	1.467	1.983	1.967	1.717	1.900	1.917	1.667	2.317	2.083

TABLE 9. RESULTS OF MANN-WHITNEY TWO-SIDED TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-1 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR AMMUNITION

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
45	<.01	High	Yes

statistic was significant at less than the .01 level. This result is intuitive because the demand algorithm will have to compute ammunition demand based on the number of units as well as by the type and quantity of weapons used. Since a Corps-sized model will have many more units as well as many more types of units a strong correlation between unit size and the time taken by the algorithm to compute ammunition demand seems reasonable.

The Demand Generator uses input from three spreadsheets in the computation of ammunition demand, [Ref. 4:p. 4.24]. These are:

- List of ammunition type codes, their weight, volume, and nomenclature;
- List of weapons and the rate at which they consume particular types of ammunition; and
- List of units, types, and the quantity of weapons they use.

The time to run the demand generator showed a generally increasing trend as battle intensity increased from low to high for both the two-brigade and corps models (Figures 2 and 3). In the case of the two-brigade model the pattern was not consistent and included local maxima and minima. This is attributable to multiple interactions between all levels of the battle intensity and consumer residual percentage factors in the two-brigade model (Figure 4). The end result was a complex response surface pattern. The time to run the demand generator showed a medium level of sensitivity to the battle intensity parameter in the two-brigade model, and generated a low level of sensitivity to the battle intensity parameter in the corps model. The Kruskal-Wallis Statistic was significant at the .2 level for the two-brigade model and exceeded .25 for the corps model (Table 10). The sensitivity pattern extended

CLASS 5 TWO BDE MODEL: MOE1 VS BI, LOG (CRP)

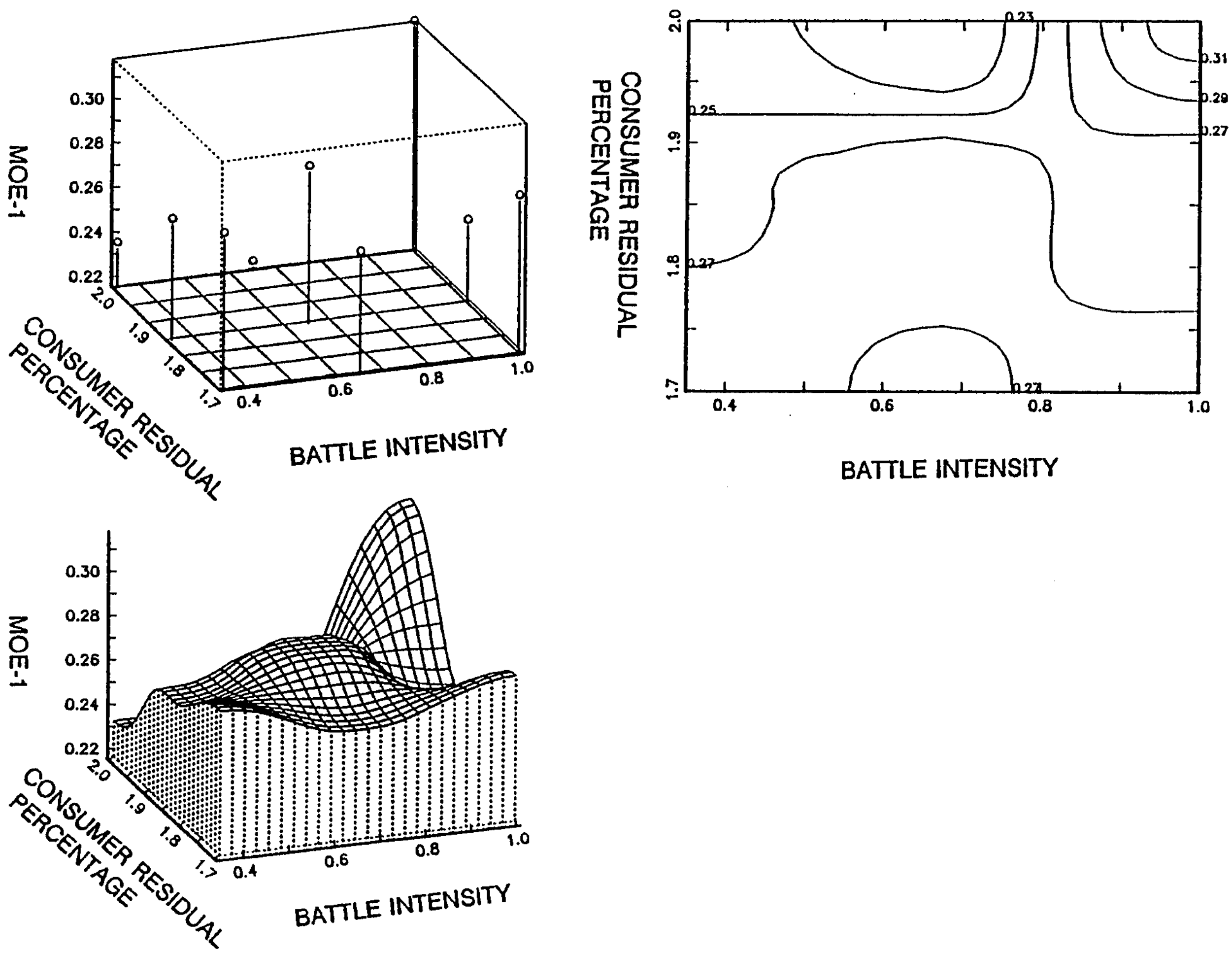

Figure 2. Data, Response Surface, and Contour Plots of MOE-1 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Two-Brigade Model.

CLASS 5 CORPS MODEL: MOE1 VS BI, LOG (CRP)

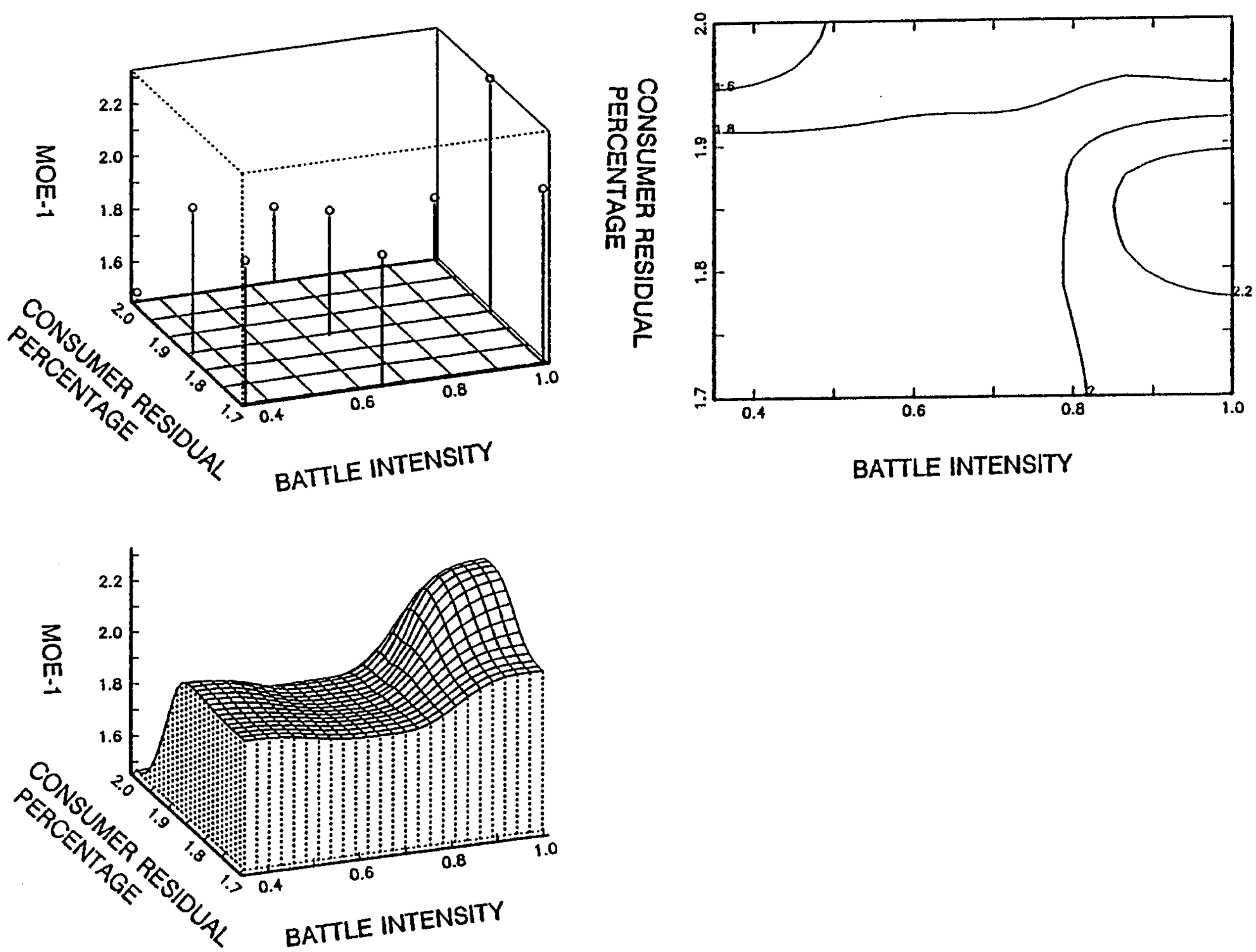

Figure 3. Data, Response Surface, and Contour Plots of MOE-1 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Corps Model.

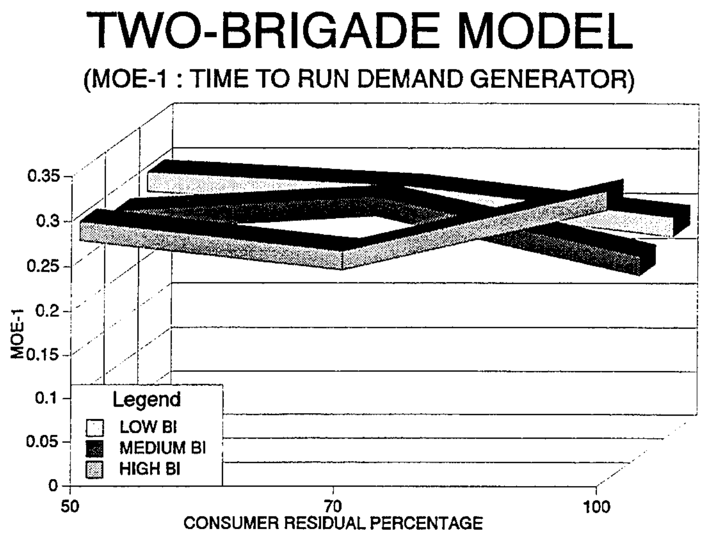

Figure 4. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Two-Brigade Model, MOE-1.

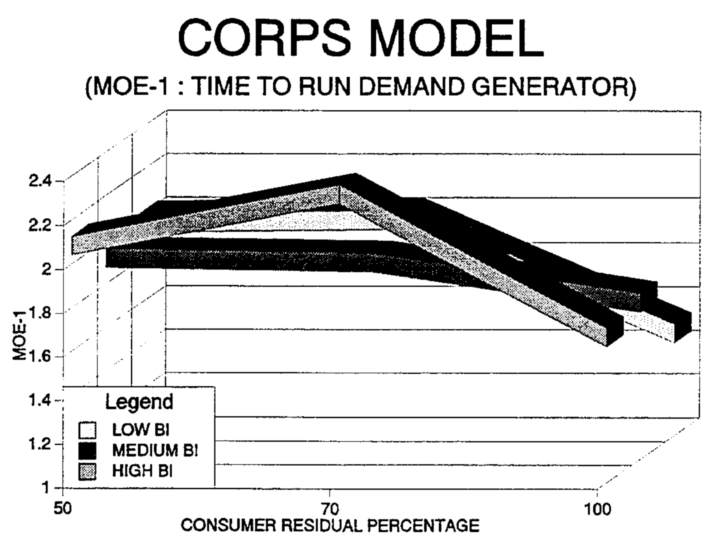

Figure 5. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Corps Model, MOE-1.

over the entire range of battle intensity in the two-brigade model but only covered the medium to high intensity range in the corps model.

TABLE 10. RESULTS OF KRUSKAL-WALLIS TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-1 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR AMMUNITION

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_0
Battle Intensity	2BDE	3.057	.227	Medium	No
	Corps	1.155	>.25	Low	No
Consumer Residual Percentage	2BDE	3.369	.201	Medium	No
	Corps	5.422	.07	High	Yes

The interaction between the battle intensity and consumer residual percentage factors on the time to run the demand generator warrants closer examination. In general, because higher levels of battle intensity cause higher quantities of ammunition to be demanded, the time associated with the demand generation process will increase with increasing battle intensity. However, the demand generation process also generates orders. It then analyzes the volume and tonnage of the product orders and determines whether the order should be shipped from the ammunition transfer point (high volume, high tonnage orders) or the ammunition supply point (low and medium volume, low and medium tonnage). It does this by considering each ammunition transfer point and sorting the demands by decreasing tonnage [Ref. 4:p. 4.24].

This entire demand generation process is impacted by the consumer residual percentage, because of its impact on the tonnage distribution among unit orders, as well as by the battle intensity, which impacts the level of demand. The response curve (Figure 2), appears to be dominated by the interaction effects of both parameters rather than by the main effects of either. Despite the interactions between battle intensity and consumer residual percentage, the overall low sensitivity of the time to run the demand generator to battle intensity, in the corps model, appears counterintuitive.

The time to run the demand generator showed an increasing trend as the consumer residual percentage decreased for both the two-brigade and corps models (Figures 2 and 3). This result is intuitive as decreasing consumer residual percentage generates a larger number of smaller sized orders. The exception was under the conditions of high battle intensity for the two-brigade model. The time to run the demand generator showed low sensitivity to consumer residual percentage within the two-brigade model. The significance of the Kruskal-Wallis statistic was .201 (Table 10). However, the time to run the demand generator was highly sensitive to consumer residual percentage in the corps model. The significance of the Kruskal-Wallis statistic was .07 (Table 10). The time to run the demand generator was sensitive to consumer residual percentage over the entire range of values in the two-brigade model. The corps model's sensitivity was limited to the 100 to 70 percent consumer residual percentage range. The overall pattern was that consumer residual percentage dominated at low and medium levels of battle intensity. This domination was more intense in the corps model because of the higher volume of ammunition being processed. At high levels, battle intensity dominated consumer residual percentage because of its strong impact on the volume of demand. Based on an understanding of the processes involved, this result appears to be logical.

2. Fuel

The time to run the demand generator showed the same high sensitivity to a change in unit size from two-brigade to corps as in the case of ammunition (Table 11). This result is immediately intuitive for the same reasons as in the case of ammunition.

TABLE 11. RESULTS OF MANN-WHITNEY TWO-SIDED TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-1 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR FUEL

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
45	<.01	High	Yes

The time to run the demand generator showed a highly variable pattern of sensitivity to battle intensity in the two-brigade model which seemed to be dominated by interaction with the consumer residual percentage (Figures 6 and 8). The corps model was virtually insensitive to battle intensity as depicted by a level response surface over most of the battle intensity range (Figure 7). Factor mean plots displayed very limited interaction effects at the corps level (Figure 9). The magnitude of the sensitivity was low in both two-brigade and corps models with significance greater than .25 (Table 12).

TABLE 12. RESULTS OF KRUSKAL-WALLIS TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-1 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR FUEL

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
Battle Intensity	2BDE	.727	>.25	Low	No
	Corps	1.379	>.25	Low	No
Consumer Residual Percentage	2BDE	3.879	.15	Medium	No
	Corps	5.492	.07	High	Yes

The insensitivity of the time to run the demand generator to battle intensity is intuitive. Fuel usage depends on factors such as terrain (paved road vs. cross country), and rate of movement [Ref. 13:p. 2.19]. It is quite possible to have high fuel usage during the advance to contact phase of operations when battle intensity is zero, and low fuel usage after contact during an intense battle which has a low rate of movement. Indeed, with the exception

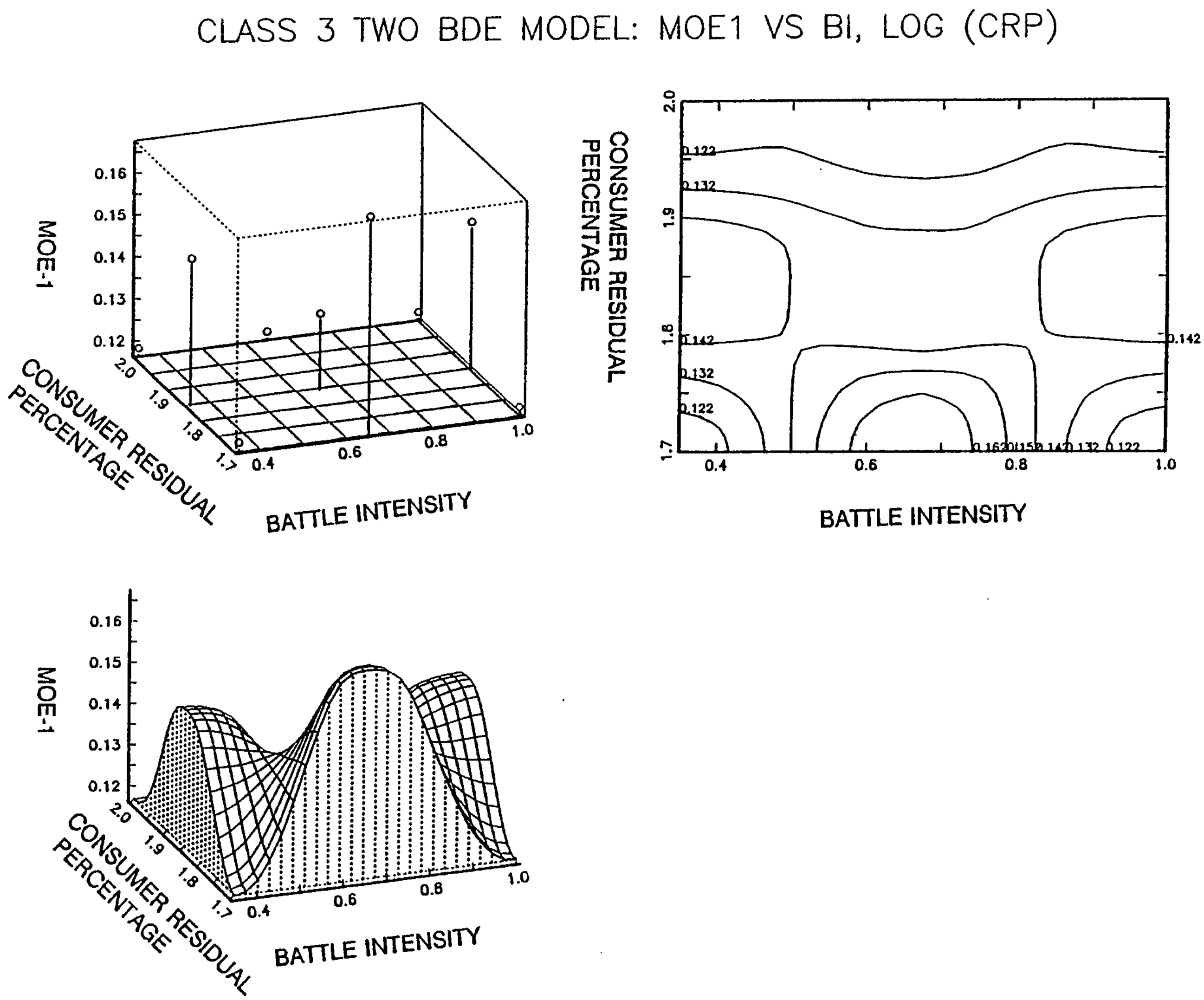

Figure 6. Data, Response Surface, and Contour Plots of MOE-1 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Two-Brigade Model.

CLASS 3 CORPS MODEL: MOE1 VS BI, LOG (CRP)

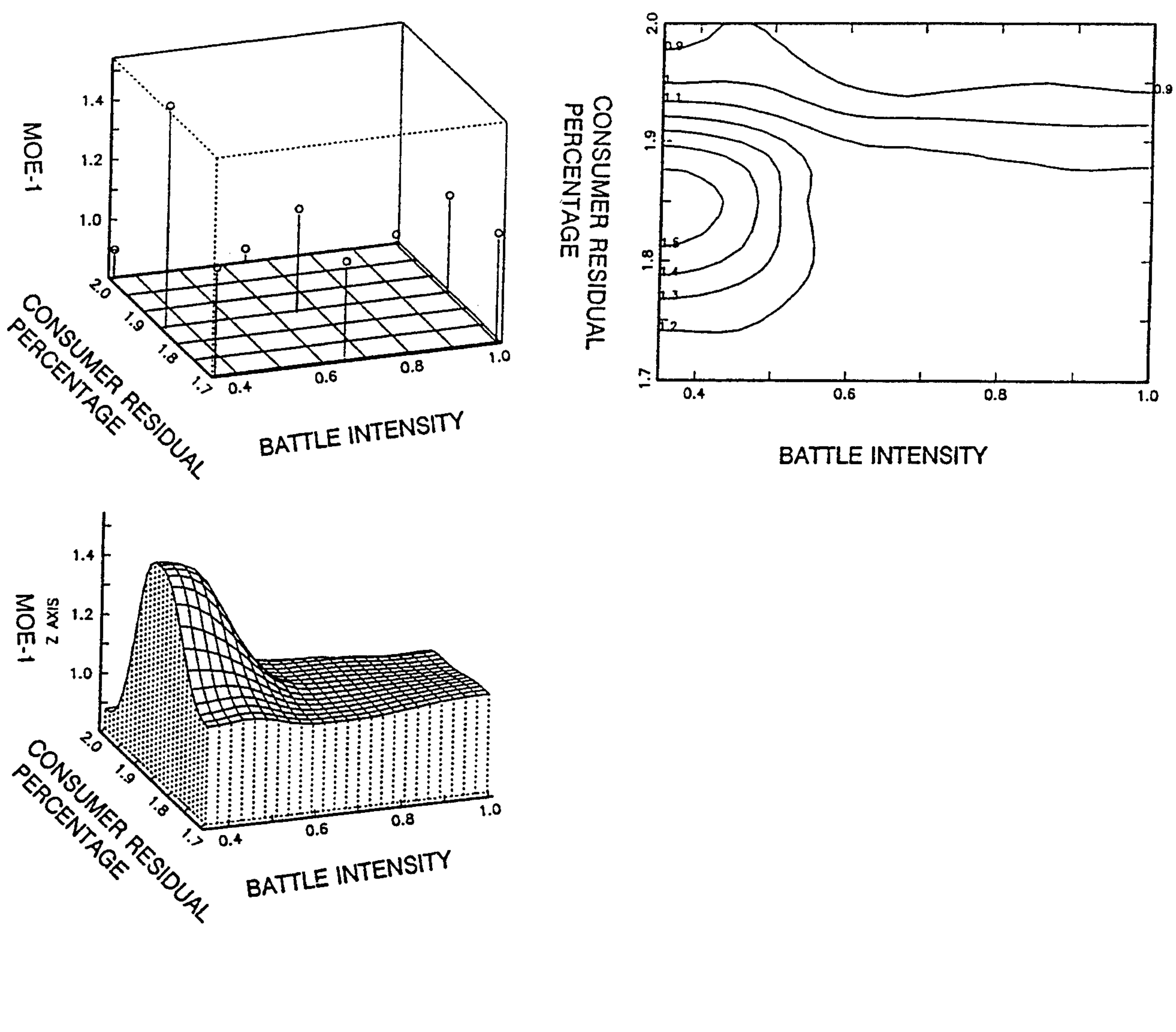

Figure 7. Data, Response Surface, and Contour Plots of MOE-1 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Corps Model.

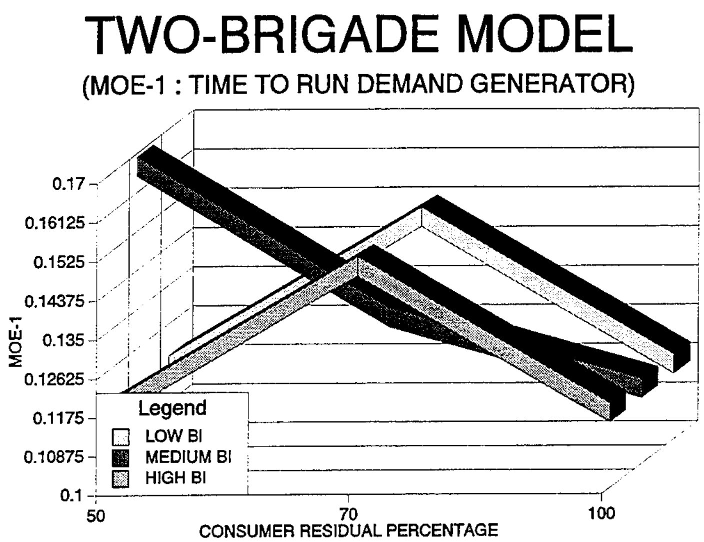

Figure 8. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Two-Brigade Model, MOE-1.

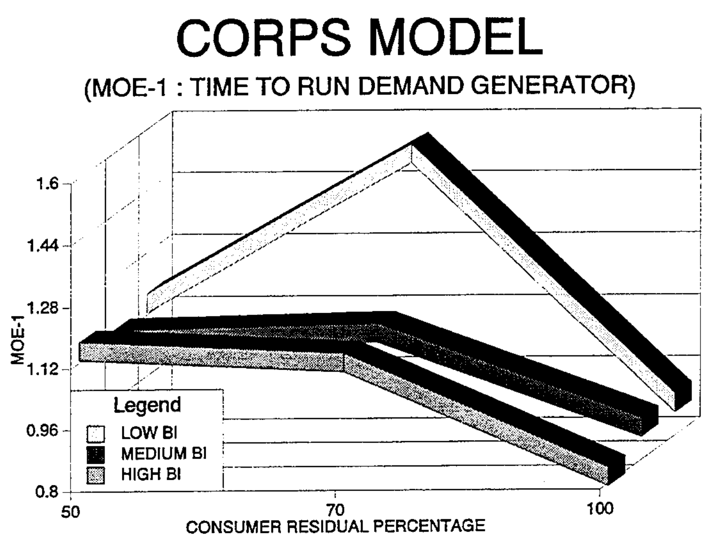

Figure 9. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Corps Model, MOE-1.

of certain lubricants [Ref. 13:p. 2.11], the military planning factors used to plan fuel usage have no relationship to battle intensity. Since battle intensity does not impact any factors which would influence the run time for fuel demand, the observed sensitivity results should be considered appropriate.

The time to run the demand generator displayed medium sensitivity to consumer residual percentage in the two-brigade model and high sensitivity in the corps model. The Kruskal-Wallis test statistic was significant at the .15 level for the two-brigade model and at the .07 level for the corps model (Table 12). The response surface indicated that the sensitivity extended over the entire range of consumer residual percentage values. However, the direction of the sensitivity was positive from 50 percent to 70 percent consumer residual percentage, then decreased from 70 percent to 100 percent, (Figures 6 and 7).

The high level of sensitivity is intuitive as varying the consumer residual percentage will have a strong impact on the order generation segment of the Demand Generator. As the consumer residual percentage is decreased, you reduce the size of each unit delivery while increasing the frequency of unit deliveries. The direction of the sensitivity is not altogether intuitive. One would expect an increase in time to run the Demand Generator as the consumer residual percentage is decreased. The decrease in the time to run the Demand Generator when the consumer residual percentage is decreased beyond 70 percent appears counter-intuitive and requires more in-depth study.

B. MOE-2: TIME TO RUN DISTRIBUTION PLANNER

The time to run the distribution planner (MOE-2) is analyzed first for the ammunition data, then for the fuel data.

1. Ammunition

When ammunition was considered, the time to run the distribution planner showed a strong positive response to the change in unit size from a two-brigade to a corps-sized model. The Mann-Whitney test indicated a high level of sensitivity to the change in unit size. The test statistic was significant at less than the .01 level (Table 13). This result is intuitive because the time needed for distribution planning is largely dependent on the number of supply points to be serviced and the number of supply points is directly proportional to the unit size. The two-brigade model has two ammunition supply points while the corps model has ten.

TABLE 13. RESULTS OF MANN-WHITNEY TWO-SIDED TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-2 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR AMMUNITION

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
45	<.01	High	Yes

For each supply link in each problem scenario, the Distribution Planner conducts the following analyses:

- Determines movement load, departure, arrival and unload times for user-unit demand orders and stockage objective orders;
- Selects the best route for each movement;
- Selects the mode of transportation for each shipment; and
- Determines a feasible size for the shipment (for example, breaking one order into multiple shipments) [Ref. 4:pp. 4-29].

With ammunition, the time to run the distribution planner exhibited a low level of sensitivity to battle intensity at both the two-brigade and corps level. The Kruskal-Wallis statistic for both models was significant at greater than .25, (Table 14). However, the comparison of the

TABLE 14. RESULTS OF KRUSKAL-WALLIS TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-2 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR AMMUNITION

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
Battle Intensity	2BDE	1.567	>.25	Low	No
	Corps	2.22	>.25	Low	No
Consumer Residual Percentage	2BDE	5.708	.06	High	Yes
	Corps	5.422	.07	High	Yes

actual test statistics (1.567 v. 2.22) showed that the corps model was more sensitive to battle intensity than the two-brigade model. This difference in sensitivity became more evident on inspecting the response surface curves, (Figures 10 and 11). The two-brigade model results were essentially flat in the battle intensity plane while the corps model displayed a distinct trend of increasing values of the time to run the distribution planner, with an increase in battle intensity. The sensitivity patterns of both the two-brigade and corps models were consistent over the entire range of battle intensity values. There were no interaction effects between the levels of battle intensity and the consumer residual percentage (Figures 12 and 13).

The sensitivity pattern displayed by the time to run the distribution planner to battle intensity is intuitive when one considers that the number of supply linkages is a more dominant factor in the supply distribution process than the quantity of supplies required. However, the quantity of supplies required will have an impact on subelements of the distribution planning process, for example, determining the need to partition unit orders into multiple shipments. Hence, a low level of sensitivity to battle intensity is expected. The incongruity between the response curve for the corps model and the sensitivity results from hypothesis testing is probably due to an additive interaction effect between the size of the model and the battle intensity parameter. A two division unit uses twenty-three types of ammunition while a

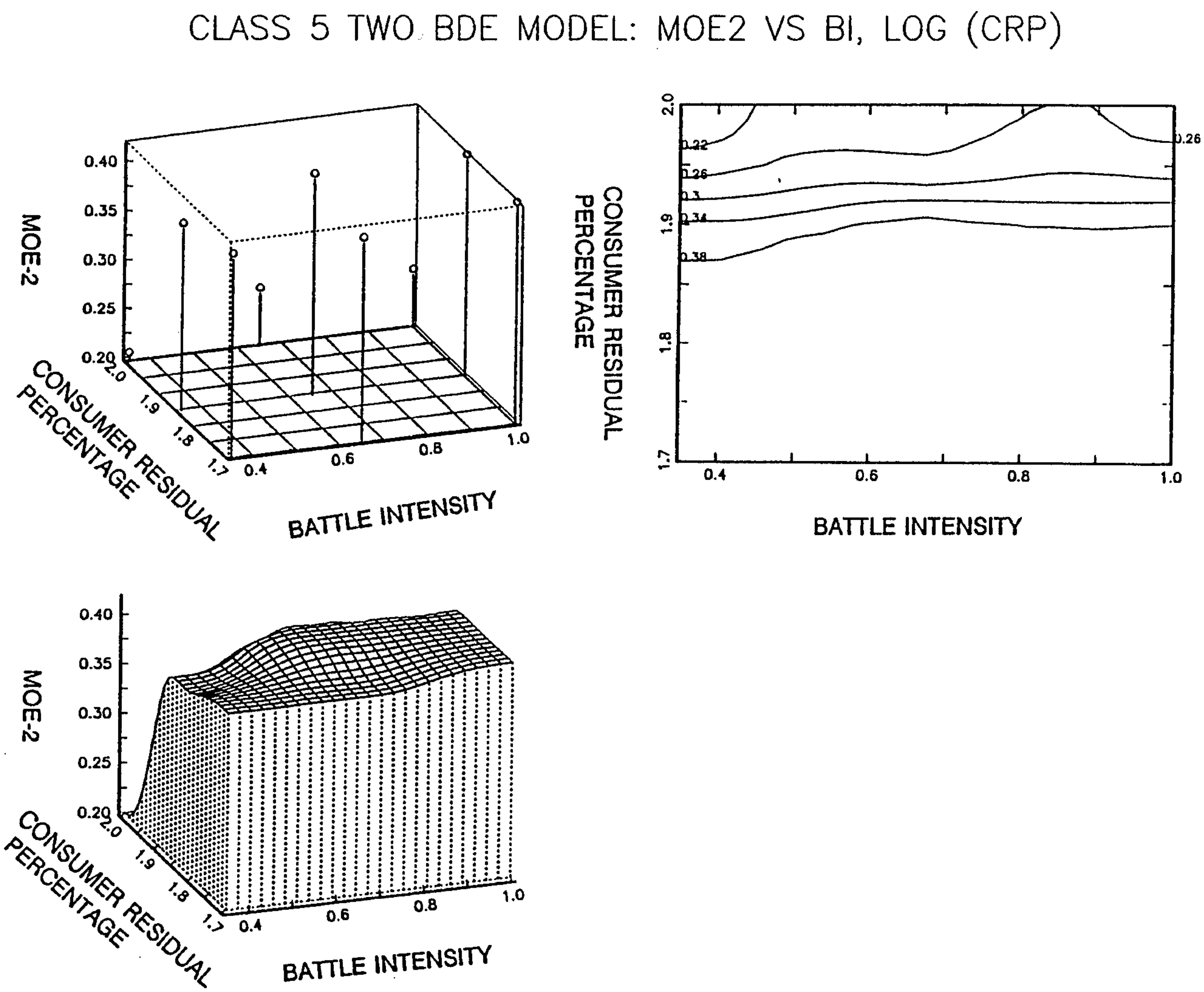

Figure 10. Data, Response Surface, and Contour Plots of MOE-2 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Two-brigade Model.

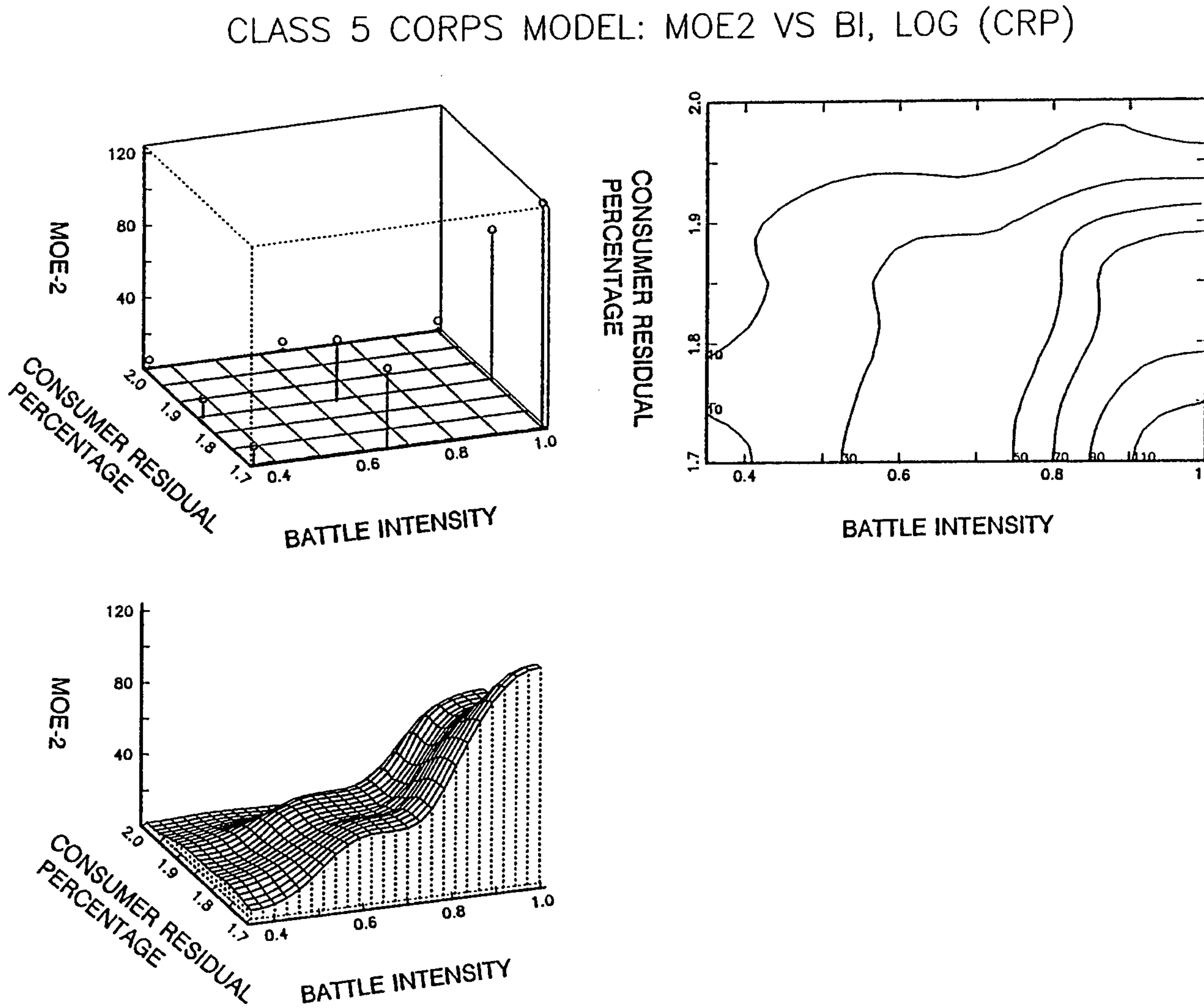

Figure 11. Data, Response Surface, and Contour Plots of MOE-2 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Corps Model.

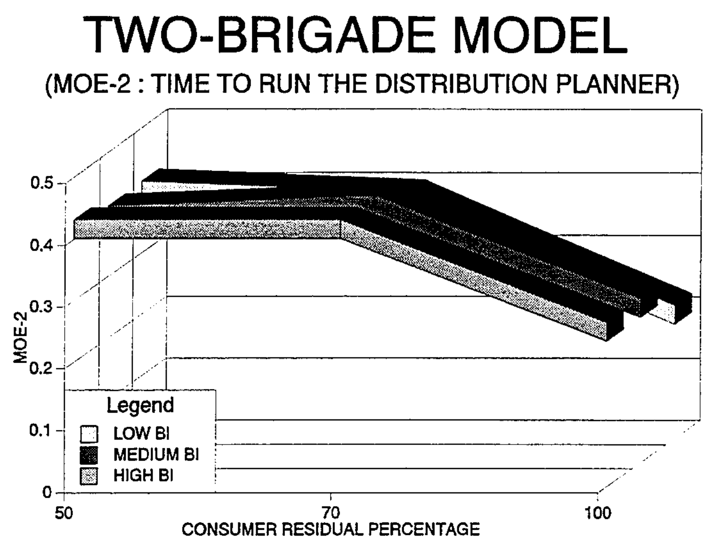

Figure 12. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Two-Brigade Model, MOE-2.

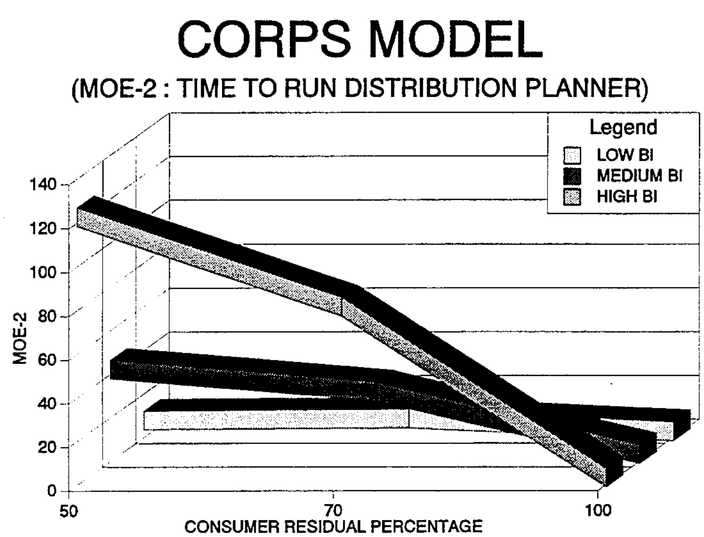

Figure 13. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Corps Model, MOE-2.

corps-sized unit uses fifty-three types of ammunition [Ref. 3:p.7]. Thus, in a corps model, as battle intensity is increased, the effect is not just to increase the quantity demanded for a fixed number of products, as is basically the case with fuel. There is a multiplicative effect of generating larger quantities of a greater number of products with obvious increased impact on the time required for distribution planning.

The time to run the distribution planner was highly sensitive to consumer residual percentage at both the two-brigade and corps levels. The Kruskal-Wallis statistic was significant at the .06 level for the two-brigade model and at the .07 level for the corps model (Table 14). The two-brigade model showed an increase in time required for distribution planning as consumer residual percentage was decreased from 100 to 70 percent. The time to run the distribution planner was insensitive to decreases in consumer residual percentage beyond 70 percent (Figure 10). In the corps model, the time to run the distribution planner increased as consumer residual percentage decreased over its entire range (Figure 11).

The high level of sensitivity of the time to run the distribution planner to the consumer residual percentage is linked to the fact that changing the consumer residual percentage impacts most functions of the distribution planner algorithm. For example, the algorithm calculates a time-phased expected demand for transportation and the requirement for fuel to make these deliveries. Decreasing the consumer residual percentage completely alters the time-phased requirements of each unit and indeed makes the requirement pattern more complex, thus increasing the computation time required by the algorithm. The partial range of sensitivity in the two-brigade model is not intuitive and is probably related to unique features of the implementation of KBLPS. The full-range sensitivity pattern observed in the corps model is the expected pattern.

2. Fuel

When fuel was considered, the time to run the distribution planner showed the same strong sensitivity to a change in unit size from the two-brigade to corps level. As in the case of ammunition, this sensitivity is largely driven by the increase in number of supply points. The Mann-Whitney test statistic was significant at less than the .01 level (Table 15).

TABLE 15. RESULTS OF MANN-WHITNEY TWO-SIDED TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-2 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR FUEL

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
45	<.01	High	Yes

The time to run the distribution planner was essentially insensitive to battle intensity over the entire range of this parameter for both the two-brigade and corps models. The Kruskal-Wallis statistic was significant at greater than .25 for each model (Table 16). The actual values of the test statistics were .251 (two-brigade) and .422 (corps). The response curves were essentially flat in the battle intensity plane over the entire range of this parameter (Figures 14 and

TABLE 16. RESULTS OF KRUSKAL-WALLIS TEST OF MEANS TO TEST THE SENSITIVITY OF MOE-2 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR FUEL

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_0
Battle Intensity	2BDE	.251	>.25	Low	No
	Corps	.422	>.25	Low	No
Consumer Residual Percentage	2BDE	7.322	.026	High	Yes
	Corps	7.200	.028	High	Yes

15). Slight undulations in the two-brigade model were associated with limited interaction effects with the consumer residual percentage parameter (Figure 16). The predominantly flat contours associated with battle intensity in the corps model (Figure 15), suggest that there is no interaction with the consumer residual percentage parameter. This observation is supported by the corresponding factor means plot (Figure 17) where the parallel plots indicate no interaction between

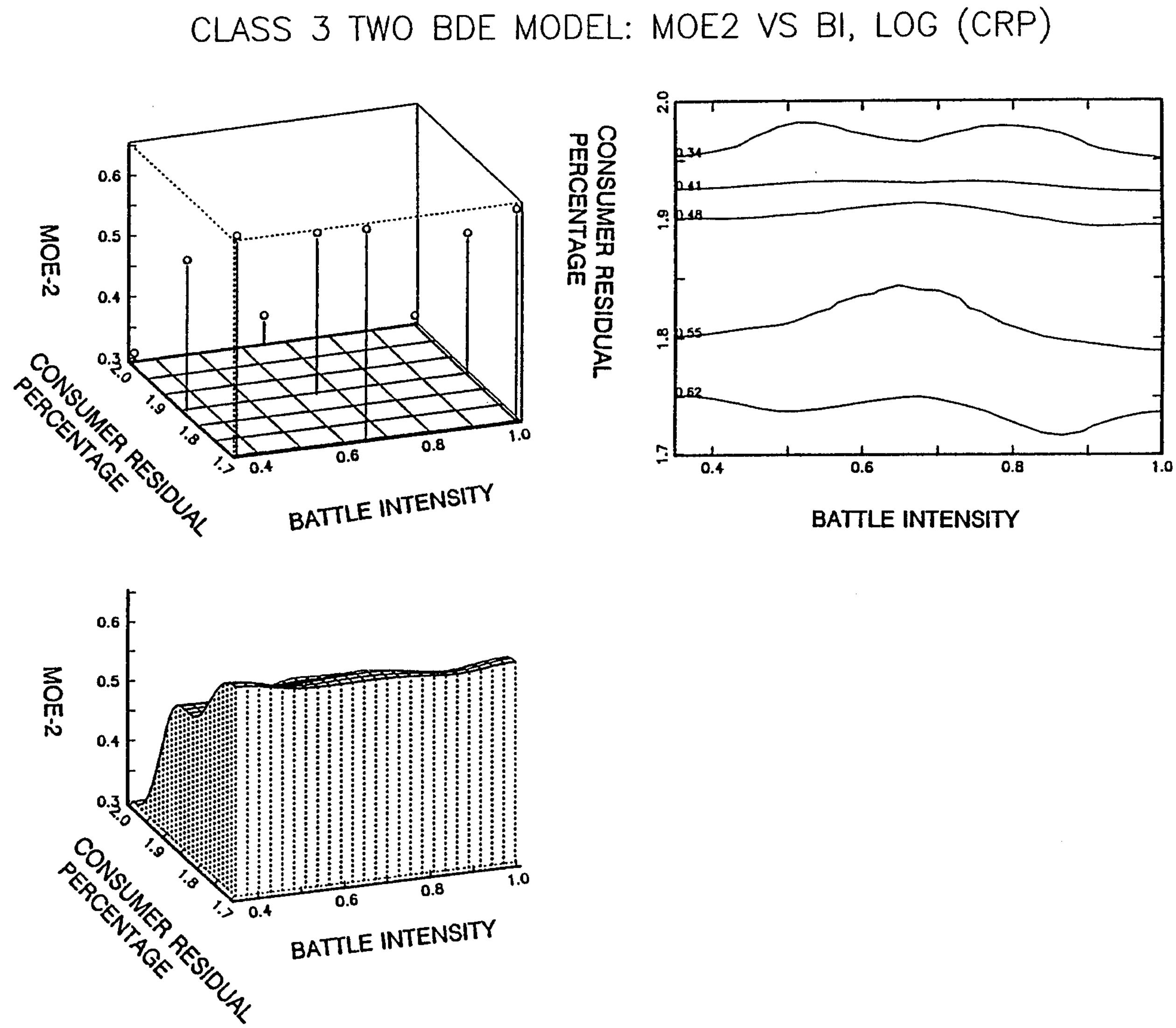

Figure 14. Data, Response Surface, and Contour Plots of MOE-2 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Two-brigade Model.

CLASS 3 CORPS MODEL: MOE2 VS BI, LOG (CRP)

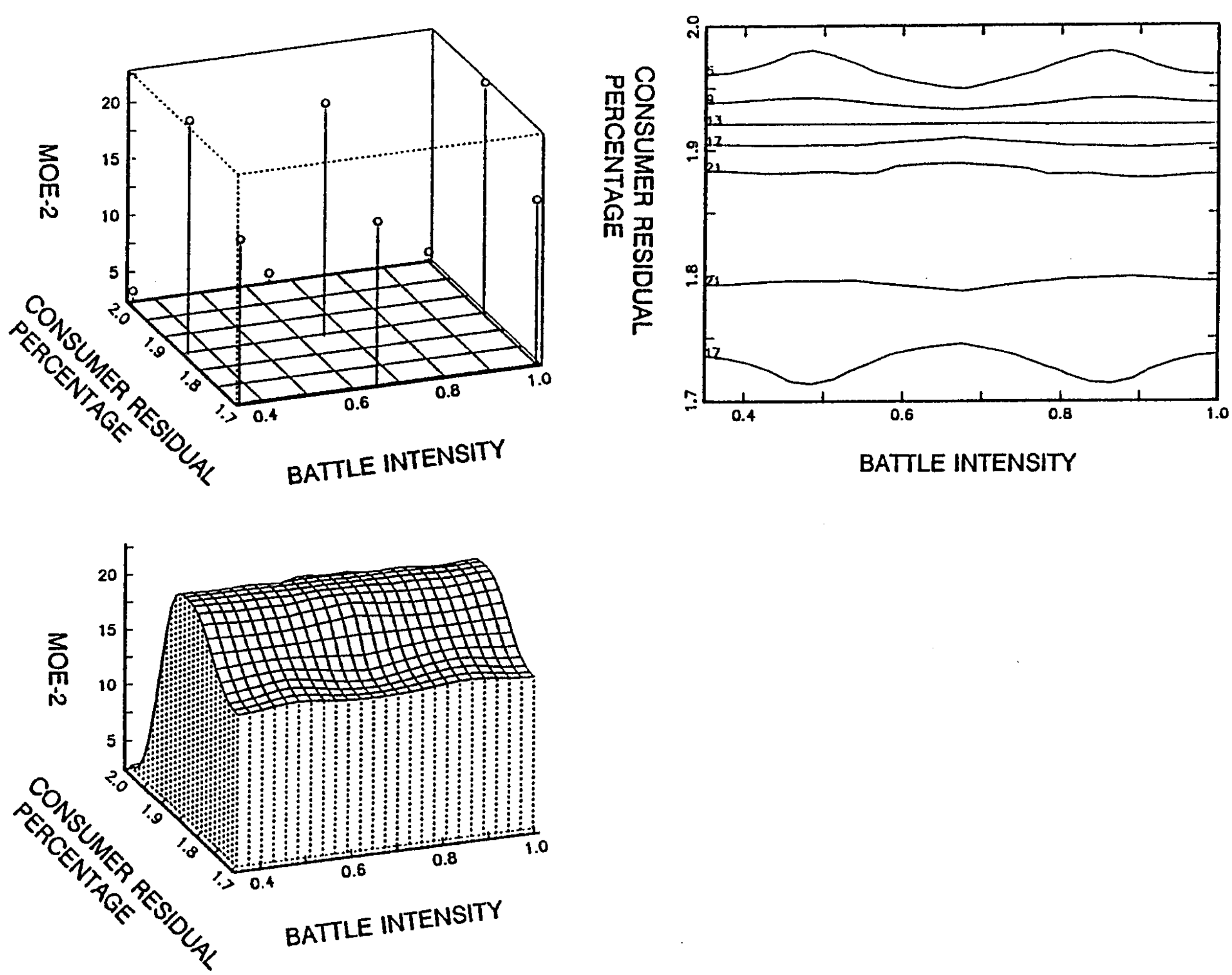

Figure 15. Data, Response Surface, and Contour Plots of MOE-2 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Corps Model.

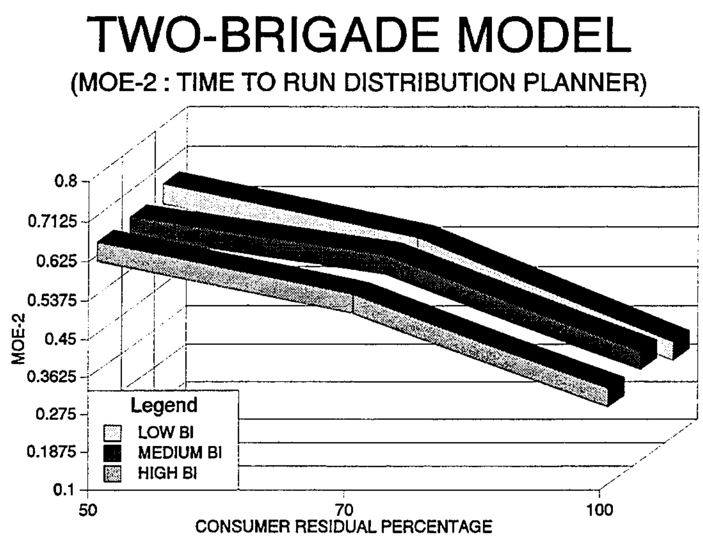

Figure 16. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Two-Brigade Model, MOE-2.

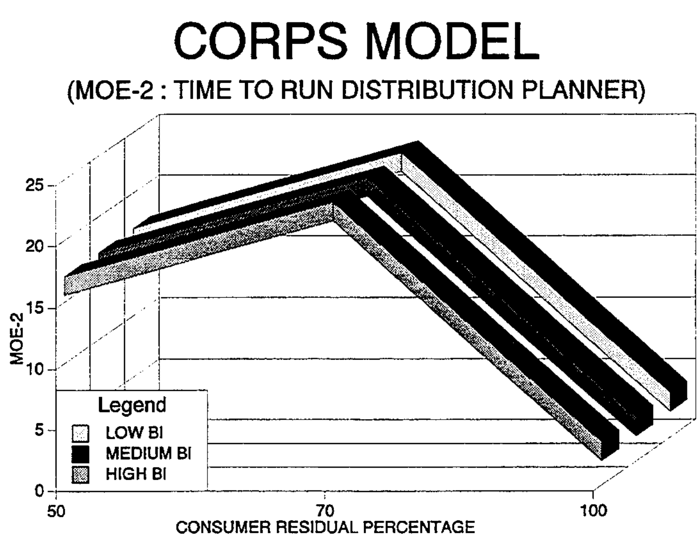

Figure 17. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Corps Model, MOE-2.

the battle intensity and consumer residual percentage parameters. It was shown previously that fuel demand was fairly independent of battle intensity. Further, the KBLPS process merely distributes the quantities derived from the demand generator. No changes in quantity take place. Thus, it is logical that the time to run the distribution planner displayed no sensitivity to the battle intensity parameter.

The time to run the distribution planner was strongly sensitive to consumer residual percentage in both the two-brigade and corps models. The Kruskal-Wallis test statistic was significant at the .026 level in the two-brigade model and the .028 level in the corps model (Table 16). The sensitivities extended over the entire range of consumer residual percentage values. However, the patterns of sensitivity were different. In the two-brigade model, decreasing consumer residual percentage increased the time to run the distribution planner for all values of consumer residual percentage (Figure 14). This sensitivity pattern is intuitive. In the corps model, decreasing consumer residual percentage increased the time to run the distribution planner down to the 70 percent consumer residual percentage level. Beyond that point, further decrease in the consumer residual percentage caused a decrease in the time required to run the distribution planner (Figure 15).

Only some of the above results are intuitive. The high level of sensitivity between the time to run the distribution planner and consumer residual percentage is intuitive. It is related to the impact consumer residual percentage has on the time-phased requirements of the model, and the resulting effect on the distribution planner's constraint-directed search algorithm. The sensitivity pattern displayed in the two-brigade model is intuitive, i.e., the continuous increase in the time to run the distribution planner as consumer residual percentage decreases. The parabolic sensitivity pattern displayed in the corps model is not immediately intuitive, i.e., the reason for the peak in the time to run the distribution planner when the consumer residual percentage reaches 70 percent is unclear.

C. MOE-3: PERCENTAGE FILL OF ORDERS GENERATED

The percentage fill of orders generated (MOE-3) is analyzed first for the ammunition data, then for the fuel data. As noted in the methodology chapter, section D.3, the lack of randomness in the data on the percentage fill of orders generated, precludes the use of confidence intervals and hypothesis tests with this data. Nonetheless, if we are careful about interpretation, some numerical measures usually associated with statistical analysis can be useful in interpreting our results. Namely, the value of the Mann-Whitney and Kruskal-Wallis test statistics can be computed and compared with results from the time to run the demand generator and distribution planner to interpret their sensitivity values.

1. Ammunition

When ammunition is considered, the percentage fill of orders generated showed a high sensitivity to changing the unit size from a two-brigade to a corps sized model (Table 17). This result is intuitive for a number of reasons.

TABLE 17. INTERPRETATION OF MANN-WHITNEY TEST STATISTIC TO DETERMINE THE SENSITIVITY OF MOE-3 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR AMMUNITION

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
123	N/A	High	N/A

First, there is the issue of the increased number of product types (23 to 53) associated with the corps model and the increased number of unit customers with specialized ammunition requirements. This makes the distribution planning process much more complex with the likely outcome of a reduced percentage fill of orders generated. There is also the scenario-unique issue of the road network. The Saudi Arabian desert did not offer numerous alternate main supply routes. Thus, as one changed the scenario from a two-brigade to a corps sized model, one encountered the challenge of the ability of the main supply routes to handle the increased volume of traffic. The intuitive result is thus a decrease in percentage fill of orders generated.

The percentage fill of orders generated showed moderate sensitivity to battle intensity in the two-brigade model and strong sensitivity to battle intensity in the corps model (Table 18).

TABLE 18. INTERPRETATION OF KRUSKAL-WALLIS TEST STATISTIC TO DETERMINE THE SENSITIVITY OF MOE-3 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR AMMUNITION

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_0
Battle Intensity	2BDE	3.787	N/A	Medium	N/A
	Corps	7.200	N/A	High	N/A
Consumer Residual Percentage	2BDE	.471	N/A	Low	N/A
	Corps	.622	N/A	Low	N/A

The percentage fill of orders generated was sensitive to variations in battle intensity over the entire range of this parameter in both the two-brigade and corps models. However, the pattern of sensitivity was inconsistent in the two-brigade model, possibly due to interaction effects between the battle intensity and consumer residual percentage parameters (Figure 18). The overall effect was to increase percentage fill of orders generated as battle intensity increased which appeared counterintuitive (Figure 20). In Figure 19, we see that there are no interaction effects among

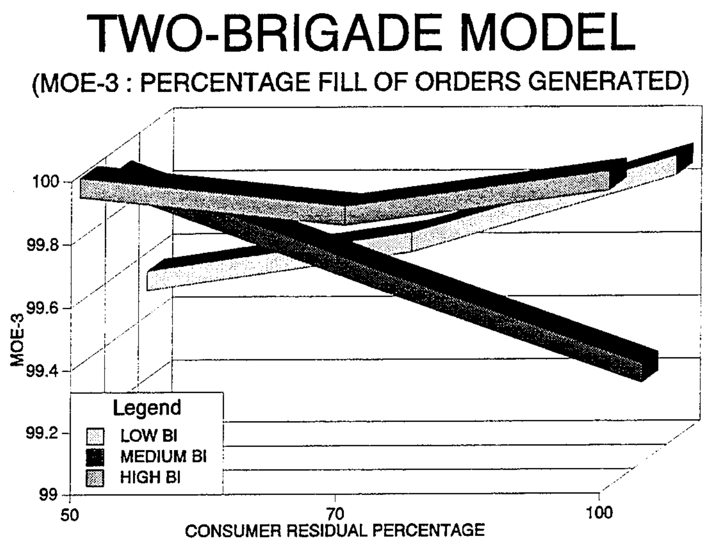

Figure 18. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Two-Brigade Model, MOE-3.

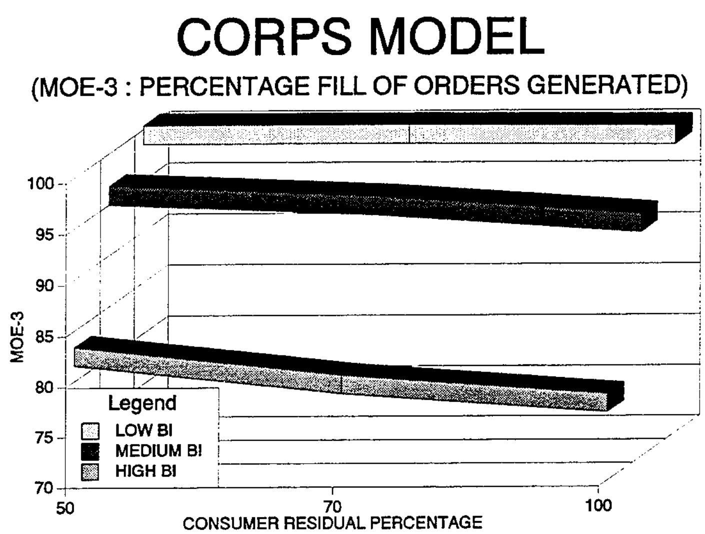

Figure 19. Factor Means showing Battle Intensity and Consumer Residual Percentage Interaction for Ammunition Data in the Corps Model, MOE-3.

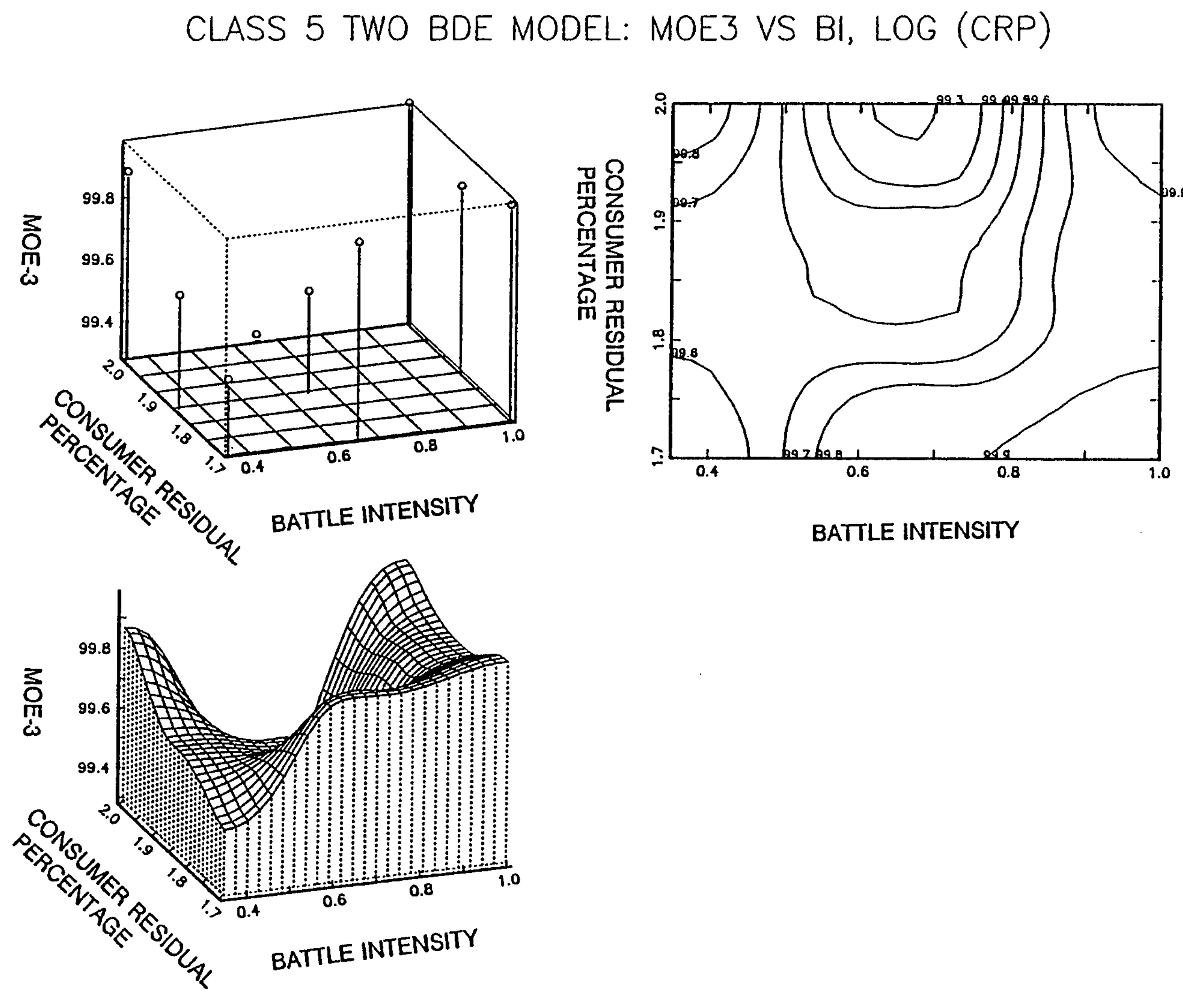

Figure 20. Data, Response Surface, and Contour Plots of MOE-3 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Two-brigade Model.

the battle intensity and the consumer residual percentage parameters in the corps model. Further, the corps model displayed a consistent pattern decreasing percentage fill of orders generated with increasing battle intensity (Figure 21). This is the intuitive result.

As battle intensity increases, demand, and thus the tonnage of ammunition to be distributed increases. This increase in demand, constrained by the fixed number of vehicles to perform deliveries and the capacity of the main supply routes, should logically result in a decreasing percentage fill of orders generated.

The low level of sensitivity displayed by the percentage fill of orders generated to changes in consumer residual percentage appears counterintuitive, particularly at the corps level. One might expect that complications in the distribution process linked to decreasing the consumer residual percentage from 100 to 50 percent would have at least a moderate impact on the efficiency of the distribution process.

2. Fuel

With fuel, the percentage fill of orders generated was only moderately sensitive to a change in unit size from the two-brigade to corps level (Table 19). This reduced level of sensitivity compared with the result for ammunition is intuitive. As unit size increases, the quantity demanded increases. However, the number of products demanded remains

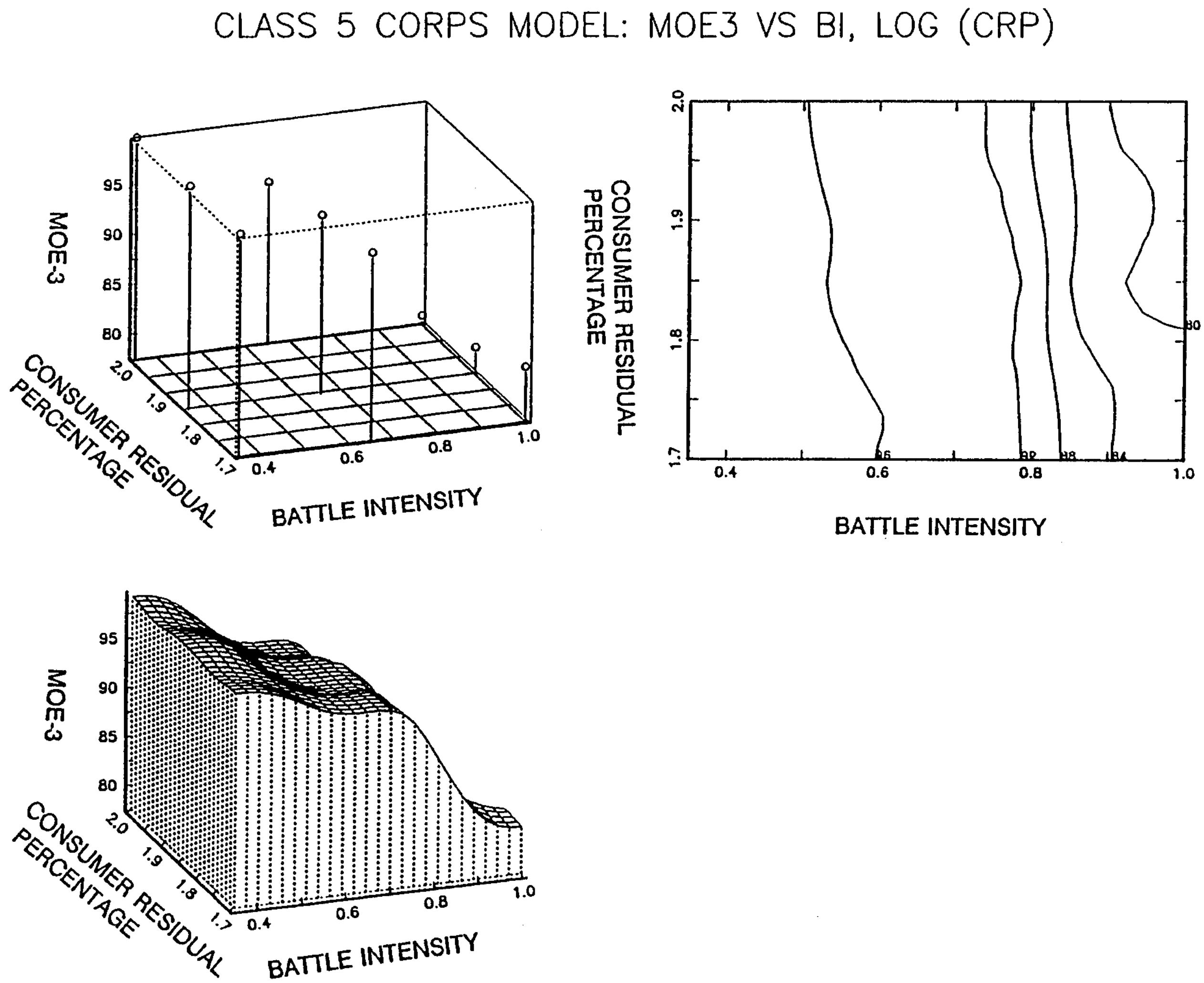

Figure 21. Data, Response Surface, and Contour Plots of MOE-3 vs. Battle Intensity and Log Consumer Residual Percentage for Ammunition Data in the Corps Model.

TABLE 19. INTERPRETATION OF MANN-WHITNEY TEST STATISTIC TO DETERMINE THE SENSITIVITY OF MOE-3 TO THE TWO LEVELS OF UNIT SIZE USED IN THE STUDY FOR FUEL

Test Statistic	Sig. Level	Sensitivity Level	Reject H_o
99	N/A	Medium	N/A

essentially the same. Thus, fuel distribution is not subject to the challenges of distributing many specialized products when unit size increases as is the case with ammunition. In addition, fuel distribution uses some mix of flexible pipeline, tankers, and flexible pods transported by helicopters. As a result, fuel distribution does not feel the impact of congested main supply routes to the same degree as ammunition distribution, when unit size increases.

The percentage fill of orders generated was insensitive to battle intensity over the entire range of this parameter for both the two-brigade and corps models (Figures 22 and 23). The Kruskal-Wallis test statistic for the two-brigade model was zero. For the corps model, the value of the test statistic was .072 which was significant at the greater than .25 level (Table 20). This result is fairly intuitive. So far the data has shown that factors that influence the quantity of supplies demanded and/or the delivery process, influence the efficiency of the distribution process. Battle intensity has been shown to have little or no effect on the quantity of fuel demanded. Further, except in the instance of

CLASS 3 TWO BDE MODEL: MOE3 VS BI, LOG (CRP)

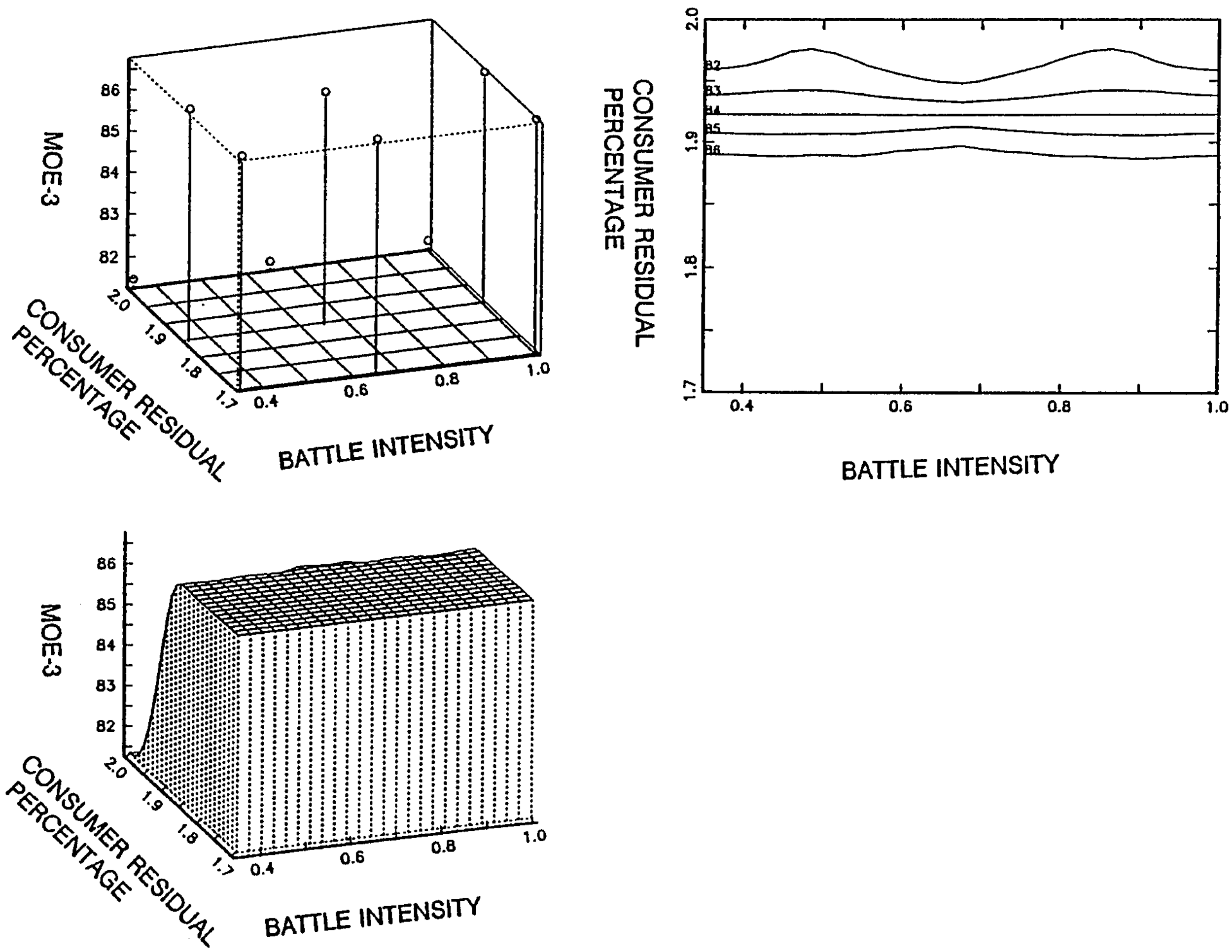

Figure 22. Data, Response Surface, and Contour Plots of MOE-3 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Two-Brigade Model.

CLASS 3 CORPS MODEL: MOE3 VS BI, LOG (CRP)

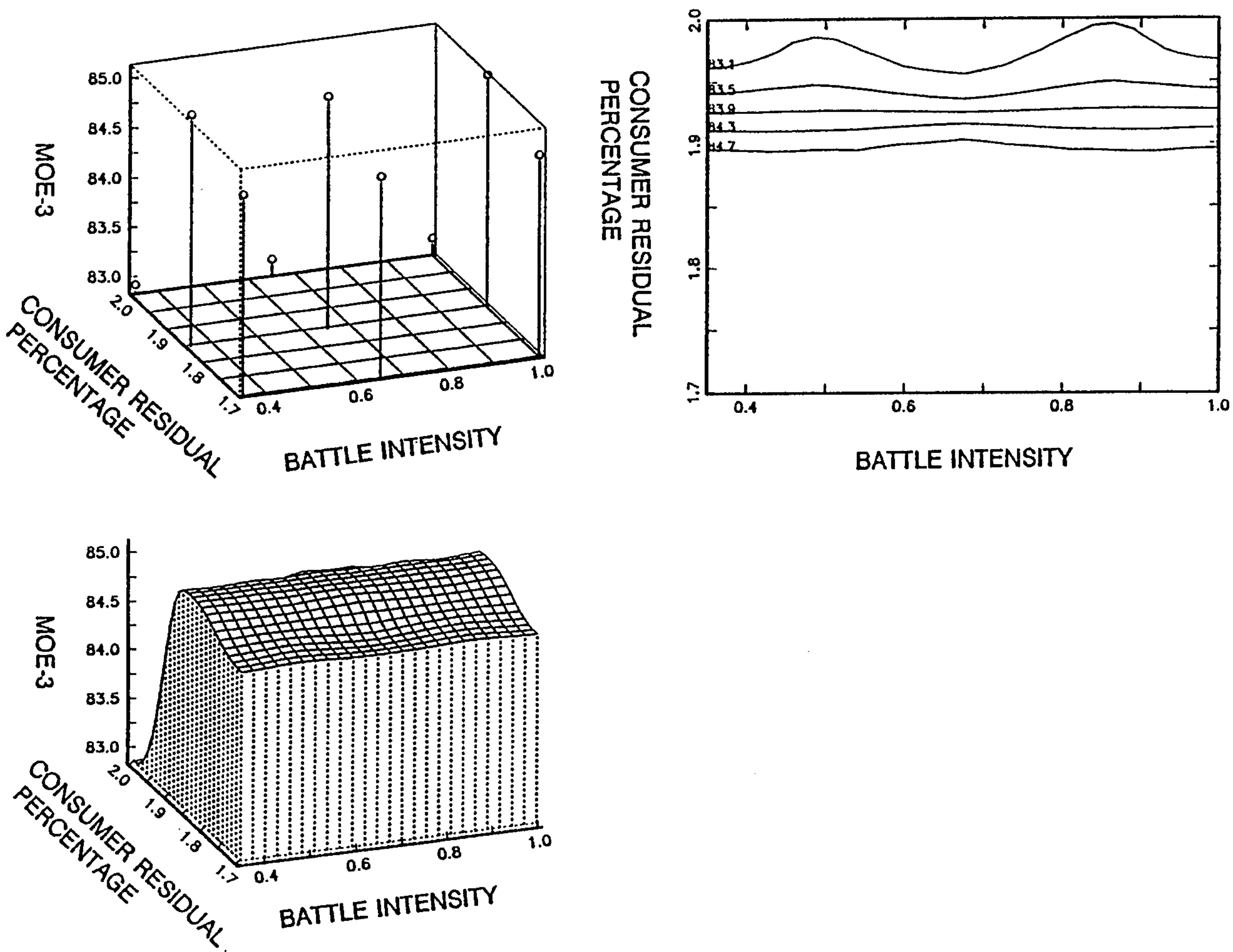

Figure 23. Data, Response Surface, and Contour Plots of MOE-3 vs. Battle Intensity and Log Consumer Residual Percentage for Fuel Data in the Corps Model.

TABLE 20. INTERPRETATION OF KRUSKAL-WALLIS TEST STATISTIC TO DETERMINE THE SENSITIVITY OF MOE-3 TO BATTLE INTENSITY AND CONSUMER RESIDUAL PERCENTAGE FOR FUEL

Parameter	Unit Size	Test Statistic	Sig. Level	Sensitivity Level	Reject H_0
Battle Intensity	2BDE	.000	N/A	Low	N/A
	Corps	.072	N/A	Low	N/A
Consumer Residual Percentage	2BDE	8.000	N/A	High	N/A
	Corps	7.71	N/A	High	N/A

a deep attack by the enemy to disrupt supply flow, which is not modeled here, battle intensity on the front lines would have little impact on the fuel delivery process through the corps area. Thus, it is logical that battle intensity should have little or no effect on the efficiency of the fuel distribution process.

The percentage fill of orders generated was strongly sensitive to consumer residual percentage in both the two-brigade and corps models (Table 20). The range and direction of sensitivities showed some differences in the two sizes of models. In the two-brigade model, the percentage fill of orders generated increased as consumer residual percentage decreased from 100 percent to 70 percent. From 70 percent to 50 percent, the percentage fill of orders generated remained constant (Figure 22). In the corps model the pattern was the same from 100 to 70 percent consumer residual percentage. However, as consumer residual percentage decreased from 70 to

50 percent, the percentage fill of orders generated also decreased (Figure 23). Thus, a maximum distribution efficiency was observed at 70 percent consumer residual percentage in the corps model. There was limited interaction effect in the two-brigade model (Figure 24), and no interaction effect in the corps model (Figure 25). This observation is also conveyed in the response surface curves by their uniformity.

In as much as consumer residual percentage influences the quantity and timing of fuel deliveries, we would expect the percentage fill of orders generated to be sensitive to consumer residual percentage. However, the high degree of sensitivity and the pattern of sensitivity is not intuitive. Decreasing consumer residual percentage from 100 percent means delivering smaller quantities of fuel more often to fill the total requirement for a given period of time. One might expect such a practice to decrease the efficiency of distribution. However, in both the two-brigade and corps models, decreasing the consumer residual percentage from 100 to 70 percent generated a continuous increase in the percentage fill or orders generated. If we accept these results as accurate, we must also recognize that they have strong doctrinal implications.

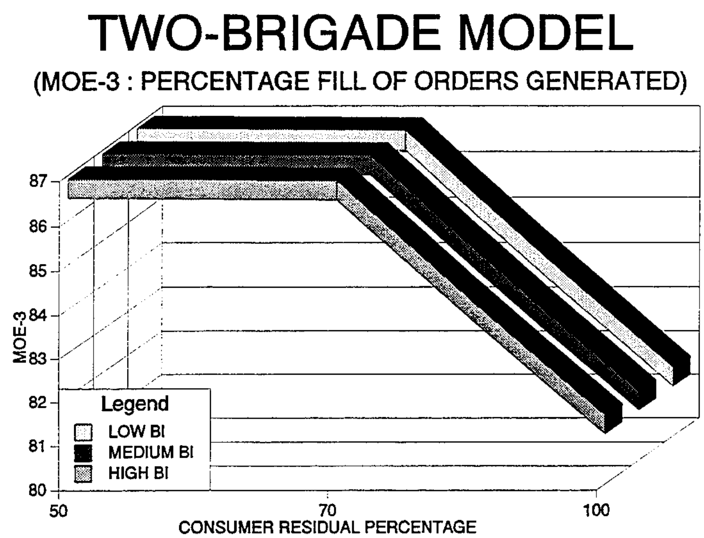

Figure 24. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Two-Brigade Model, MOE-3.

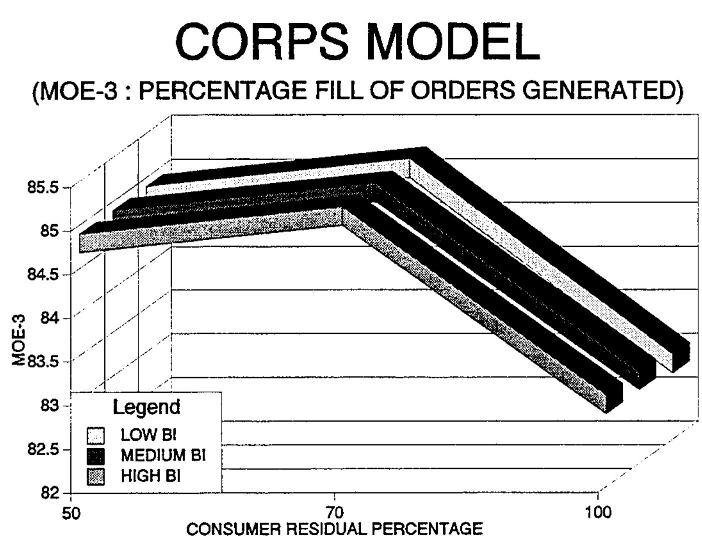

Figure 25. Factor Means Plot showing Battle Intensity and Consumer Residual Percentage Interaction for Fuel Data in the Corps Model, MOE-3.

With the completion of this analysis, we will now proceed to end this study with a presentation of the major conclusions and recommendations forthcoming from the analysis. These are presented in the final chapter.

VI. CONCLUSIONS AND RECOMMENDATIONS

The purpose of this thesis was to conduct a limited results validation of the KBLPS model using the method of sensitivity analysis. Three parameters of the model were selected for variation: unit size; battle intensity; and minimum residual percentage. These parameters were varied in the context of a 2 x 3 x 3 fixed factorial model. Three measures of effectiveness were applied to each parameter:

1. Time to run demand generator;
2. Time to run distribution planner; and
3. Percentage fill of orders generated.

The study sought to obtain answers to four questions:

1. Is the model sensitive to changes in the values of the selected parameters?
2. Do changes in the selected parameters generate intuitive changes in the models output?
3. Are there any interaction effects among the parameters on the measures of effectiveness?
4. What values of input parameters yield the best supply distribution plan for given unit sizes as measured by the percentage fill of orders generated?

This chapter presents conclusions which can be logically drawn from the results of the study. These conclusions are framed within the context of the research questions. Doctrinal implications of the distribution planning results are also discussed. The conclusions are followed by the salient results of the study. Finally, recommendations are provided to include both proposals for action and the manner in which they can be implemented.

A. CONCLUSIONS

The main conclusions of this study are outlined below.

1. Magnitude of Sensitivity

KBLPS appears to be very sensitive to changes in unit size. All the measures of effectiveness were highly sensitive to the change in unit size except the percentage fill of orders generated in the fuel model.

The magnitude of sensitivities displayed by KBLPS to changes in battle intensity and consumer residual percentage appear to be realistic for the most part. The level of sensitivity displayed by each measure of effectiveness to battle intensity and consumer residual percentage, and whether or not these sensitivities were intuitive, are summarized in Tables 21 and 22. Nine of the twelve sensitivity values were considered to be intuitive in the ammunition model. All twelve magnitudes were considered to be intuitive in the fuel model.

2. Direction of Sensitivity

The direction-of-sensitivity data supported the general level of intuitiveness of the model's output. Nine of twelve results were considered intuitive for the ammunition models. Seven of twelve results were considered intuitive

TABLE 21. SENSITIVITY MAGNITUDE VALUES FOR THE AMMUNITION MODELS. L=LOW MAGNITUDE, M=MEDIUM MAGNITUDE, H=HIGH MAGNITUDE. ITALICIZED VALUES WERE NOT INTUITIVE

	Battle Intensity		Consumer Residual Percentage	
MOE	**2BDE**	**CORPS**	**2BDE**	**CORPS**
1	M	*L*	M	H
2	L	L	H	H
3	M	H	*L*	*L*

TABLE 22. SENSITIVITY MAGNITUDE VALUES FOR FUEL MODELS. L=LOW MAGNITUDE, M=MEDIUM MAGNITUDE, H=HIGH MAGNITUDE

	Battle Intensity		Consumer Residual Percentage	
MOE	**2BDE**	**CORPS**	**2BDE**	**CORPS**
1	L	L	M	H
2	L	L	H	H
3	L	L	H	H

for the fuel models. Of major concern, however, was the inverted parabolic shape that described the relationship between the consumer residual percentage parameter and the measures of effectiveness in four instances. The inverted parabolic shape suggested that the action of decreasing consumer residual percentage from 100 percent increased the corresponding measure of effectiveness to a maximum value associated with a consumer residual percentage of 70 percent. Further decrease in the consumer residual percentage resulted in a decrease in the corresponding measure of effectiveness. This result appears counterintuitive because decreasing the consumer residual percentage reduces the size of each supply delivery, increases the number of deliveries, and should progressively complicate the supply planning process.

3. Range of sensitivity

In all cases, each measure of effectiveness was expected to display either sensitivity or lack there of to each of the parameters over its entire range of values. This was recognized in nine of twelve ammunition data results and ten of twelve fuel data results. This further supports the quality of data generated by KBLPS.

4. Interaction Effects

Several cases of interaction effects among parameters on the measures of effectiveness were identified. The strongest effects were in the two-brigade model, with the time to run the demand generator, for both fuel and ammunition. The main effects dominated in the corps-sized models.

5. Distribution Plans and Their Doctrinal Implications

Conventional wisdom in supply distribution has always been to fill supply requisitions in order of priority. This corresponds to a 100 percent consumer residual percentage policy. Deviations from this policy only occur when there are critical shortages of supplies. A check with the commander of the XVIII Airborne Corps' Material Management Center during the Desert Shield/Storm actions indicates that the above conventional wisdom was the governing policy.

The results of sensitivity analysis in this study indicate that such a policy seems reasonable for ammunition. The percentage fill of ammunition orders generated was fairly insensitive to varying levels consumer residual percentage. Thus, one would expect that filling ammunition requisitions by priority would maximize overall unit operational efficiency, and thus enhance mission accomplishment.

In the case of fuel, such a policy results in a suboptimal percentage fill of orders generated. The results indicated that the highest percentage fill of orders generated was obtained when the consumer residual percentage was set at 70 percent. This result leads us to inquire into the relationship between the percentage fill of orders generated and overall unit operational efficiency. Does maximizing percentage fill of orders generated increase or decrease overall unit operational efficiency? Is the conventional wisdom in supply distribution the best way of managing fuel distribution? Certainly, these are important questions that need to be addressed.

B. SUMMARY OF RESULTS

The results of this study suggest that KBLPS is a good model for planning fuel and ammunition supply operations at the corps level. At the two-brigade level, interaction effects among parameters appeared to dominate the main effects of these parameters. The result was sensitivity patterns which were complex and difficult to interpret. This may be a signal that a two-brigade scenario should be considered for exclusion from the model's domain.

C. RECOMMENDATIONS

The results of this study are very encouraging with regard to the validity of the KBLPS output based on the observed sensitivities. However, this study was limited in scope, and a more comprehensive study of this nature could prove useful in validating the full scope of data output from the model.

In the case of fuel distribution, other logistics models should be used to validate the result that a maximum percent fill of orders generated is associated with a consumer residual percentage of approximately 70 percent. Further, studies need to be conducted to see if maximizing percentage fill of orders generated improves overall unit operational efficiency. If the above is true, the concept of using a 70 percent consumer residual percentage for fuel should be tested in field exercises.

APPENDIX A. AMMUNITION DATA

X1	X2	X3	Y1	Y2	Y3
21	1	100	.233	.200	99.87
21	1	70	.267	.383	99.63
21	1	50	.283	.400	99.51
21	2	100	.217	.250	99.29
21	2	70	.283	.417	99.59
21	2	50	.267	.400	99.90
21	3	100	.317	.250	99.98
21	3	70	.250	.417	99.87
21	3	50	.283	.417	99.96
192	1	100	1.467	2.600	99.32
192	1	70	1.983	8.433	99.46
192	1	50	1.967	7.717	99.43
192	2	100	1.717	3.000	93.09
192	2	70	1.900	31.983	94.85
192	2	50	1.917	42.100	95.89
192	3	100	1.667	3.233	77.72
192	3	70	2.317	81.483	79.60
192	3	50	2.083	122.500	82.44

X1 = UNIT SIZE IN BATTALIONS

X2 = BATTLE INTENSITY (1=LIGHT; 2=MEDIUM; 3=HEAVY)

X3 = CONSUMER RESIDUAL PERCENTAGE

Y1 = CPU TIME TO RUN DEMAND GENERATOR IN MINUTES

Y2 = CPU TIME TO RUN DEMAND PROCESSOR IN MINUTES

Y3 = % FILL OF ORDERS GENERATED

APPENDIX B. FUEL DATA

X1	X2	X3	Y1	Y2	Y3
21	1	100	.117	.300	81.35
21	1	70	.150	.533	86.66
21	1	50	.117	.650	86.70
21	2	100	.117	.333	81.35
21	2	70	.133	.550	86.66
21	2	50	.167	.633	86.70
21	3	100	.117	.300	81.35
21	3	70	.150	.517	86.66
21	3	50	.117	.633	86.70
192	1	100	.883	2.867	82.86
192	1	70	1.533	22.533	85.10
192	1	50	1.150	16.317	84.79
192	2	100	.833	2.800	82.94
192	2	70	1.133	22.417	85.10
192	2	50	1.117	16.283	84.79
192	3	100	.817	2.750	82.94
192	3	70	1.117	22.333	85.10
192	3	50	1.150	16.317	84.79

X1 = UNIT SIZE IN BATTALIONS

X2 = BATTLE INTENSITY (1=LIGHT; 2=MEDIUM; 3=HEAVY)

X3 = CONSUMER RESIDUAL PERCENTAGE

Y1 = CPU TIME TO RUN DEMAND GENERATOR IN MINUTES

Y2 = CPU TIME TO RUN DEMAND PROCESSOR IN MINUTES

Y3 = % FILL OF ORDERS GENERATED

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