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Team 5: Using Experimental Design and Data Analysis to Study the Enlisted Specialty Model for the U.S. Army GI

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INTRODUCTION

During the International Data Farming Workshop (IDFW) 20, Team 5 worked in direct support of MAJ Erdman's thesis. MAJ Erdman's thesis work is being conducted for the Army G1, which is the branch of the Army that is in charge of all Army personnel. The G1 is responsible to develop, manage and execute all manpower and personnel plans, programs and policies – across all Army Components – for the entire Army team [1].

The Army manpower program is a 30.6 Billion dollar annual investment. Its size, diversity in the skills it needs, the cost in terms of dollars, and years to produce skilled Soldiers requires that the manpower program be closely managed. The G1 uses the Active Army Strength Forecaster (A2SF) which consists of three mathematical models to manage this manpower program. These three models are used in conjunction with one another to ensure the Army has an adequate number of people by grade and skill in order to fight the Nation's wars. One of these three models is the Enlisted Specialty (ES) model, which specifically forecasts the enlisted soldiers in the Army.

The ES model was originally built to replace the Military Occupational Specialty Level System (MOSLS) that was built in the early 1970s by General Research Corporation, which is now a part of AT&T Government Solutions [2]. MOSLS was an earlier generation of the current ES model and had essentially the same mission to balance Military Occupation Specialties (MOS) and grade level requirements with the available population of Soldiers. AT&T Government Solutions continues to provide direct support to the Army G1 when they are exercising the model.

Every month the Army G1 uses the Enlisted Specialty (ES) model. The ES model consists of a simulation and optimization that forecasts the Army's enlisted manpower program by MOS and grade across a 7 year planning horizon. The ES model simulates the predicted flow of Army personnel on a monthly basis using historical data to determine the rates and factors for future transactions. Personnel inventory is comprised of two components, the individual account which is made up of Soldiers not available for operational assignments due to training, transition, holdee status or student status, and the operating strength account which is made up of Soldiers available for assignment against an authorization

The optimization portion of the model minimizes the absolute deviation between the operating strength portion of the personnel inventory and the authorizations to best meet the Force Structure requirements while satisfying all the constraints. The objective function in the ES model is to minimize the Operating Strength Deviation (OSD), which is the absolute deviation between the operating strength portion of the personnel inventory and the strength authorizations. Minimizing the OSD is goal of the Army G1 in meeting the Force Structure requirements while satisfying all the constraints. Once the ES model has run to completion, the resulting manpower inventory (by month, skill, and grade) are analyzed and become input for the Analyst Projection Assistance System (APAS) in Human Resources Command (HRC) to be used for personnel distribution planning.

The objective function in the ES model is a weighted sum of the decision variables in the model. The weights of the decision variables are known to change the outcome of the optimization, but it is unclear which weights have the most impact on the resulting OSD. The fundamental questions in MAJ Erdman's thesis are the following:

1. What are the objective function coefficients that have the greatest effect on the absolute deviation between the operating strength and the authorizations?
2. What objective function coefficients are robust with respect to deviations from target strength?

Answers to these questions are expected to help ensure that the target number of Soldiers with the correct skill sets and grade are met. Conducting data analysis necessary to answer the first question is the focus of the work for Team 5 during IDFW 20.

The next section provides a brief overview of the methodology including the experimental designs conducted followed by the results of the data analysis. Finally, insights gained from the workshop and follow-on work are discussed.

METHODOLOGY

The ES model consists of 859,633 variables with 224,473 constraints. Several iterations of the optimizer and simulation are used to converge on a feasible solution. The optimizer prescribes promotions, accessions and reclassifications [2]. The simulator is used to adjust for changes in behavior due to different promotion, accession, and reclassification programs within the Army. The optimization model is solved in CPLEX. A number of iterations of the optimization are performed in order to converge on an optimal solution. The final iteration of the optimizer produces a forecast that is an integer value and resolves any final discrepancies in the ES projections. As the program is currently configured it takes approximately four hours to determine rates and factors and then 17 hours for the model to process through all 15 simulation and optimizations iterations.

In order to meet the objectives of the first research question, traditional experimental design techniques were followed. Design of Experiment (DOX) is a systematic way of exploring a problem where variations are present. The experiments are designed so they can conduct simultaneous examination of multiple factors and explore input factors and their relation to output responses. This allows researchers to identify, compare, and contrast current values while minimizing the number of experiments that need to be conducted. Practicing good experimental design techniques allows for the most cost-effective (in terms of computer processing time, money, etc.) collection of data for future analysis.

Experimental design methodology was used by executing the steps below:

Step 1: Identify input factors, output factor(s) (response variable)

Step 2: Selected ranges that the input factors can take on

Step 3: Identify a screening experiment that will allow the estimation of main effects and potentially two factor interactions

Step 4: Run experiments

Step 5: Analyze data from experiments

Step 6: Based on results suggest an additional experiments required

The input factors are the 52 coefficient values in the objective function, which are presented in Figure 1. The output response is OSD. The levels for each of the 52 input factors are also presented in Figure 1.

A screening experiment allows the researcher to search for a subset of effects that have the most influence on the response variable. The goal of the first research objective in this work is to determine which of the 52 Objective Coefficient Variables were of importance in terms of the response variable, OSD. A Plackett-Burman design was used to study this. The Plackett-Burman is a non-regular factorial design with a low number of experimental requirements, which was important in the case of the ES model because of the long simulation run length. A non-regular design is one that involves partially confounded factors. The Plackett-Burman design created consisted of 56 runs.

Results of the Plackett-Burman design as well as a small set of additional experiments that were conducted during IDFW 20 are presented in the next section.

RESULTS

This section presents the results of the initial experimental design and provides a brief description of the additional experiment and follow-on analysis conducted during the workshop.

Grade Coefficients	Min Range	Max Range	Default Value
Promotion Factors E3	-200	-1	-120
Promotion Factors E4	-30	-1	-4
Promotion Factors E5	-30	-1	-4
Promotion Factors E6	-30	-1	-4
Promotion Factors E7	-30	-1	-4
Promotion Factors E8	-30	-1	-4
Promotion Factors E9	-30	-1	-4
Reclass Factors E3	3000	7000	5000
Reclass Factors E4	1	400	5000
Reclass Factors E5	1	400	200
Reclass Factors E6	1	400	200
Reclass Factors E7	1	400	200
Reclass Factors E8	1	400	200
Reclass Factors E9	1	400	200
Strength Factors E3	0	200	0
Strength Factors E4	1	4000	2000
Strength Factors E5	1000	5000	3000
Strength Factors E6	2000	6000	4000
Strength Factors E7	3000	7000	5000
Strength Factors E8	4000	8000	6000
Strength Factors E9	5000	9000	7000
Target Factors E3	0.01	1	0.1
Target Factors E4	0.01	1	0.1
Target Factors E5	0.01	1	1
Target Factors E6	0.01	1	1
Target Factors E7	0.01	1	1
Target Factors E8	0.01	1	1
Target Factors E9	0.01	1	1

Non-Network Constraint Coefficients	Min Range	Max Range	Default Value
MOSS Shred Target	0.01	0.32	0.13
NCO Constraint	0	0	0
SL1 Constraint	0.1	0.5	0.3

Objective Function Arc Coefficients	Min Range	Max Range	Default Value
Conversion	-9500	-5500	-7500
MOS Deletion	0	0	0
Demotions	-6000	-6000	-6000
LOSSES (ETS)	-9999	-8000	-9999
LOSSES (Other)	-9999	-8000	-9999
LOSSES (PML)	-50	-50	-50
LOSSES (Retirement)	-9999	-8000	-9999
LOSSES (Training)	-9999	-8000	-9999
Promotion (VBU)	-7000	-3000	-5000
Percent Bound on Pool Flows	100	100	100
Reclassification (Mandatory)	-9999	-8000	-9999
Reclassification (Reenlistee)	-9999	-8000	-9999
Reclassification (Voluntary)	0	100	1
Same-Grade Reclassifications	0	100	10
THS	-9100	-5100	-7100
BCT Training	0	65	31
NPS Without Training	1200	5200	3200
OSUT Training	0	65	33
PS with Training	0	65	34
PS Without Training	1500	5500	3500
Training Deletions to Pools	0	80	40

Figure 1: 52 Objective Coefficient Variables with minimum, maximum, and default values

A graphical representation of the OSD response for each of the 56 runs from the initial Plackett-Burman design are depicted in Figure 2.

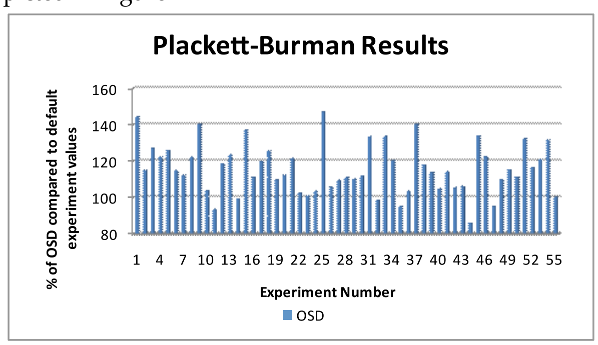

Figure 2: Placket-Burman Results

The software package JMP®, a product of SAS Institute, was used to analyze the data from the experimental design runs. Initial analysis consisted of performing a stepwise regression. The inputs to the stepwise regression included all of the main effects and two factor interactions. Note that this amount of terms indicates that the design is super saturated. The stepwise linear regression in JMP uses lengths method to identify statistically important coefficients.

Once the Stepwise regression results were completed Least Squares regression was used to build a linear regression model including only the significant terms as indicated by the stepwise regression results. The significant input factors are presented in Figure 3.

Parameter Estimates	
Term	**Estimate**
Intercept	352091.21
Strength Factors E4	3428.0933
SL1 Constraint	-1130.819
Promotion Factors E5*Promotion Factors E6	-2845.178
Promotion Factors E8*Target Factors E4	5925.8127
Reclass Factors E5*Strength Factors E5	2284.1627
Reclass Factors E6*Target Factors E7	-2795.389
Reclass Factors E6*SL1 Constraint	1341.4701
Reclass Factors E9*Strength Factors E8	-2333.568
Strength Factors E3*SL1 Constraint	-3604.157
Strength Factors E4*LOSSES (ETS)	-2307.061
Strength Factors E4*NPS Without Training	-2806.16
Strength Factors E5*PS Without Training	-2011.372
Strength Factors E7*Target Factors E9	17766.789
Strength Factors E8*PS Without Training	4506.6355
Demotions*Reclassification (Reenlistee)	1662.5679
LOSSES (Retirement)*NPS Without Training	1189.8346
BCT Training*OSUT Training	9892.3711

Figure 3: JMP® Output of Significant Factors from Plackett-Burman Experiments

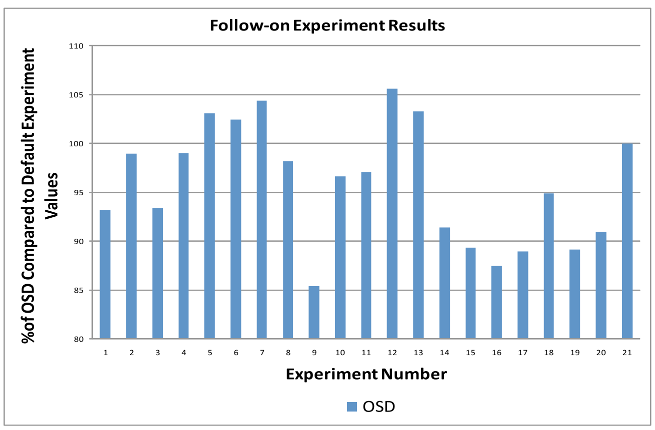

Figure 4: Follow-on Experiment Results

In order to ensure that these terms are in fact significant, follow-on experiments were conducted. The follow-on experiment consisted of changing only the top nine factors from the previous experiment and holding the other 42 coefficients at their default values. A space filling experiment was used in order to provide more degrees of freedom to test for significance of higher order polynomial terms and to provide any de-aliasing necessary for the terms identified as significant. Once complete the results of the 20 runs were processed and compared to the default coefficient OSD listed as experiment 21 on Figure 4.

Manipulation of the nine coefficients in the follow-on experimental design resulted in 75% of the OSDs being below the current default OSD. These results are encouraging and show that these nine coefficients are important and can be used to reduce the overall OSD in future experiments.

All of the experiments completed were cross validated to see which coefficients (linear, squared, or interaction) were robust with respect to predictive abilities. The data points were placed into JMP® except for 10 randomly excluded points. Stepwise regression was executed and JMP® selected the coefficients and that played a significant role in predicting the OSD. To prevent over fitting only the top 10 significant terms were taken from the Stepwise regression and used in the Least Squares regression. Limiting Least Squares to only the top 10 coefficients eliminated the problem of over fitting the data but still resulted in the R2 and adjusted R2 being above the .90 level.

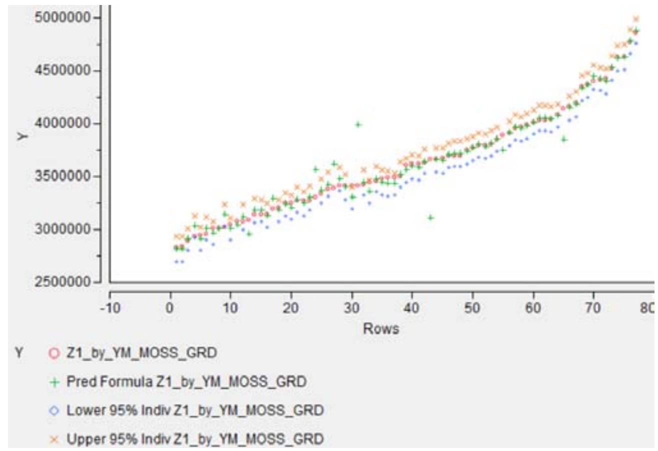

Figure 5: Cross validation plot

CONCLUSIONS

The DOX principles guided the execution of experiments on the ES model and ensured a comprehensive exploration of the problem space and efficient use of computer processing resources. The DOX provided valuable insight into how the coefficient inputs affect the OSD. The initial screening experiments also highlighted what areas require additional experiments.

Based off the work conducted at the IDFW, Team 5 was able to illustrate that the ES model outcome can be predicted by using a small subset of the significant coefficients. The cross validation of the current work shows that the coefficients still require more experimentation in order to produce a good working model for predicting the OSD. Based off the work conducted here additional experiments will be executed and a working mathematical model will be formulated.

REMARKS

The research into the ES model is ongoing and is expected to be completed by the end of June. The hope continues to be that this research will gain new insights into the ES model and help the United States Army personnel optimization.

REFERENCES

[1] http://www.armyG1.army.mil/

[2] Hall, Andrew O. Validation of the Enlisted Grade Model Gradebreaks. Winter Simulations Conference, 2004: 921-925

[3] Montgomery, Douglas C. Design and Analysis of Experiments 7th Edition. New York: John Wiley & Sons, 2009.