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THE USE OF SIMULATION TO EVALUATE STRATEGIC AEROMEDICAL EVACUATION POLICY AND PLANNING

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ABSTRACT

This paper describes the first iteration of a top-down approach for building a computer simulation model for use in the evolution and evaluation of strategic aeromedical evacuation policy and planning. The model is modular in nature, completely data driven, quickly adaptable to scenario changes, and meant for use as a policy/planning aid for the Air Mobility Command Surgeon and his staff. In addition, this paper demonstrates the value of using factor analysis in validating a simulation model. It is seen that these techniques can also be employed by a decision-maker to identify the most important factors in a model and describe the relationships between them.

1 INTRODUCTION

Wartime aeromedical evacuation (AE) can be defined as the medically supervised movement of casualties by air transportation to and between medical treatment facilities. AE seeks to improve casualty recovery rates and sustain the morale of combat forces by providing those forces the knowledge that lifesaving medical resources are available and can be quickly and effectively provided to any location in the world (Department of the Air Force 1992b). Strategic AE refers to the movement of casualties from the theater of operations to the continental United States (CONUS). It is a complex operation that involves the integration of medical personnel and policies with airlift concepts and capabilities.

Military analysts within the Air Mobility Command (AMC) Analysis Group at Scott Air Force Base, Illinois, have traditionally used deterministic linear programming techniques to estimate the number of aircraft the United States Air Force (USAF) requires for given contingency scenarios. However, this group desired to develop a stochastic approach to validate their resource recommendations, and more importantly, to study the interrelationships between key factors comprising strategic AE. As the possibility for many smaller campaigns around the world increases, USAF medical planners also require a flexible, analytical tool which captures the major elements of this important mission in order to quickly evaluate differing medical airlift plans and policies. The model described in this paper was developed to meet these objectives.

1.1 A Brief History of Strategic AE

Strategic aeromedical evacuation has its roots in the Vietnam War when, for the first time, the USAF airlifted casualties directly from the theater of operations (Saigon) to Andrews AFB in the CONUS, reducing the total patient travel time by as much as three days (Department of the Air Force 1992a). This new concept saved countless lives. Since then, the minimization of both the travel time from the theater of operations to the CONUS and the number of times a patient is handled during this transit to a hospital has guided nearly all basic efforts to improve strategic AE operations.

Stimulated by these two goals, in May of 1986, Congress authorized the Military Airlift Command, now the Air Mobility Command, to use aircraft from the Civil Reserve Air Fleet (CRAF) to accomplish strategic AE during wartime. For the first time, dedicated aircraft were assigned to this important mission.

During the recent Gulf War, with our airlift capabilities stretched beyond their limits, our forces experienced miraculously low casualty rates. Fortunately, the question of how well the AE system could have serviced mass casualties, originally anticipated to reach into the thousands, did not demand a real answer. It is expected that AE will play an even more visible and prominent role in future warfare.

1.2 Concepts of Aeromedical Evacuation

Management of casualties from the theater to the CONUS is accomplished through a multi-echelon system of care. As described in a report by Battelle Memorial Institute (1990), there are five separate echelons distinguished by the level of care that each echelon is capable of providing. The first echelon (1E) resides on the battlefield at the point of contact and is characterized by self aid or buddy care. The second echelon (2E) provides emergency treatment and tries to return minimally injured casualties to duty as soon as possible. Those who can't be returned to duty are stabilized for movement to a higher echelon facility. Movement from 2E facilities to third echelon (3E) facilities is normally the responsibility of the parent service (Department of the Air Force 1992b). The purpose of a 3E facility is to provide surgical and other specialty care within the combat zone. Fourth echelon (4E) facilities, located within the communications zone (rear part of the theater of operations), offer complete medical facilities including enhanced surgical and other medical subspecialties. These 4E facilities also serve as the aeromedical ports of embarkation (APOEs) for patients to the CONUS. Finally, hospitals located within the CONUS represent the fifth echelon (5E).

CONUS hospitals consist of DOD, Veterans Administration (VA), and civilian hospitals within the National Disaster Medical System (NDMS). The NDMS is a national plan to care for the victims of large-scale natural disasters using military and civilian resources. NDMS will also provide beds to wartime casualties (Lee 1986).

Strategic AE is driven by a process known as patient regulation, in which a casualty is matched to a CONUS hospital capable of providing the appropriate level of medical care. Regulation results in a requirement to move a specific patient to a specific hospital (Department of the Air Force 1992b). The regulation process identifies and tracks stabilized patients within the theater, finds appropriate beds for them at a destination hospital in the CONUS, and coordinates airlift for the needed transportation.

2 MODEL DEVELOPMENT

The simulation model was written using the personal computer version of SIMSCRIPT II.5. The use of SIMSCRIPT was specified by the sponsor and turned out to be a good choice since it allowed a modular, data-driven design (as described later) to be readily incorporated and is very portable, requiring only slight input/output modifications to run on different machines.

2.1 Assumptions and Limitations

This research models only the strategic operation of the Boeing 767 CRAF for medical evacuation, i.e., the aircraft operations and patient movement from the designated aerial ports of embarkation in the theater of operations to the CONUS receiving hubs. It does not explicitly model patient movement below the 4E level in the theater of operations nor does it consider the physical redistribution of patients in the CONUS once they have been delivered to a regional hub. (The reason for this is to concentrate on the strategic element of AE, not its interaction with tactical theater or CONUS airlift.) The methodology is built around the assumption that strategic AE missions are primarily demand driven, responding directly to the number of casualties requiring airlift. It assumes ample support personnel, flight crews, support equipment, etc. to sustain 767 operations and to handle casualties.

The simulation controls the number of concurrent strategic flights to a particular 4E facility by means of a resource called MOG (an acronym for maximum on ground). While the name implies ramp space allocated for aircraft, it can be used for the most limiting constraint at the 4E facility, say the number of medical personnel available to onload patients or the number of medical aircrews available to fly strategic missions.

2.2 Model Design

In order to be able to respond efficiently to the "what-if" nature of a contingency planning environment, a data-driven design was incorporated in developing the model. By this we mean that only the general structure of the AE process is modeled by the simulation code, while any aspects relating to specific scenarios is controlled solely through the input data. These scenarios may differ in the intensity of conflict, location and number of medical facilities, quantity of airlift and medical resources available, or AE strategy and policies employed. Divorcing these aspects from the simulation code enables the analyst to quickly change the array of options under consideration by medical planners by editing the input data structure, and not by recoding the simulation.

In order to provide as flexible a model as possible, a modular approach was taken in developing the simulation code, with each module either representing a particular process (or major element) of strategic AE or providing control of the simulation. This provides a convenient structure for modifying or embellishing the model, say by incorporating tactical AE, if desired.

In all, fifteen different modules or routines make up the simulation program. The modules which model the strategic AE process perform the following functions:

• create the appropriate numbers and types of patients at the appropriate times;
• perform the patient regulation function;
• search every 3E facility which needs to transport patients and "move" these to the appropriate APOE (4E facility) for subsequent AE to the CONUS;
• check the demand for strategic AE for each 4E;
• schedule strategic AE missions by assigning specific aircraft (if any are available) to specific routes;
• perform the event scheduling required to represent the activities associated with flying a strategic AE mission;
• match aircraft as they become available against missions that have been previously delayed; and
• check within each CONUS region and discharge patients one they have healed.

3 SCENARIO

Although the model is not scenario dependent, it is beneficial to use a representative scenario to exercise, evaluate, and to some extent validate the capabilities of the methodology. The following scenario, provided by the sponsors of this research, serves this purpose and also provides a baseline for analyzing the simulation output.

A 180-day period of conflict fought in two separate theaters, Southwest Asia (SWA) and the Far East. (This places a great demand on AE airlift operations since aircraft are flying in two separate directions from the CONUS with one of the destinations being approximately half way around the world.) The SWA theater contains three APOEs that are each fed by two 3E facilities. The Far East theater has two APOEs that are also each fed by two 3E facilities. This accounts for a total of five APOEs serviced by ten 3E facilities.

A total of 45 Boeing 767-200 series aircraft with a capacity of 102 patients each are available from the CRAF. These aircraft are based on either the east or west coast of the United States. Each can be used to fly any one of 37 different routes between the basing locations, the APOEs, and the CONUS destinations.

Casualties begin arriving on day one in the SWA theater and 40 days later they begin arriving in the Far East. Figure 1 shows the rate at which approximately 67,000 patients will arrive over the 180 day period. Patients are of eight different types and must be assigned to hospital beds in the CONUS appropriate for their type of injury. A total of 142,000 beds are available in the six CONUS regions for patients, with 37,000 available at DOD hospitals, 34,000 at VA hospitals, and the rest at NDMS hospitals.

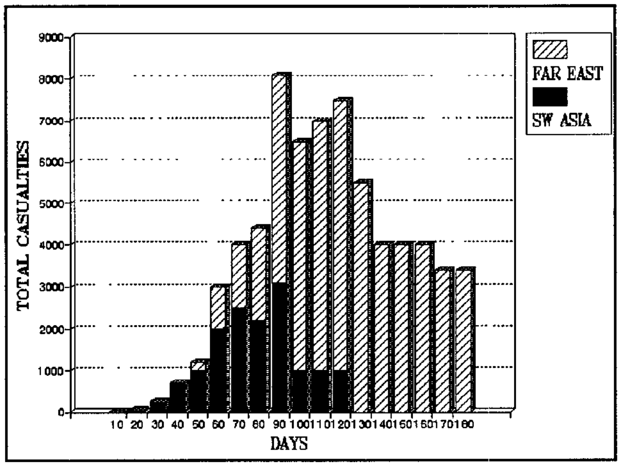

Figure 1: Two Theater Casualties

4 VERIFICATION AND VALIDATION

The fact that the personal computer version of SIMSCRIPT allows code to be compiled separately in modules facilitated the initial verification of each module to ensure that the corresponding code worked as desired. The code was verified in a traditional manner by tracing the values of relevant variables and statistics within both scaled-down and deterministic versions of the scenario, checking the output for reasonableness, and subjecting it to a number of structured walk-throughs with members of the research team and the sponsoring organization.

Validating a model such as this is a much more formidable task since it portrays a system that, although currently foreseen and planned for, does not yet exist. That is, the strategic AE process being modelled is actually nothing more than a plan, based on general policies, to employ during periods of conflict a set of resources that are used in different ways during peacetime. The Boeing 767 aircraft are presently airliners that will come from the CRAF. Likewise, 93 percent of the personnel that will execute the plan will come from the Air Reserve Component (Department of the Air Force 1992b).

The authors have aggressively pursued the three-step approach for model validation described by Law and Kelton (1991). The first step, referred to as gaining "high face validity," describes how this research began. There have been two face-to-face meetings with both the end user (the AMC medical planning staff) and the organization that will inherit and exercise the tool. These meetings with the "system experts" produced the framework and assumptions for the simulation model. In addition, dozens of other telephone conversations with these and other experts in closely related fields have helped to define reasonable assumptions about model fidelity, values for input data, and model logic.

The second step toward validating a computer model is to test its assumptions empirically. The primary tool used to accomplish this was a preliminary, univariate analysis. This provided a quantitative way to test whether or not the simulation responded in the way expected when a single factor or policy was changed. The results of this analysis also helped to guide the choice of appropriate factors (and their levels) used in a more extensive designed experiment.

The last step is to examine whether or not the simulation output is representative of the real world. Since there is no ongoing AE process to measure in this case, one must rely on what experts in the field think is representative. We found factor analysis to be particularly well-suited for this task since it can provide a simplified description of the complex interrelationships that exist among the multiple output variables which, in turn, can then be compared against the insights and intuition of the system experts.

We discuss these last two validation steps in more detail in the following sections.

5 UNIVARIATE ANALYSIS

The objective of this analysis was to assess model validity by examining the effects of changing one input factor at a time on a single measure of system performance--the average time patients spend in the strategic AE system, as measured from the time a patient is stabilized (and thus eligible for AE) to the time he/she arrives at the CONUS region. Five input factors that were expected to be important were identified and "baseline" levels for each were postulated. These are [with baseline levels in brackets]:

1. Frequency of regulation [once every 8 hours];
2. Regulation policy ["organization-then-region"];
3. Number of Boeing 767 aircraft available [45];
4. Command and control structure [centralized];
5. Resources available at the APOE as measured by MOG [3].

In the baseline scenario, patients are regulated every eight hours and are first assigned to DOD beds in the closest CONUS region. Once a certain specified proportion of DOD beds in that region are filled, patients are assigned to DOD beds in the next closest region. Once all DOD beds are filled in all regions, patients are then assigned to VA beds in nearest region order. If all these are filled, they are then assigned to NDMS beds, again in nearest region order. We refer to this as the "organization-then-region" fill policy.

An alternative regulation policy is to search for a bed for a given patient first within a region in DOD-VA-NDMS order. Once a region is full, the search continues in the next closest region. This is referred to as the "region-then-organization" fill policy.

The baseline case also assumes that command and control of the CRAF fleet is "centralized" in the sense that the aircraft are under the control of a single integrated manager and can be assigned to routes in either theater as needed. An alternative structure, described here simply as "decentralized," places the aircraft under the control of the theater commanders and limits their service to routes specific to their assigned theater.

Five replications of the simulation were performed for the baseline scenario and for twenty-three others which differed from the baseline case (or each other) by changing the level of one factor. Table 1 summarizes the results for the baseline case and seven of the most interesting alternatives.

Table 1: Results of Univariate Analysis

Policy/Resource Change	Mean Time in System (hours)
Baseline Scenario	73.1
Theater Regulation Frequency: Once Every 4 Hours	68.1
Regulation Policy: "Region-then-organization"	56.2 **
Cmnd./Control: Decentralized	74.6
Number of Aircraft: 15	75.0
Cmnd./Control: Decentralized Number of Aircraft: 15	116.8 **
MOG Resource: 2	108.4 **
MOG Resource: 4	73.8

** Mean time in system differs from baseline by $\geq$ 6 hours at the 5% level of significance.

The choice to regulate first across CONUS regions produced the most dramatic improvement, a nearly 25% reduction in average time in system. In fact, the average time in system for every run that used the regulation policy "region-then-organization" was about 25% smaller than when the "organization-then-region" policy was used. Increasing the regulation frequency to once every 4 hours for each theater was the only other policy change that decreased time in system. Decreasing the regulation frequency increased time in system.

It was, at first, surprising that decreasing the number of aircraft from 45 to 15 only slightly increased the time in system, as did changing to decentralized command and control. On the other hand, when the combination of these two changes was applied, average time in system ballooned to 116.8 hours. This, however, reflects the fact that 15 aircraft are essentially adequate to handle the demand provided that they can be assigned to either theater as needed. When they are dedicated to theaters, missions may be delayed in one theater while aircraft sit idle in the other.

Time in system was seen to be insensitive to increases in MOG from its baseline value of three. However, when 1 unit of MOG was removed, time in system rose dramatically to 108.4 hours. This suggests that the use of MOG to represent the aggregated resources at an APOE has introduced a lack of fidelity that requires attention.

In all, however, the results of this one-at-a-time analysis suggested that the model was performing in accordance with the experts' intuition. To then investigate the magnitude or relative importance of the five main input factors and to check for the existence of possible interactions between them, an analysis of variance (ANOVA) was performed on the results from a full 2^5 factorial experiment wherein each factor was varied between two relatively high and low levels. The factor level settings are displayed in Table 2. Five replications were performed at each design point.

Table 2: Factor Levels for 2^5 Experiment

Input Factor	Low	High
Regulate Frequency	8 hours	24 hours
Regulation Policy	Region-then-Organization	Organization-then-Region
Number of Aircraft	15	45
Command/Control	Centralized	Decentralized
MOG Resource	2	4

All main effects and all but two of the two-way interactions (and some three-way interactions) turned out to be significant. Among main effects, the MOG resource seems most influential, followed by the regulation policy and number of aircraft. These results generally confirm the experts' intuition of what factors are important. The number of significant two- and three factor interactions highlights the fact that AE is a complicated business that possesses many tradeoffs. This suggests that it would be worthwhile to pursue a broader analysis which investigates the relationships between factors.

6 MULTIVARIATE ANALYSIS

The desire to understand the general impact and interrelationships of the major strategic AE elements influenced the choice of statistical techniques used to study the simulation output. The purpose was not to perform a definitive analysis to determine a patient's mean time in system for a given scenario but rather, for a representative scenario, to investigate the major drivers affecting strategic AE. This not only serves the analyst in validating the simulation, but also serves the medical contingency planning community by confirming or denying their intuition of the process, and providing a framework for better understanding the possible tradeoffs amongst the key elements and policies for strategic AE.

Multivariate statistical techniques are particularly useful for studying the correlations between many variables. The primary technique which we apply is factor analysis. [The description of factor analysis which follows is based on discussions found in both Dillon and Goldstein (1984) and Morrison (1976).]

In particular, we apply factor analysis to the output obtained from the results of the experiment described earlier in Table 2. Five replications of the simulation were performed at each of the 32 design points and the following seven output variables were observed:

1. Average time patients spend in the AE system;
2. Average time in system for the Far East theater;
3. Average time in system for the SWA theater;
4. Average aircraft utilization (ute) rate;
5. Maximum aircraft utilization rates over the length of the conflict (measured every ten days);
6. Average number of patients in all 3E facilities;
7. Percentage of missions that were delayed because there were no aircraft available to fly the mission.

Factor analysis assumes that the output variables are linear functions of a small number of unobservable "common factors" and an unobservable "unique" or "specific factor." That is, it assumes a model of the form

$$\mathbf{X}_i = \lambda_{i1}\mathbf{Y}_1 + \lambda_{i2}\mathbf{Y}_2 + \cdots + \lambda_{im}\mathbf{Y}_m + \mathbf{e}_i$$

for each i = 1, 2, ... , 7 where

$\mathbf{X}_i$ = vector of responses for the i^{th} output variable;

$\mathbf{Y}_j$ = a vector representing the j^{th} unobservable common factor and whose elements are assumed to be independent standard normal random variables;

$\mathbf{e}_i$ = a vector representing the unique factor associated with response variable i whose elements are assumed to be normally distributed with zero mean;

λ_{ij} = the "factor loading" which relates the j^{th} common factor to the i^{th} response variable;

and the $\mathbf{e}_i$'s are assumed to be independent random vectors that are, in turn, independent of the common factors. In this case, the factor loading λ_{ij} represents the correlation between the i^{th} output variable and the j^{th} factor and thus relates the degree to which a specific variable loads on the specific factor.

We (somewhat arbitrarily) assume that the appropriate number of common factors to use in this case is m = 3. This is based on the common judgement that more than two or three factors are generally not needed and are difficult to interpret. [It is also consistent with the results of a preliminary principal components analysis, as described in Wolfe (1993).] A set of factor loadings for our observed output is summarized in Table 3. Loadings (or correlations) whose absolute values are greater than 0.3 can be considered significant.

Table 3: Factor Loadings

Output Variable	λ_{i1}	λ_{i2}	λ_{i3}
Avg. Time in System (TIS)	0.94147	0.17157	0.28393
SWA TIS	0.29847	0.00998	**0.95153**
Far East TIS	**0.97443**	0.18704	0.09489
Avg Ute Rate	0.18852	**0.97940**	0.04248
Max Ute Rate	0.08291	**0.99009**	0.05140
Avg # in 3E	**0.92299**	0.16875	0.33837
% Delayed	0.63350	**0.72505**	-0.10480

(Interestingly, it is possible to obtain an infinite number of sets of factor loadings for a specific set of observations of the output variables, with each set corresponding to a different rotation or reflection of the coordinate axes of the m-dimensional common-factor space. The loadings displayed in Table 3 result from a "varimax rotation" which has mathematical properties usually associated with a set of meaningful and interpretable common factors.)

The factor loadings (i.e., the λ_{ij}'s) can be used to help interpret what the factors represent. Usually, the highest loadings for each component are identified and the analyst then attempts to assign a meaning or interpretation to each factor accordingly. In our case, it appears from Table 3 that the first factor is an overall measure of patient handling since it the highest loadings occur for patient time in system (overall and Far East) and the number in 3E hospitals awaiting transport. The second factor appears to be a measure of aircraft use since heavy loadings are obtained for the two utilization rates and the percentage of missions delayed. The third factor has a high loading only for a single variable, time in system for the Southwest Asia theater.

To help better understand what these factors mean, one can additionally estimate the values of the common factors corresponding to each observation from our simulation experiment, usually referred to as the "factor scores." These are obtained by estimating "scoring coefficients" which are used to compute the factor scores as linear combinations of the values of the output variables and are obtained using regression methods. Table 4 displays the standardized scoring coefficients that can be used to compute the factor scores for each of the 160 observations in the designed experiment.

Table 4: Standardized Scoring Coefficients

Output Variable	Factor 1	Factor 2	Factor 3
Avg. Time in System (TIS)	0.32554	-0.08946	0.00328
SWA TIS	-0.20543	0.04381	1.00472
Far East TIS	0.40838	-0.10965	-0.22851
Avg Ute Rate	-0.13453	0.44238	0.08680
Max Ute Rate	0.29686	-0.08090	0.07353
Avg # in 3E	0.19609	0.20549	-0.27770
% Delayed	0.63350	0.72505	-0.10480

Figures 2 through 4 show the results of plotting the standardized scores corresponding to the average responses observed over the five replications performed at each of the 32 design points in our simulation experiment. By studying these figures, in conjunction with the input parameters associated with each observation, one can assign a label to each of the factors and begin to better understand which input parameters influence each factor.

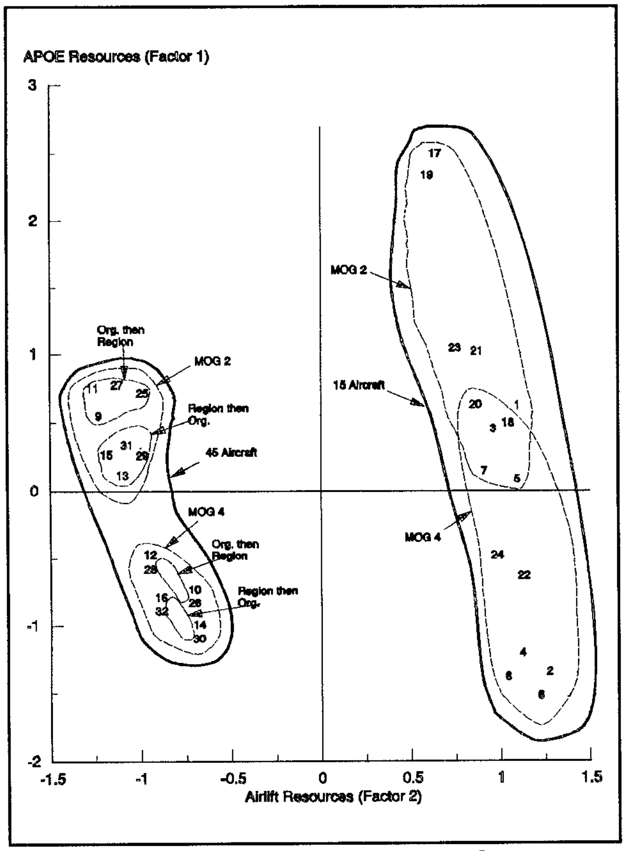

Figure 2: Factor 1 vs. Factor 2

Figure 2, the plot of Factor 1 versus Factor 2, reveals several things. First, there are two distinct groups of data along the Factor 2 axis which clearly correspond to the number of aircraft. Factor 2 is thus labeled "Airlift Resources." This is consistent with the fact that the variables which describe aircraft utilization load high on this factor.

It is also interesting that several items influence the variance along the Factor 1 axis. The primary variable is MOG, with higher values of MOG being toward the bottom of the graph. For this reason Factor 1 is labeled "APOE Resources." Within each MOG subgroup, another set of groups is defined by the regulation policy, with "region-then-organization" producing lower Factor 1 scores. In general, because the overall time in system and the time in system for the Far East theater load heavily on Factor 1, the lower the Factor 1 score, the lower are these measures of performance.

Figure 3, the plot of Factor 1 versus Factor 3, again reveals the importance of MOG on the Factor 1 scores. In general, observations with positive factor scores have a MOG value of 2, while those with negative scores

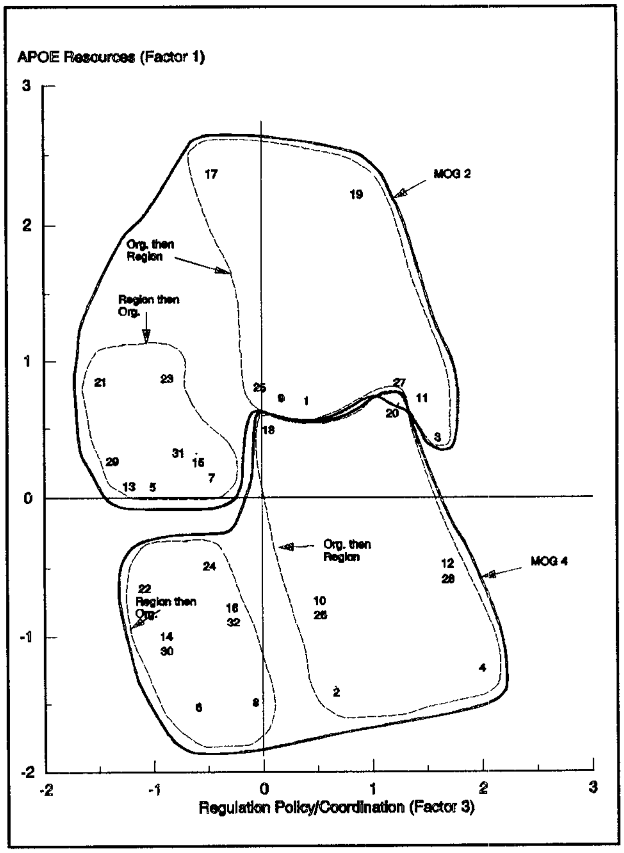

Figure 3: Factor 1 vs. Factor 3

have a MOG value of 4. The exceptions are observations 18 and 20, whose positions are attributed to a low number of aircraft used in conjunction with a decentralized command and control policy.

The variance in Factor 3 indicated by the groupings along the Factor 3 axis in Figure 3 is clearly attributed to the regulation policy. Therefore, Factor 3 is labeled "Regulation Policy/Coordination." Additionally, the observations within the "region-then-organization" groups tend to be more tightly clustered than those within the "organization-then-region" groups. This is because the former policy is more flexible in handling fewer airlift in a decentralized command and control structure.

Figure 4, the plot of Factor 2 versus Factor 3, again shows a big split in the observations along the Airlift Resources (Factor 2) axis. Note that the higher the number of aircraft, the lower the factor score. Since the utilization rates load heavily on this factor and since the ute rates are inversely related to the number of aircraft, a higher number of aircraft produces lower ute rates and, thus, lower factor scores.

Again, the variance along the Factor 3 (Regulation Policy/Coordination) axis is defined by the regulation policy and the regulation frequency. Interestingly, since

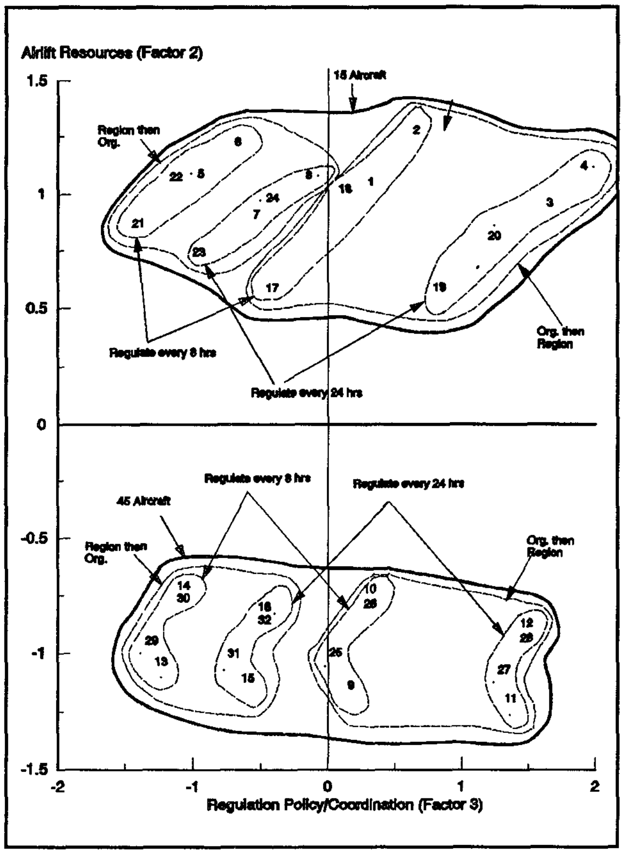

Figure 4: Factor 2 vs. Factor 3

Factor 3 is heavily loaded by time in system for the SWA theater, as time in system for the Southwest Asia theater decreases, so too does the Factor 3 score. Finally, with 15 aircraft, the tradeoffs between regulation policy and frequency are more complex than they are with 45 aircraft. This makes sense since the more resources one has, the more options there should be.

Many, many more inferences can be made from these plots. The point is that they unveil what the main factors are and how they are related, and spur both the modeler and the planner to ask key what-if questions.

7 INSIGHTS & CONCLUSIONS

Three main factors appear to significantly affect strategic AE operations: resources located at an APOE, the regulation policy used, and the number of aircraft available. The prominent role of MOG on "APOE Resources" factor again suggests that model fidelity could be enhanced by modeling APOE operations more explicitly. A large amount of interaction exists between the major elements of strategic AE, indicating that there is vast potential for tradeoffs, depending on the end user's objectives.

There are many possible uses for this simulation model. Some particular objectives that could be accommodated and which would be of interest to medical planners are:

- to assist CRAF activation planning in estimating the cost of different activation options (e.g., numbers of aircraft or aircraft capacities) based on an expected utilization rate of the fleet;
- to identify the set of regulating policies that will work best under the most common scenario conditions;
- to identify and plan for bed shortages by patient type;
- to study the effect of limiting bed availability to certain organizational types, such as just DOD, or DOD and VA only;
- to study broad medical resource allocation tradeoffs, for example, the tradeoff between assigning trained medical personnel to aircrews or assigning them to 3E or 4E facilities.

There are many more topics that could be discussed, but the point is that the model has the fidelity and flexibility to address these types of questions fairly quickly. Further, the use factor analysis can also simply this analysis by focusing attention on a few key common factors. After the model is used to answer some of these type questions, no doubt it will spur the medical planners to explore even more options and ask more questions. The proper application of this tool should, in the end, result in better medical contingency plans.

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