3-2000

# Using Simulation to Model an Army Recruiting Station with Seasonality Effects

David C. Longhorn

**USING SIMULATION TO MODEL AN ARMY RECRUITING STATION WITH SEASONALITY EFFECTS**

THESIS

David C. Longhorn, Second Lieutenant, USAF

AFIT/GOR/ENS/00M-18

**DEPARTMENT OF THE AIR FORCE**
**AIR UNIVERSITY**

***AIR FORCE INSTITUTE OF TECHNOLOGY***

**Wright-Patterson Air Force Base, Ohio**

| REPORT DOCUMENTATION PAGE | | | Form Approved OMB No. 074-0188 |
|---|---|---|---|
| Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503 | | | |
| **1. AGENCY USE ONLY (Leave blank)** | **2. REPORT DATE** March 2000 | **3. REPORT TYPE AND DATES COVERED** Master's Thesis | |
| **4. TITLE AND SUBTITLE** USING SIMULATION TO MODEL AN ARMY RECRUITING STATION WITH SEASONALITY EFFECTS | | | **5. FUNDING NUMBERS** |
| **6. AUTHOR(S)** David C. Longhorn, Second Lieutenant, USAF | | | |
| **7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)** Air Force Institute of Technology<br>Graduate School of Engineering and Management (AFIT/EN)<br>2950 P Street, Building 640<br>WPAFB OH 45433-7765 | | | **8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT/GOR/ENS/00M-18 |
| **9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)** MAJ Robert Fancher (Robert.Fancher@usarec.army.mil) (502) 626-0720<br>Headquarters, USAREC, ATTN: RCPAE-RP<br>1307 Third Avenue<br>Fort Knox, KY 40121-2726 | | | **10. SPONSORING / MONITORING AGENCY REPORT NUMBER** |
| **11. SUPPLEMENTARY NOTES** LT COL J.O. Miller, AFIT/ENS (John.Miller@afit.af.mil) (937) 255-6565 | | | |
| **12a. DISTRIBUTION / AVAILABILITY STATEMENT** APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED. | | | **12b. DISTRIBUTION CODE** |

**ABSTRACT (*Maximum 200 Words*)**


One of the toughest jobs in the Army is that of the recruiter. As the Army begins the 21st century, it is faced with having to support an increasing number of deployments with fewer soldiers. Soldiers face long and difficult days with the possibility of deployments away from families. Given these factors, it is easy to appreciate the plight of the Army recruiter.

Previous research at the Air Force Institute of Technology (AFIT) has focused on simulating station level Army recruiting in terms of general processes and recruit types. This study is a follow-on work aimed at enhancing the current Army recruiting model to allow for recruiting seasonality effects. Past recruiting data will be analyzed for trends in recruit accessions categorized by recruit types during the year, and then these trends will be incorporated into the model. Next, we will design simulation experiments to test different recruiting policies. Finally, we will conduct output analysis of the enhanced recruiting model using common techniques of simulation analysis. Much like the previous research in this area conducted at AFIT, this study is intended to help the United States Army Recruiting Command (USAREC) better understand the successes and failures of its recruiters.


| 14. SUBJECT TERMS | | | **15. NUMBER OF PAGES** |
|---|---|---|---|
| Army Recruiting, Simulation, Seasonality, Recruiter Effectiveness | | | 158 |
| | | | **16. PRICE CODE** |
| **17. SECURITY CLASSIFICATION OF REPORT** | **18. SECURITY CLASSIFICATION OF THIS PAGE** | **19. SECURITY CLASSIFICATION OF ABSTRACT** | **20. LIMITATION OF ABSTRACT** |
| UNCLASSIFIED | UNCLASSIFIED | UNCLASSIFIED | UNC |

**NSN 7540-01-280-5500**

**Standard Form 298 (Rev. 2-89)**
**Prescribed by ANSI Std. Z39-18**
**298-102**

AFIT/GOR/ENS/00M-18

USING SIMULATION TO MODEL AN ARMY
RECRUITING STATION WITH SEASONALITY EFFECTS

THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science

David C. Longhorn, B.S.

Second Lieutenant, USAF

March 2000

AFIT/GOR/ENS/00M-18

# THESIS APPROVAL

Student: David C. Longhorn, Second Lieutenant, USAF    Class: GOR-00M

Title: Using Simulation to Model an Army Recruiting Station With Seasonality Effects

Defense Date: 18 February 2000

| Committee: | Name/Title/Department | Signature |
|---|---|---|
| Advisor | J.O. Miller, Lt. Colonel, USAF<br>Assistant Professor<br>Department of Operational Sciences | |
| Reader | Kenneth Bauer, Ph. D.<br>Professor<br>Department of Operational Sciences | |
| Reader | Jack Kloeber, LTC, USA<br>Assistant Professor<br>Department of Operational Sciences | |

**Acknowledgements**

I would like to thank my wife, Theresa, and my son, Nicholas, for their patience and understanding during the course of this study. Both of you gave me the motivation needed to complete this endeavor. Thanks also to my valuable and experienced thesis committee: Advisor Lt Colonel J.O. Miller, and readers Dr. Kenneth Bauer, and LTC Jack Kloeber. In addition, MAJ Robert Fancher of USAREC provided much needed recruiting data and support. Finally, thank you to my AFIT classmates for their support and friendship.

## Table of Contents

## List of Figures

## List of Tables

## List of Acronyms

| Acronym | Definition |
| --- | --- |
| AFIT | Air Force Institute of Technology |
| AFQT | Armed Forces Qualifying Test |
| ASVAB | Armed Services Vocational Aptitude Battery |
| DEP | Delayed Entry Program |
| FY | Fiscal Year |
| GED | General Equivalency Diploma |
| GFA | Graduate-Female-Alpha |
| GFB | Graduate-Female-Beta |
| GMA | Graduate-Male-Alpha |
| GMB | Graduate-Male-Beta |
| MAJ | Major (Army) |
| MORS | Military Operations Research Society |
| SFA | Senior-Female-Alpha |
| SFB | Senior-Female-Beta |
| SMA | Senior-Male-Alpha |
| SMB | Senior-Male-Beta |
| TQM | Total Quality Management |
| USAREC | United States Army Recruiting Command |
| V&V | Verification and Validation |

## Abstract

One of the toughest jobs in the Army is that of the recruiter. Recruiters are tasked with the awesome job of convincing young men and women to lay down their lives and freedoms for their country, and oftentimes for less money than can be earned in the safer environment of America's booming economy. Recruiters face enormous pressure from commanders to meet the mandated Army manning levels set each year by Congress. As the Army begins the 21$^{st}$ century, it is faced with having to support an increasing number of deployments with fewer soldiers. Soldiers face long and difficult days with the possibility of deployments away from families. Given these factors, along with the increasingly negative attitudes of today's youth regarding military service and the fierce competition among the services for recruits, it is easy to appreciate the Army recruiter.

Previous research at the Air Force Institute of Technology (AFIT) has focused on simulating station level Army recruiting in terms of general processes and recruit types. This study is a follow-on work aimed at enhancing the current Army recruiting model to allow for recruiting seasonality effects. Past recruiting data will be analyzed for trends in recruit accessions categorized by recruit types during the year, and then these trends will be incorporated into the model. Next, we will design a simulation experiment to test different recruiting policies. Finally, we will conduct output analysis of the enhanced recruiting model using common techniques of simulation analysis. Much like the previous research in this area conducted at AFIT, this study is intended to help the United States Army Recruiting Command (USAREC) better understand the successes and failures of its recruiters.

# Chapter 1 - Introduction

## Statement of the Problem

Army recruiters face some of the most formidable challenges in the military. Most recruiters are the only link between the civilian and military worlds due to the relatively small number of Army bases throughout the country. Also, convincing young men and women to enter military service over more lucrative civilian professions is an art possessed by a rare few. *Army Times* magazine reports in its March 15, 1999 issue that even fast food restaurants offer pay and benefit packages competitive with what the military offers new soldiers.

The recruiter must be professional and remain motivated despite frequent rejections. In addition to these stresses, recruiters face enormous pressure from commanders to meet the mandated Army manning levels set by Congress. The current Army manning level is a force of 480,000 soldiers. For the second time in as many years, the Army has failed to meet its recruiting goals. Such failures have prompted the Army's Chief of Staff, General Eric Shinseki, to make recruiting and manpower the Army's #1 priority. If recruiting trends continue on their present course, the Army will experience a severe personnel shortage in years to come (see Table 1.1).

Table 1.1 Army Recruiting Missions and Projected Shortages

| Fiscal Year | Mission Regular Army | Projected Shortage | Mission Reserve Army | Projected Shortage |
|---|---|---|---|---|
| FY99 | 74,500 | 6,500 | 45,584 | 9,000 |
| FY00 | 83,600 | 11,000* | 46,041 | 9,800* |
| FY01 | 85,800 | 10,500* | 45,233 | 7,800* |

Note: * Assumes accomplishment of previous year's mission

Such recruiting failures can have serious consequences as stated in the August 30, 1999 issue of *Army Times*, "A prolonged recruiting pinch would jeopardize readiness and national security, and wreck short and long-term planning strategies" (McHugh, 22). Recruiters have been failing in their mission to bring new soldiers into the Army, and many reasons for these failures have been proposed. Some cite the lack of an adequate number of recruiters and small advertising budgets. Others blame the massive military drawdown of the early 1990s which may have given the impression that the military wasn't hiring (Murray and McDonald, 25). Still others believe the youth of today are simply not interested in military service. The level of negative propensity, defined as youth stating they will definitely not enter the military, has reached its highest level (55%) in the 25-year history of the All-Volunteer Force. In addition, positive propensity, defined as youth indicating they will definitely enter the military, has remained low (11.4%). Some explanations for these attitudes may be due either to a lack of national pride or perhaps the smaller monetary military benefits as opposed to those likely in the civilian sector of today's strong economy.

Whatever the reasons proposed for the shortage of troops, no one can dispute the fact that recruiters are integral to the enlistment process. Few potential recruits (also known as applicants or prospects) simply walk through the recruiter's door, ask for forms, and sign up for military duty. Most of them enter the military only after much effort on the part of recruiters who identify prospective recruits, provide them with information, and woo them with tales of military benefits (Murray and McDonald, 55).

This research enhances a previously developed computer simulation model, which has been used to simulate the Army recruiting process at the station level. The current model faces many generalities including a lack of recruiting seasonality effects (i.e. the idea that the number of applicants contracted and shipped into the Army depends on the time of year). Our overall goal is to increase the credibility, flexibility, and validity of the current Army recruiting model. The enhancements proposed will make this model more helpful to analysts at USAREC. This study will specifically involve:

1. Analyzing recent USAREC data with respect to the number of contracts made during different times of the year based on various recruit types: male/female, high school graduate or not, high/low ASVAB (Armed Services Vocational Aptitude Battery) score.

2. Analyzing the same USAREC data with respect to recruit shipping patterns and DEP (Delayed Entry Program) losses during different times of the year, also based on different recruit types as defined above.

3. Incorporating these seasonality effects into the recruiting model.

4. Allowing for modifications to contract patterns, shipping patterns, and DEP losses as a function of both time of year and recruit type.

5. Conducting output analysis with the enhanced model to examine station level performance for different recruiting policies.

**Army Solutions**

Numerous programs have been initiated in response to the recent recruit shortages. These programs rely on various methods to halt the recruiting crisis, including advertising, recruiting policy changes, and pay/benefit issues. In terms of advertising, the Army is calling for more money and alternative advertising schemes. Recently, the Army has pushed its long-lasting catch phrase, "Be all you can be", to the background of its commercials in an effort to reach new audiences. In addition, the Army is considering airing commercials on MTV and during professional wrestling matches and basketball games. These efforts are aimed at telling the next generation soldier, from the so-called Generation Y, that 'Enlisting is cool'.

The Army is also changing the ways in which it recruits today's youth. A new program called GED-Plus, in which high school dropouts may join the Army prior to earning a General Equivalency Diploma (GED), reaches out to a portion of the recruiting population never previously tapped. Also, a new program called College First allows recruits to defer military service until they complete two years of college education. Both of these programs give more options to recruiters trying to attract more youth into the Army. These programs are certainly ambitious and hope to curb the recruit shortfall; however, some argue that a program such as GED-Plus will result in lower standards and therefore lower quality soldiers. Another ambitious program recently undertaken by the Army, the Corporal Recruiting Program, involves allowing younger enlisted members in the E-4 ranks to try their hands at recruiting. The motivation behind the program is that potential recruits will be more likely to identify with the younger recruiters and hopefully more receptive and willing to join the Army.

Many leaders feel that the relatively small pay and benefits offered by the military is the prime reason young people avoid military service. Various fixes have been proposed within the last few years, including revamping the Montgomery G.I. Bill and other tuition aid packages. The soldiers seem to agree with the idea. As reported in the May 3, 1999 issue of Army Times, over 90% of recruits listed education as their #1 priority (McHugh, 16). However, these recruiting methods may lead to the "recruiter paradox", the idea that increasing education benefits will likely result in a loss of soldiers to the civilian world. Others suggest increasing education benefits relative to the number of years in military service, thereby offering a balance between recruiting and retention. Clearly the Army feels it has a serious recruiting problem and must try different approaches to solve, or at least slow, the problem.

**Background**

In 1997-98, Lieutenants James D. Cordeiro and Mark A. Friend developed an Army recruiting model as part of an AFIT thesis for USAREC. Their work provided a strong computer simulation upon which recruiting processes could be examined in terms of time spent on various tasks and the resultant number of recruits contracted. Using their detailed workflow model, improvements to recruiter time utilization could be discovered and implemented with the goal of increasing recruiter effectiveness. However, their model simulated only a general recruit type and furthermore did not allow for contract and shipping seasonality effects.

In 1998-99, AFIT graduate student Captain Edward L. McLarney modified Cordeiro and Friend's computer model by incorporating Station Commander leadership effects along with individual recruiter personalities. The methodology used for this modification involved survey methods. The surveys were administered to recruiters to ascertain the effects of their personalities, along with the leadership traits of their commander, on recruit accessions. However, due to unforeseen administrative problems, the full results of the surveys could not be included in his thesis effort.

McLarney further enhanced the recruiting model by adding the ability to process recruits with different attributes. Three different attribute factors, each with two levels, were incorporated: high school graduation status (Yes/No), ASVAB score (High/Low), and gender (Male/Female). This recruit construct, along with the absence of recruiting seasonality in the model, provides the prime motivation for this research effort.

**Justification**

This study will explore the various time and quality dependencies suspected in the Army recruiting process. The implications could have dramatic effects on military recruiting. For example, if it can be shown that high quality recruits are most likely to be contracted during certain months, then maximum recruiting efforts can be justified during those months. Furthermore, we might also determine that low quality recruits, although likely to sign up for duty, are highly likely to drop their military service commitment before shipping to basic training. The enhanced simulation will provide a tool whereby new recruiting policies can be analyzed.

**Approach**

Previous research at AFIT has focused on simulating station level Army recruiting in terms of general processes without modeling the seasonality of recruiting. The approach taken with this thesis effort involves the following steps:

1. Determine specifically the kinds of data needed for the research. Initial data requirements include a breakdown of the timing and number of recruits contracted and lost from the DEP during the year at various Dayton, Ohio recruiting stations, with the specific attributes of applicants also identified.

2. Determine the availability of USAREC data meeting our above requirements. The data should be of sufficient quantity and quality for an appropriate analysis.

3. Obtain this historical data from USAREC.

4. Analyze the data to determine recruit seasonality trends with respect to contracts and DEP losses. The results of this analysis will be incorporated into the model.

5. Make appropriate model enhancements to allow for faster runtimes.

6. Compare the original model's output from previous studies against the enhanced model's output. Interpret any significant differences.

7. Conduct an experimental design using the enhanced model. The motivation is to examine the effects of different recruiter policies. Interpret any significant results using output analysis.

Throughout this research effort we will employ common practices of an effective simulation study. In Simulation Modeling & Analysis (Law and Kelton, 107), the authors propose some general steps of a simulation study. These steps include:

1. Formulate problem and plan the study

2. Collect data and define a model

3. Check model and data validity

4. Construct a computer program and verify

5. Make pilot runs

6. Check validity of pilot runs

7. Decide which system designs to simulate (i.e. experimental design)

8. Make production runs

9. Analyze output data

10. Document, present, and implement results of study

These ten steps follow a flow as depicted in Figure 1.1. We will be working off an existing model; therefore, some of the steps will require much less effort than expended by the previous AFIT researchers.

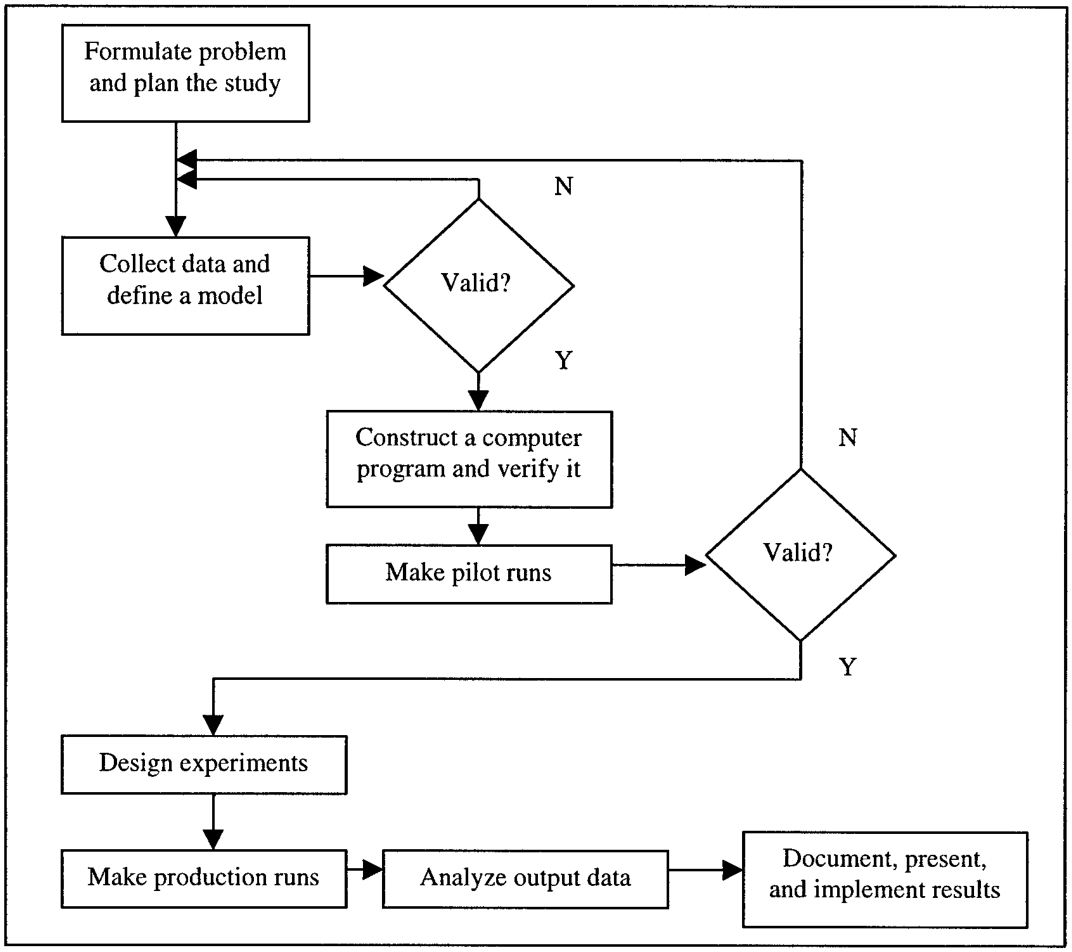



Figure 1.1 Steps in a Simulation Study

**Scope**

This study will focus on two main areas. The first area will involve the enhancement of the current model. In this phase, USAREC data will be analyzed for trends in recruit contracting and shipping during the year. These trends will then be incorporated into an enhanced computer model.

The second area of this study will involve output analysis on the enhanced model. Various recruiter policies will be used as model input and the effects on station performance will be evaluated.

## Organization

This document is organized into six chapters. Chapter 1 introduces the problem and gives background. Chapter 2 contains the literature review on this subject and gives more background on the Army recruiting process. In the next chapter, we explain the methodology used in this research. Chapter 4 discusses input analysis and model enhancements. Then, in Chapter 5 we explain an experimental design and present the simulation output analysis. Chapter 6 gives conclusions and recommendations for future research.

We provide appendices as support of our research. We mentioned that, due to administration problems, McLarney was unable to analyze his survey responses. As part of an AFIT graduate course, we analyzed the survey responses from a multivariate analysis standpoint. Appendix A presents the analysis results on the complete set of survey responses. Other appendices provide printouts of our enhanced Army recruiting model, supporting data analysis, and simulation output.

# Chapter 2 - Literature Review

## General

To successfully simulate an Army recruiting station, we needed to establish a firm grasp on Army recruiting practices and doctrine. As an introduction to military recruiting we reviewed Army recruiting manuals and had conversations with a recruiting expert (MAJ Robert Fancher of USAREC). We also attended a MORS (Military Operations Research Society) mini-symposium dedicated to the current military recruiting problems. To further familiarize ourselves with the Army's specific recruiting problems, we consulted weekly-published *Army Times* magazines. Each issue contained articles from key recruiting officials and Army leaders concerning recruiting problems. From these combined efforts we were able to better understand Army recruiting, and more importantly, shape our research to aid USAREC with these problems.

In addition to the actual recruiting processes and issues, we needed to understand the current SIMPROCESS Army recruiting model developed by Cordeiro and Friend (1997-8) and later enhanced by McLarney (1998-9). This section of the report reviews the current literature we researched concerning the Army recruiting process.

## Basic Recruiting Procedures

Army recruiting procedures are distinct from the recruiting procedures of most other institutions. Companies, such as IBM or McDonald's, typically put out job advertisements in the local newspapers and/or billboards. Interested people see these messages and either call for an interview or send in a resume hoping for a job interview. In cases involving recruiting college-educated people for high quality jobs, some employers may visit colleges in hopes of attracting the interest of soon-to-be graduates. The Army would be nonexistent if these practices were employed exclusively, simply because today's youth are just not willing to give up many of their personal freedoms for a military commitment. The Army recruiting process differs significantly. The entire process can be represented with five general phases, as shown in Figure 2.1.

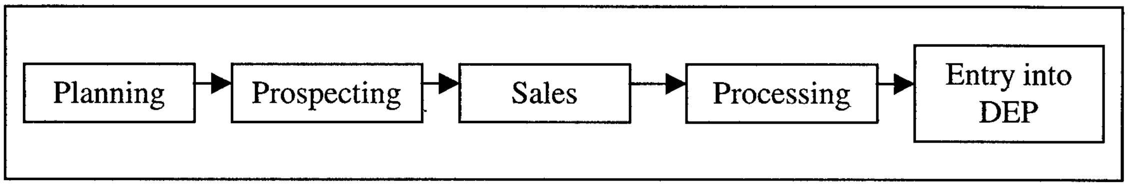



Figure 2.1 Five Phases of the Recruiting Process

*Planning* is the first phase of the recruiting process. This phase involves devising some standard objectives and "game plans" for both short and long-term recruiting. Previously, USAREC had adopted trends in accordance with TQM (Total Quality Management) practices. In accordance with these practices, the Army devised plans to implement a reform program known as Recruiting 2000 (Cordeiro and Friend, 4). In this system, the emphasis was on the recruiting unit rather than the individual recruiter. Recently, however, the emphasis has been on the individual recruiter. "If the individual succeeds, he receives praise and awards. If the individual fails (possibly despite trying) he is held accountable" (McLarney, 1.2). Thus the individual recruiter is held accountable for recruiting shortages, regardless of how hard that individual may have tried to meet his or her mission.

The next phase in the recruiting process is *Prospecting*. This phase is critical to Army recruiting because prospecting is the art of getting people interested in military service. Hopefully, these interested people will then visit a recruiter and listen to what the Army has to offer. Recruiters conduct prospecting through a combination of four methods: face-to-face, telephone, referrals, or walk-ins. A particularly important prospecting venue is the local high school. If the recruiter has a strong rapport with the high school guidance counselor, the recruiter has a good chance of recruiting that school's high quality students into the Army. The Army mandates that recruiters visit local high schools at least once per year; however, good recruiters will spend more time than mandated establishing networks within the school systems. One of the most successful forms of prospecting is through telephone inquiries. Telephone prospecting allows for the most potential recruits to be reached with minimal cost and effort. However, recruiters most often dislike this form of prospecting due to the frequent rejections.

The third phase in the recruiting process is *Sales*. In this phase, recruiters pitch the Army to the prospect, hoping for continued interest and a willingness to take qualifying tests. Regardless of the applicant, the recruiter must try to convey to the applicant that the Army has what he or she wants, be it an occupation, benefits, excitement, education, or lasting friendships. USAREC dedicates a pamphlet, Pamphlet 350-7: Recruiter Salesmanship, to the sales process. Recruiters are introduced to basic psychology principles, time organization skills, recognition of current market conditions, and instruction on giving appropriate sales pitches. The sales phase is felt to be the key element in the recruiting process because this is where you either "hook" or lose an applicant. Thus, the sales phase will either produce prospects willing to continue with the recruiting process or result in the prospect refusing military service.

*Processing* is the fourth phase in the recruiting process. This phase entails the formal evaluation of a potential recruit. Such evaluations include criminal background checks, ASVAB testing, and physical testing. Anywhere within this phase the prospect may decide against the Army or perhaps fail qualification standards, for such reasons as mental ability, moral faults, or physical limitations. Upon verifying the applicant fit for duty, his or her skills, and to some extent desires, are matched to an Army job. This phase may take an abundant amount of time. Moral or physical waivers have been known to take up to several months for processing. In addition, the recruiter may have to retest an applicant who has failed to achieve the minimum Armed Forces Qualifying Test (AFQT) score. We note that the AFQT score is derived from subtests of the ASVAB. See Table 2.1 for AFQT categories and score percentiles. For our study, we refer to those in categories I, II, and IIIA as Alphas (high ASVAB) and those in categories IIIB as Betas (low ASVAB).

Table 2.1 AFQT Breakdown of Categories by Scores

| **AFQT Category** | **Score Percentile** |
|---|---|
| I | 93-99 |
| II | 65-92 |
| IIIA | 50-64 |
| IIIB | 31-49 |
| IV | 10-30 |
| V | 1-9 |

The final recruiting phase before the applicant enters basic training and active duty is the *Entry into the Delayed Entry Program (DEP).* This phase is also known as *DEP Sustainment.* These programs allow for the recruit to remain attached to the Army while waiting for military training slots to open or perhaps for the recruit to graduate from high school or college. It is very important that recruiters not leave the recruits stranded in the DEP for long periods of time without updates. Some recruits, especially juniors in high school waiting until graduation, may wait in these programs for up to a year before entering basic training. If the recruit decides against the Army during this delay, the time and effort expended contracting this applicant would have been wasted.

However, as important as it is for recruiters to expend time and energy for the recruits in the DEP, they must also not neglect their responsibility to contract more recruits. Good recruiters are able to utilize their time effectively and maintain a balance between prospecting new applicants and seeing to the needs of recruits waiting in the DEP. The five phase process described above is only given as a high-level representation of the recruiting process. Many small, yet important, tasks remain for a recruiter during the process.

**Previous Army Recruiting Work at AFIT**

In 1997-98, Cordeiro and Friend developed a SIMPROCESS computer simulation to model individual recruiter tasks. SIMPROCESS is an icon-based simulation tool based on MODSIM, developed by the CACI Company. The goal of their work was to improve individual recruiter time utilization. To accomplish this goal they first accurately modeled recruiter tasks, and then they examined the relationship between time spent on recruiting tasks and the resultant number of recruits contracted.

The first step taken by Cordeiro and Friend was the identification of the general recruiting processes, as identified in the previous section. Cordeiro and Friend incorporated two different paths within the *Processing* phase: normal and immediate.

Normal processing is the standard avenue taken by an applicant. Applicants in this phase have only shown a moderate interest in joining the Army and thus are more likely to reject military service. Immediate processing, on the other hand, deals with applicants with a firm commitment to joining the Army. With such an applicant, "the experienced recruiter will attempt to enlist the applicant as soon as possible before the applicant changes his or her mind" (Cordeiro and Friend, 39). The applicants in the immediate processing track still remain subject to the usual tests and qualifications.

Cordeiro and Friend recognized the appropriate level of detail to be modeled concerning recruiter tasks. Instead of modeling every small task, such as filling out a specific form, they aggregated groups of tasks and used the average time to complete all aggregated tasks. For example, they aggregated the completion of various forms into a process denoted as *Processing Paperwork* (Cordeiro and Friend, 40).

Once the tasks were aggregated into their respective processes, Cordeiro and Friend introduced methods of statistical variation to account for the randomness of processing times. The predominate distribution used for processing times was the triangular distribution, denoted $Triang(a,b,c)$. The parameters respectively correspond to the minimum, most likely, and maximum time durations expected for a particular process. This distribution is often used when little real data is available for an accurate time distribution to be estimated. Cordeiro and Friend also recognized that this distribution was well-suited to the recruiter since it is much easier to characterize task completion times in terms of best, average, and worst (Cordeiro and Friend, 64).

After Cordeiro and Friend had a working computer simulation of individual recruiters, they designed experiments to test the sensitivity of the recruiting process to various model inputs. The three model inputs used in the sensitivity study were the amount of collateral time imposed on the recruiter, the amount of time allotted to prospecting, and the amount of processing time allowed during the workweek. Varying these parameters revealed valuable insights into how the recruiting process worked. Cordeiro and Friend caution users of their model not to focus solely on ways to increase the output of the model. This near-sighted approach fails to consider the random behavior which the real system exhibits and the model simulates (Cordeiro and Friend, 126). The results of the output analysis showed that the number of recruits contracted was sensitive to the factors of prospecting and collateral duties, but not to the factor representing processing. They also discovered that the driving force behind the recruiting process was the time spent prospecting.

In 1998-99, McLarney examined the effects of leadership styles and policies on recruiter productivity. McLarney also addressed the effects of recruiters with different personality traits and the differences in processing various applicant types. Modeling applicants of different types was an enhancement strongly needed in the simulation, as Cordeiro and Friend modeled only a typical applicant. Specifically, McLarney classified applicants in one of eight groups. Table 2.2 gives a description of the different groups.

Table 2.2 Description of Applicant Type

| **Type** | **Description** |
|---|---|
| GMA | High School Graduate, Male, High ASVAB |
| GMB | High School Graduate, Male, Low ASVAB |
| GFA | High School Graduate, Female, High ASVAB |
| GFB | High School Graduate, Female, Low ASVAB |
| SMA | High School Senior, Male, High ASVAB |
| SMB | High School Senior, Male, Low ASVAB |
| SFA | High School Senior, Female, High ASVAB |
| SFB | High School Senior, Female, Low ASVAB |

Very little work had previously been done in the area of simulating leadership traits; thus, McLarney broke new ground with this enhancement. McLarney first researched Total Quality Management (TQM) principles in his literature search, which mirrored some of the elements of successful recruiting. McLarney referenced Putting Total Quality Management to Work by Marshall Sashkin and Kenneth J. Kiser, which described TQM techniques to identify and solve problems along with focusing on the customer. However, TQM only offered direction for managing an organization. "There were no concrete tools (example survey, etc.) given which could help assess the climate of an organization with regard to TQM" (McLarney, 2.5). McLarney instead focused on other leadership philosophies to include "Goal Setting Theory" and "The Big Five". These philosophies provided McLarney's research a platform upon which insight into recruiter productivity could be gained based on different leadership traits.

McLarney then developed a recruiter survey, which would be used to gain information from recruiters linking leadership and personality traits to recruiter success. Due to shipping delays with the surveys, McLarney was unable to incorporate the survey results into his research. Instead, he used the sample survey results of 30 recruiters from the local Dayton, Ohio Recruiting Company for the analysis. Four factors from the survey seemed to most affect recruiter productivity: CSG (Clear and Specific Goals), RFG (Reward for Goals), SUP (Supportive Leader), and EFFIC (Efficacy). With respect to recruiting, efficacy shows the degree to which the recruiter feels he/she is capable of recruiting success (McLarney, 5.3).

To model different types of applicants, McLarney obtained data from USAREC showing the number of each prospect type contracted by month in fiscal year 1998.

McLarney then averaged the data for that time period and derived proportions for each prospect type. See Table 2.3 for the prospect proportions used by McLarney. Using these proportions and if-then-else statements within the model, McLarney was able to use a simple *Unif(0,1)* random draw to assign a simulation entity to a specific prospect type.

Table 2.3 Average Contracted Proportions

| **Type** | **Proportion** | **Type** | **Proportion** |
|---|---|---|---|
| SMB | 0.09 | SFB | 0.03 |
| GMB | 0.21 | GFB | 0.03 |
| SMA | 0.15 | SFA | 0.04 |
| GMA | 0.34 | GFA | 0.11 |

Data from (McLarney, 4.9)

Once McLarney had modified the model, he proceeded with output analysis using experimental design techniques. By using an experimental design, McLarney was able to examine the effects of each factor: CSG, RFG, SUP, EFFIC. The experimental design used was a half-fraction design with four factors, each with two levels.

The previous work done by Cordeiro/Friend and McLarney provided a useable and realistic computer simulation of the Army recruiting process. Each team tackled important aspects of the recruiting process and successfully incorporated these aspects into a SIMPROCESS model.

Our research will tackle both the incorporation of recruiting seasonality into the model and also output analysis to gain further insights into the current recruiting dilemma faced by USAREC. The next section details the various time issues recruiters must deal with on a daily basis.

**Time Issues/Seasonality of Recruiting**

Time is a precious commodity to an Army recruiter. Workdays are long and much time can be spent on an applicant who later decides not to enter military service. The time a recruiter spends contracting an applicant can be broken into two main areas: time to get an initial interview with a potential applicant and time to process an interested applicant. Furthermore, these times are dependent on the quality attributes of the applicant. Many of the past analyses concerning recruitment supply have followed the notion that different quality recruits require different levels of effort to attract into the service (Murray and McDonald, 58). Indeed, it is suspected that low quality applicants require less time to schedule an initial interview. In contrast, high quality applicants require much more recruiter time to stir interest in the Army and agree to an interview.

For our study we define low quality applicants as high school seniors with low ASVAB scores and high quality applicants as high school graduates with high ASVAB scores. The reason recruiters typically regard graduates with a higher priority is that graduates can usually be quickly shipped to basic training.

Adding to the recruiter's burden is the pressure to recruit the "better" high quality applicants. Such enlistments are beneficial to the Army for obvious reasons, but also beneficial to the individual recruiter because signing higher quality recruits brings more personal praise and rewards than signing the lower quality recruits. "An increase in the number of low quality recruits will take time and resources away from activities that would increase high quality enlistments" (Murray and McDonald, 56). In addition, recruiters typically face many more rejections from the high quality applicants than from the low quality applicants. Taken all together, it is clear that recruiters have difficult choices to make concerning how to spend their time.

The second time variable recruiters encounter involves the processing times needed to get the recruit through the recruiting process. It is expected that different quality applicants require different processing times. For example, low quality applicants might need to take the ASVAB several times to achieve a qualifying score, whereas high quality applicants (once interested in military service) might be relatively easy to get through the entire process.

Finally, the quantity and quality of recruits contracted during the year may also vary with the particular time of year. For example, recruiters must meet quotas every quarter. Therefore, a recruiter might try to pull in low quality recruits up front and is thus left with the high quality recruits to pull in later. Furthermore, one should not expect the number of applicants to be constant during the year. Certain months and times of year are notorious for not producing an adequate number of recruits. An example of this trend was recently supported in the July 26, 1999 issue of *Army Times*. The article, "Monthly recruiting sign-ups worst in 26 years", details the Army recruiting shortfalls for the third fiscal quarter of 1999. The data certainly suggests a large variation in the number of recruits contracted during different months. Table 2.4 shows the recruiting shortages for the third quarter of FY99.

Table 2.4 FY99 Third Quarter Recruiting Shortfalls

| **FY99 Month** | **Recruiting Shortfall** |
|---|---|
| April | 1,350 |
| May | 230 |
| June | 430 |

## Summary

This chapter further described the Army recruiting process. The five general recruiting stages were introduced and explained. Next, we reviewed the previous Army recruiting work by AFIT graduate students Cordeiro/Friend and McLarney. Finally, the issue of various processing times for different prospect types and also the concept of seasonality of recruiting was examined.

The purpose of our research is to aid USAREC by developing a more realistic and efficient Army recruiting simulation. However, we first needed to learn more about current recruiting problems. While our literature review was helpful, we only came to fully recognize the magnitude and importance of the problem during our attendance at the MORS Mini-Symposium on Recruiting and Retention in the 21st Century. For three days, hundreds of recruiting experts and decision makers shared experiences and offered possible solutions. This experience put us on the front line of military recruiting. Throughout our research, we kept this experience in mind.

The next chapter of this thesis explains the methodology we will follow to discover recruiting seasonality trends and then incorporate these trends into the model.

# Chapter 3 – Methodology

## General

This study revolves around simulation. A simulation (or simulation model) is an abstract representation of some real-world system, in our case an Army recruiting station. Since most systems are far too complex to simulate exactly, the simulation must take into account certain simplifying assumptions about the system under investigation. In addition, the simulation can only emulate the system to a certain amount of detail and, furthermore, this level of detail is directly related to the objectives of the simulation study. The best simulations possess only the level of detail necessary to accomplish the study objectives. Our objective is to develop a more realistic and efficient Army recruiting model. We will accomplish this by first discovering seasonality trends from historical recruiting data and then incorporating these trends into a more powerful simulation model. We intend our simulation model to be a tool able to provide helpful insights, rather than exact answers, into the workings of station recruiting.

This chapter focuses on the methodology used in the study. The first section details input data analysis methods. Then we give an overview of the current Army recruiting model and the SIMPROCESS simulation language. In the third section we introduce the AweSim simulation language, which will serve as the platform for our enhanced model. The fourth section explains our simulation methodology. The final sections explain our intended model modifications and, of course, verification and validation techniques employed during this study.

## Input Data Analysis Methods

The primary focus of this study is to first discover seasonality trends in different aspects of the recruiting process, and then incorporate these trends into the recruiting model for a more complete simulation analysis. Some important questions concerning the data analysis aspect of the study must now be answered: What kinds of data should be analyzed? What time periods should the data cover? Are the data from these time periods homogeneous in nature? This section answers these questions using the recruiting data obtained during the early stages of the study from MAJ Robert Fancher, our USAREC point of contact.

We decided to analyze data only from the Dayton Recruiting Company. We give three reasons for this decision. First, data analysis for many different recruiting stations would require a level of effort greater than we could reasonably provide. Second, our physical location (AFIT) resided within minutes of these stations. We wanted to be able to visit these stations if we needed to verify data. Third, we suspect Army recruiting stations will differ greatly across the United States, primarily due to demographic factors. We did not want these exterior demographic factors influencing our analysis results.

The Dayton Recruiting Company is a unit of the 3rd Recruiting Brigade and is currently composed of six stations in the greater Dayton, Ohio area. Refer to Table 3.1 for additional information on the Dayton Recruiting Company. Although these stations are certain to differ in the number of applicants processed and contracted, we feel they will provide a fair representation for our recruiting measures of interest.

Table 3.1 Dayton Recruiting Company Information

| Station Location | Identifier | # of Recruiters |
|---|---|---|
| Xenia | 5D6A | 4 |
| Springfield | 5D6B | 7 |
| Dayton (South) | 5D6F | 4 |
| Piqua | 5D6M | 5 |
| Dayton (North) | 5D6N | 6 |
| Dayton (West) | 5D6S | 4 |

**Kinds of Data to be Analyzed.** There are two aspects of recruiting seasonality we wish to explore: the seasonality of contracting different recruits during the course of the year (termed Contract Seasonality), and recruit shipping trends while taking into account DEP losses (termed DEP Seasonality). In terms of Contract Seasonality, we need data detailing the number of applicants contracted during the year, broken down by prospect type. We will thus be able to discover patterns in contracting recruits. For example, we may find that most GFAs, Graduate-Female-Alphas, are contracted during the spring months. This data will also indicate the recruiting station from which the recruit came, thereby allowing an interpretation of any differences among stations.

In terms of DEP Seasonality, the data will include the recruit type along with the contract date, the expected date of entry into the Army, and either the recruit's actual date of entry or their date of separation from the DEP. This data will allow an interpretation of how long different recruits spend in the DEP, either before shipping to basic training or before deciding against the military. The data will also provide a means to estimate DEP loss probabilities during the year.

**Time Periods Covered by the Data.** Here we address the issue of how much data, in terms of years, will be sufficient for our purposes. We certainly want to capture only the *recent* negative trends in recruiting, thus data from "good" recruiting years would be detrimental to our purposes. Most of the current literature on the recent Army recruiting woes indicates Fiscal Year 1995 (FY95) as the beginning of the plummeting recruit shortfalls; therefore, we made the decision to analyze data exclusively from FY95 through FY99. A quick note on terminology seems appropriate here. A Fiscal Year runs from October through September. For example, FY96 starts on October 1, 1995 and ends on September 30, 1996. Furthermore, FY95-98 will represent FY95 through FY98. We will use Fiscal Year notion exclusively from here on out.

We need to determine how to partition the data in terms of time of year (days, weeks, or months). We suggest dividing the data into months, both for ease of analysis and also for incorporation into the model later. One particular concern we raise is being able to fully analyze data concerning DEP Seasonality. We know that it may take up to a year for a recruit to drop out of the DEP and decide against entering the military. Thus, an applicant contracted in August of FY99 might stay in the DEP until late in FY00. Our data for FY99 will not include this DEP loss since it is not yet known whether that recruit will enter the military or not. A quick examination of the obtained data suggested that very few contracts would ever be lost from the DEP after 12 months. The reason being that most contracts are slated to participate in basic training (and thus leave the DEP as a full-fledged Army recruit) within 12 months from their contract date. Thus, we can analyze DEP Seasonality by simply examining data from FY95-98.

**Testing Homogeneity of Data.** With this partitioning scheme in mind we can now examine the data to determine both Contract Seasonality and DEP Seasonality. However, a statistical test should be performed to determine if the data from FY95-99 (or FY95-98 in the case of DEP Seasonality) are homogeneous in nature (i.e. each year has the same distribution). The test we choose to determine homogeneous data sets is the Kruskal-Wallis test, which is an extension of the Mann-Whitney test. It is a nonparametric test since no assumptions are made about the distributions of the data. The test is described on page 408 of Law & Kelton, Simulation Modeling and Analysis. We present the test in the next subsection and use it later in Chapter 4.

**Kruskal-Wallis Test for Homogeneity of Different Data Sets.** Assume we have $k$ independent sets of data and we wish to test whether these data sets are homogeneous. Denote the $i^{th}$ sample of size $n_i$ by $X_{i1}, X_{i2}, \ldots, X_{in_i}$ for $i = 1,2,\ldots,k$ and let $n$ be the total number of observations in the $k$ data sets,

$$n := \sum_{i=1}^{k} n_i$$

We wish to test the hypothesis:

$H_0$: All of the population distribution functions are identical

$H_1$: At least one of the populations tends to yield different observations than at least one of the other populations

To form the Kruskal-Wallis (KW) test statistic, we assign rank 1 to the smallest of the $n$ observations, rank 2 to the second smallest, and so on to the largest of the $n$ observations. Let $R(X_{ij})$ be the rank of $X_{ij}$ and let $R_i$ be the sum of the ranks assigned to the $i^{th}$ sample,

$$R_i := \sum_{j=1}^{n_i} R\left(X_{ij}\right)$$

The KW test statistic $T$ is then defined as

$$T := \frac{12}{n\cdot(n+1)}\cdot\left[\sum_{i=1}^{k} \frac{\left(R_i\right)^2}{n_i}\right] - 3\cdot(n+1)$$

We will reject the null hypothesis Ho at level $\alpha$ if $T > \chi^2_{1-\alpha,\, k-1}$, where $\chi^2_{1-\alpha,\, k-1}$ is the upper 1-$\alpha$ critical value for a chi-square distribution with $k$-1 degrees of freedom. If we have duplicate values within the data set our ranking policy must change. In Practical Nonparametric Statistics, Conover suggests assigning to each of these tied values the average of the ranks that would have otherwise been assigned. For example, if we have observations 3,4,4,5 we assign rank 1 to value 3, rank 2.5 = (2+3)/2 to each of the values of 4, and rank 4 to value 5.

This test can validate the merging of the different yearly data to form a common distribution across all years. We will assume each year is independent of each other for these tests. From favorable test results we may use the entire data set and then examine recruit contract trends during the year (i.e. Contract Seasonality).

**Review of SIMPROCESS and the Current Army Recruiting Model**

SIMPROCESS is an icon-based simulation language developed by the CACI Company. A powerful advantage of this simulation language over other simulation packages is the visual display of system entities and the processes through which they flow. The hierarchical relationship between system processes and their subprocesses is graphically represented within the simulation environment. The high-level processes of the current Army recruiting model are shown in Figure 3.1.

This high-level representation allows for an easier interpretation of the simulated system. Clicking on a rectangular process folder opens all subprocesses of that particular process. Figure 3.2 shows the subprocesses of the R1Sales (Recruiter#1 Sales) process.

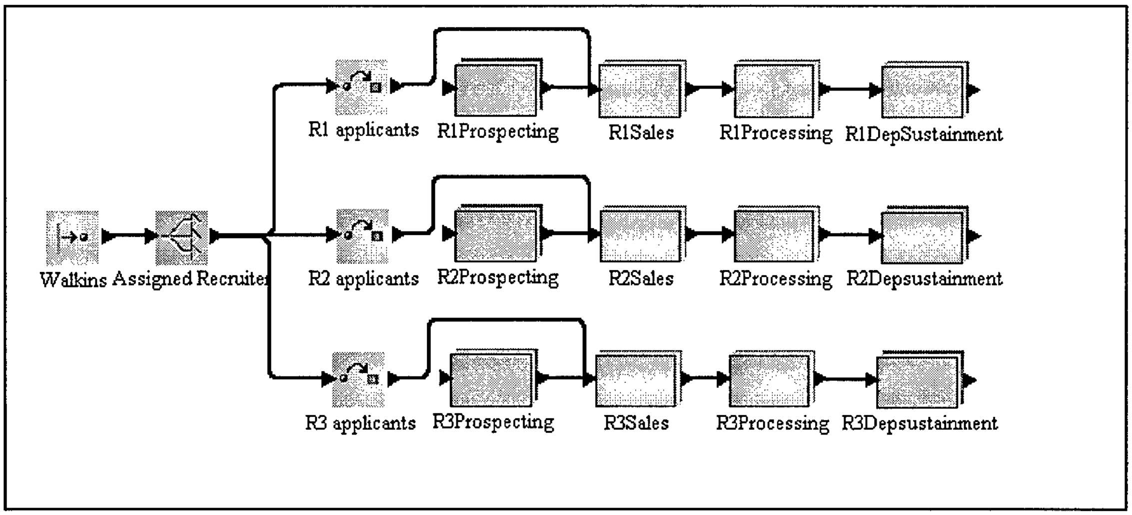



Figure 3.1 High-level Army Recruiting Model

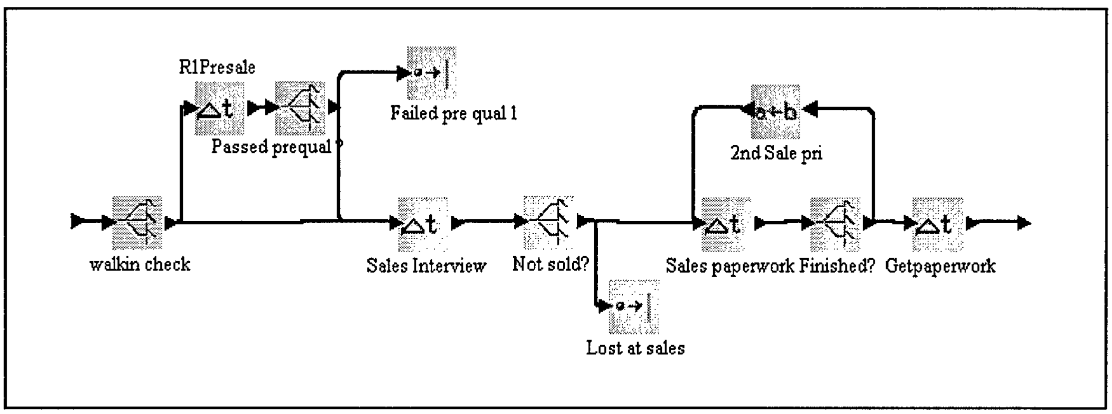



Figure 3.2 Subprocesses of R1Sales

The attractive visual features of SIMPROCESS are somewhat offset by a loss of model flexibility. First, SIMPROCESS does not allow for system interrupts. Thus, a recruiter will finish the current task even if a higher priority task requests the recruiter resource. As a work-around, Cordeiro and Friend (1998) broke up long processing times into more, but shorter, segments. After each segment, the recruiter resource was released to work on any higher priority tasks. Another severe limitation is that the language does not support the use of arrays. Previous AFIT researchers had to explicitly declare variables instead of using simpler array structures. They reduced model overhead by eliminating as many variables as possible. We determined early in our research that SIMPROCESS was stretched to its limits with the current model. To overcome this problem we planned to duplicate the model in a more powerful simulation environment.

**The AweSim Simulation Environment**

AweSim is a powerful simulation system that supports the simulation language Visual SLAM. The AweSim environment provides capabilities for network model building and execution. "Network models are powerful tools for problem-solving; as they are graphic so that the model can be displayed and understood by other modelers, managers and decision makers" (Pritsker and O'Reilly, viii). Graphical models can be built easily using AweSim's graphic modeling symbols. Figure 3.3 shows a simple AweSim model.

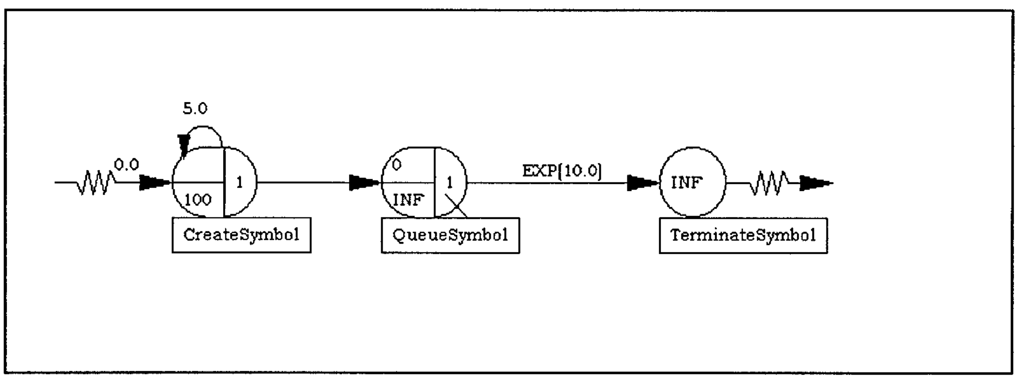



Figure 3.3 Simple AweSim Model

The create node tells us that entities are created every 5 minutes until a total of 100 have been created. The queue node gives each entity a place to wait for the system server to process each entity, which takes an exponentially distributed amount of time with a mean of 10 minutes. The final node, termination node, disposes of the entities. Here we have used only a few of AweSim's available modeling symbols and already we could model a diverse mix of systems. In addition to these modeling facilities, AweSim has extensive input/output, database, and statistical analysis utilities making it an attractive simulation tool.

For our purposes, AweSim's most valuable feature was its use of arrays. The arrays would enable us to store our recruiting model values more efficiently, as opposed to SIMPROCESS declaring a variable for each value. We wanted to develop a new AweSim recruiting model, which would mimic the SIMPROCESS model's processes. We will use the more efficient AweSim model for our simulation output analysis.

**Simulation Methodology**

As previously noted, this study relies upon simulation. We strived to follow standard simulation doctrine in this study. This section describes random number generation along with a brief discussion of the specific random variate distributions used for input modeling.

**Random Number Generation.** If a simulation is to mimic a real-world system, elements of randomness must be incorporated to account for system variations. We have numerous random processes within our Army recruiting system. Some examples include the time between applicant arrivals, the time to process a moral waiver, and the time a contracted recruit will spend in the DEP.

The uniform random distribution on the interval [0,1], denoted *Unif(0,1)*, provides the baseline random numbers used to generate most other random variates. Simulation languages must have an acceptable random number generator if any random results are to be trusted. The uniform random variates should *appear* independent and uniform over the entire interval. We stress the word *appear* because no computer simulation generates truly random numbers. In fact, all "random" numbers are in fact absolutely known beforehand as long as one knows the method of generation and the seed value.

**Triangular Distribution.** Now that we have a means to generate random numbers, we must determine the probability distributions to be used in our models. Input analysis deals with this problem. Cordeiro and Friend undertook the daunting task of building an Army recruiting model from scratch. They suffered from having very little data from which to determine the input distributions of recruiting processes.

In the absence of such data, the most popular random distribution is the triangular distribution, denoted *Triang(a,b,c)*. The parameter *a* represents the minimum time value the process may take, *b* represents the mode or most likely value, and *c* represents the maximum value. Figure 3.4 shows the *Triang(a,b,c)* distribution. Note that the mode may be different from the mean value. Most of the random variates produced in the Army recruiting model are from a triangular distribution. This representation makes it much easier for a recruiter to characterize the completion times of various tasks: minimum, most likely, and maximum. We note that these minimum and maximum values indeed may not represent the absolute minimum and maximum values, respectively. Within our study, these values can be thought of as the average minimum and the average maximum values. If our USAREC data fails to reveal different distributions, we will continue to use the triangular distribution.

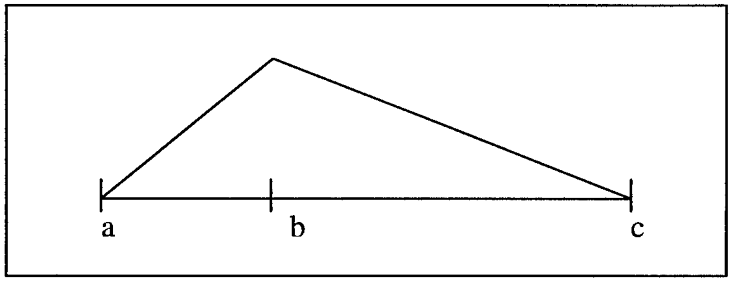



Figure 3.4  Triangular Distribution ~ *Triang(a,b,c)*

**Exponential Distribution.** The exponential distribution, denoted *Exp(λ)*, is commonly used to model the interarrival times between successive events. The parameter $\lambda$ is the constant rate. Many texts define the exponential distribution differently, so we explicitly define its density function below and provide a graphical representation of *Exp(λ)* with $\lambda = 1$ in Figure 3.5.

$$f(x) = \lambda * \exp(-\lambda * x) \qquad x \geq 0$$

$$f(x) = 0 \qquad otherwise$$

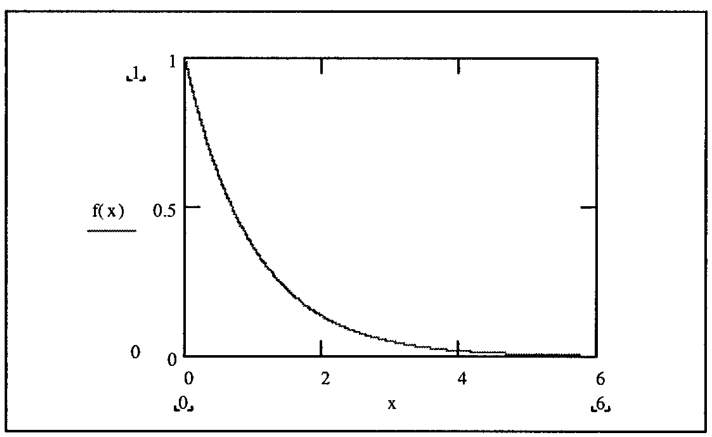



Figure 3.5  Exponential Density Function (with parameter $\lambda$=1)

The exponential distribution has mean $(1/\lambda)$ and variance $(1/\lambda)^2$. This distribution allows the possibility of very large interarrival or service times, and thus is well suited to model unpredictable processes such as arrivals to a system. Within the Army recruiting model, the *Exp*($\lambda$) random variates are used to model the interarrival times of walk-in applicants to the recruiting station (the applicants prospected by the recruiter are modeled with the triangular distribution).

In addition to allowing wide variations in event occurrences, the exponential distribution also possesses the memoryless property. To illustrate this property, think of a light bulb. If the light bulb's lifetime follows the exponential distribution, then the probability it works at least $s + t$ hours given that it has worked $t$ hours is the same as the initial probability that it works for at least $s$ hours.

**Weibull Distribution.** The previous research teams lacked sufficient recruiting data to propose an acceptable distribution for each recruit's time in the DEP. As we will show in the next chapter, our recruiting data supported a DEP time distribution different than the previously used *Triang(a,b,c)*. We found the *Weibull*($\alpha,\beta$) distribution to be the most appropriate distribution to model each recruit's respective time in DEP. The parameter $\alpha$ is the shape parameter while $\beta$ represents the scale parameter.

We suspect different types of recruits would spend different amounts of time in DEP; therefore, we want to model DEP time using a single distribution capable of representing varying times. The Weibull distribution is such a distribution, because many differently shaped distributions can be modeled with different $\alpha$ and $\beta$ parameters. In Figure 3.6 we show two different *Weibull*($\alpha$,1) distributions (both with $\beta = 1$), one with $\alpha = 2$ and another with $\alpha = 8$.

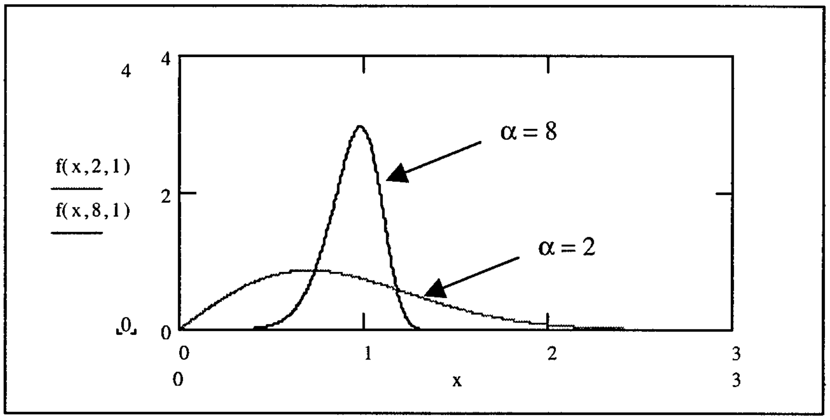



Figure 3.6 Weibull Density Function ($\alpha = 2$ and $\alpha = 8$, $\beta = 1$)

Above we have described the two primary random distributions used in the previous versions of the Army recruiting model along with a new distribution we will use to model DEP time. We now present our proposed model modifications.

## Intended Model Modifications

We intend to modify the current Army recruiting model in four general areas. Each of the areas and their proposed enhancements are described in the following subsections.

**Incorporation of "Other" Prospect Type.** The Army currently allows up to 10% of all recruits to be high school "nongraduates". This encompasses both home schooled applicants and those with GEDs (General Equivalency Diplomas). Another group of applicants, prior military service applicants, is not represented within the current recruiting model. Preliminary analysis of our recruiting data indicated this "Other", or OTH as represented within our model, group accounting for over 16% of all contracts. This being a large percentage of our contracts, we felt it necessary to incorporate these applicants into the simulated system.

We will explain the actual modeling changes within Chapter 4. Recall that we will incorporate changes to both the previous SIMPROCESS model and our newly built AweSim model.

**Determination of Prospect Input Proportions.** In the current model, each prospect had a proportion parameter representing its relative proportion with respect to total contracts. This parameter was used to assign entities a prospect type within the model. However, these proportions dealt with contract proportions, not prospect input proportions (how many of each type enter the system). We now propose a more precise determination of input proportions to the recruiting system.

An approximation for input proportions can be obtained by using the contract proportions along with the probabilities of each prospect type proceeding through the recruiting stages. We know the probabilities of each prospect type making it through the system from entry to contracting (i.e. probability of going from *Prospecting* to *Sales*, probability of going from *Sales* to *Processing*, and we can compute the probability of going from *Processing* to *DEP Sustainment*). Using this information we can "backtrack" through the system to determine the approximate input proportions. Before we illustrate this process, we need to calculate each prospect type's probability of going from *Processing* to *DEP Sustainment*. We show one of these calculations using the GMA (Graduate-Male-Alpha) type. The complete *Processing* stage with the appropriate probabilities for a GMA applicant is shown in Figure 3.7.

From Figure 3.7 we can compute the total probability of a GMA applicant making it through the *Processing* stage to *DEP Sustainment.* This probability is computed at about 0.72 and can be utilized with the other known stage probabilities for GMA's to determine an approximate GMA input proportion. For a GMA, the probability of going from *Prospecting* to *Sales* is 0.65 and from *Sales* to *Processing* is 0.28 and from *Processing* to *DEP Sustainment* is 0.72 (as calculated above); thus, the total probability of a GMA becoming a contract is (0.65)*(0.28)*(0.72) = 0.131 (assuming the stages are independent). If we combine this information for GMA's with all other applicant types we can determine the approximate input proportions for each of the nine applicant types. We present the complete results in Chapter 4.

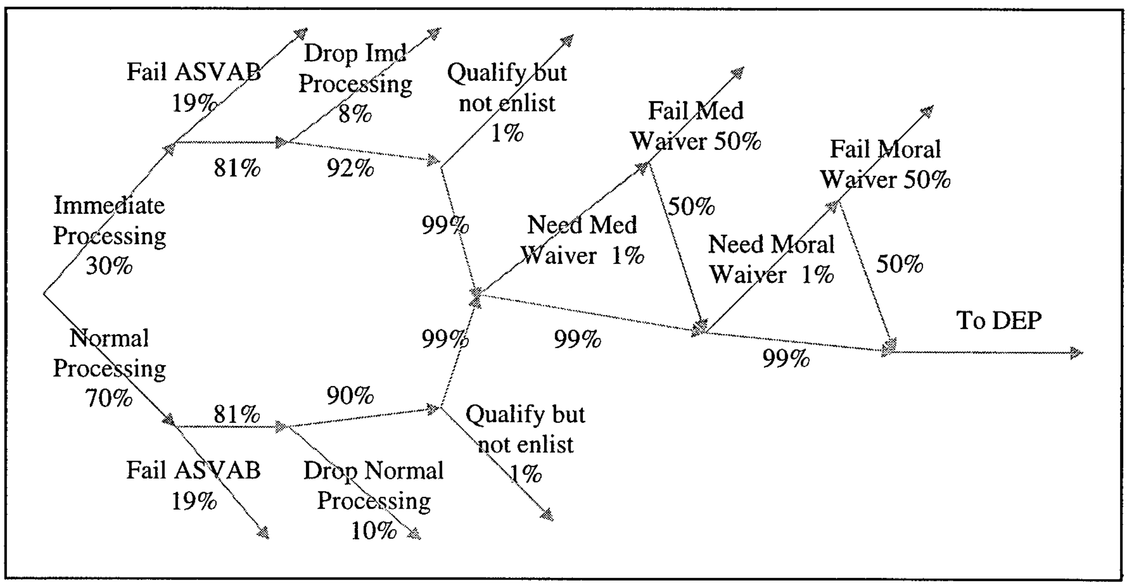



Figure 3.7 *Processing* Stage for GMA Prospect

**Contract Seasonality.** The no array limitation of SIMPROCESS greatly reduces model efficiency. The current model runs slowly due to the immense overhead associated with all the added global and local variables used in place of an array structure. This realization limits our approach when deciding how to incorporate seasonality effects. We certainly expect different monthly interarrival and prospecting rates, but adding 12 different monthly rate parameters for each of the prospect types would be quite inefficient.

Fortunately, we can capture the essence of contracting seasonality with a much simpler construct. As we will show in Chapter 4, analysis of the USAREC data shows a significant contracting boost only in the summer months: June, July, August, and September. Furthermore, although individual prospect contract proportions fluctuate during the months, these fluctuations are statistically insignificant. Thus, we can model contracting seasonality with two different seasons: non-summer and summer. These seasons will affect both walk-in generation rates and recruiter prospecting rates. We will then see an increase in applicants for each recruiter, subsequently giving the recruiter more time to process these applicants. The details of determining the actual summer and non-summer rates will be discussed in Chapter 4.

**DEP Seasonality.** Initially, we wanted to incorporate DEP Seasonality in much the same fashion as with Contract Seasonality. However, upon further examination of the DEP data, we realized that DEP Seasonality is dependent upon two factors: the amount of time in DEP and the probability of a DEP loss conditional on the length of time in DEP.

**Expected Time in DEP (Shipping Patterns).** Each recruit will spend some time in the DEP, ranging from a few days to over a year in some cases. Furthermore, the time a recruit spends in the DEP is highly dependent upon graduation status and also when they were contracted. Typically, and intuitively, graduates spend a short amount of time in the DEP because they only have to wait for a training slot to open. Recruits contracted as seniors, however, may spend up to a year in the DEP waiting for their high school graduation. The USAREC data clearly shows these trends (see Chapter 4).

Now the question becomes: How do we incorporate this into the model? The model currently uses a triangular distribution for expected time in DEP with parameters 2, 4, and 6 months (minimum, most likely, and maximum) for each recruit type. Our data suggests different distributions for graduates/OTH and seniors. It also suggests different distributions depending on when the applicant is contracted (summer versus non-summer months). Chapter 4 gives the analysis of this data and the resulting distributions and parameters. Based on the appropriate distribution parameters, each recruit type will be assigned a time in DEP.

**Probability of DEP Loss.** Once a recruit has been assigned his/her time in DEP, they cycle through the *DEP Sustainment* stage/loop within the model. In this loop, they compete for the recruiter resource for scheduled face-to-face and telephone meetings. These meetings are designed to keep the recruit interested in the Army until his/her expected shipping date.

The current model employs a standard probability of dropping from the DEP each month. McLarney's study assigned each recruit type the same standard probability of monthly DEP loss (set at 0.035). This value is incremented slightly during model execution if the recruiter is too busy with other tasks and misses a meeting. Thus, the probability of a recruit dropping from the DEP is directly related to the time in DEP. This seemed rather intuitive: the longer a recruit waits in DEP, the higher the probability of deciding against military service. We decided to leave this construct within the model because our data supports this basic principle. We will discuss our data results concerning this matter further in Chapter 4. If interested, the model user can easily change any recruit type's base probability of DEP loss.

This section explained our intended model modifications in the three areas of incorporating the OTH prospect type, modeling Contract Seasonality, and modeling DEP Seasonality through the new DEP time distribution. All model modifications were conducted in accordance with standard verification and validation techniques, as described in the following section.

**Verification and Validation Techniques**

Every credible simulation study should follow established principles of verification and validation (V&V). Furthermore, verification and validation should take place throughout the simulation study and not be merely an afterthought. Verification deals with determining whether a simulation computer program performs as intended (Law and Kelton, 299). In essence, verification concerns whether we built the model *right.* Validation deals with determining whether the simulation model is an accurate representation of the system under study (Law and Kelton, 299). This translates to whether we built the *right* model. This section explains the V&V techniques we employed throughout this study.

**Verification Issues.** The purpose of verification in our case involves incorporating our conceptual changes into a correctly working program. We already have a verified model from the previous studies; thus, we must concentrate on changing the model only to incorporate our intended enhancements. Law and Kelton point to some verification techniques we adhere to in this study.

**Modular Structure.** Cordeiro and Friend took care to assemble the current model in modular components, verifying each module for correctness. We do not propose any new modules, only changes to modules concerning the generation of applicants and the sustainment of DEP recruits. Our changes will be done one at a time, verifying the changes as we proceed.

**Structured Walk-Through.** A structured walk-through is a formal process of having key players in the modeling process walk-through each proposed change, verifying the rationale and underlying assumptions. The reason for multiple participants, instead of just the author, is that the author can become biased and often miss fatal mistakes. We intend to walk-through each proposed change with the author, at least one of the thesis advisors, and our point of contact at USAREC.

**Animation.** For the SIMPROCESS model, we have the ability to show the entities (applicants) as dots moving through the processes depicted on the computer screen. In addition, SIMPROCESS also allows for counts to be kept at each node of the model. This gives a sense of throughput and also reveals any bottlenecks in the model. For the AweSim model, we can verify how many entities make it through different parts of the system using AweSim's activity features. After program execution, the number of entities through each activity is displayed for the user. We plan to exploit these feature to help verify our intuitions about the recruiting process.

**Comparison of Sample Statistics to Historical Statistics.** After our model changes have been incorporated, we should gather statistics on various measures (i.e. number of contracts each month) and compare to historical statistics. The degree of commonality between the sample and historical statistics will provide yet another verification tool.

**Validation Issues.** "There is no such thing as an absolutely valid model" (Law and Kelton, 306). With this in mind, we can only hope for a model valid enough for its intended purposes. While verification is something that must be done in order to have a working computer model for the sponsor, validation is often not conducted at all. We recognize the importance of validation and present standard validation methods suggested by Law and Kelton.

**High Face Validity.** A model with high face validity is a model that, on the surface, appears reasonable to those knowledgeable about the modeled system (Law and Kelton, 308). For our study, people knowledgeable about the system would certainly be local Army recruiters and from a higher level, MAJ Robert Fancher of USAREC. In the early stages of the study, we will work closely with MAJ Fancher to ensure we capture the big picture and make the correct model assumptions. In the later stages, we hope to work more closely with local recruiters to validate our lower level processes.

In addition to these "system experts", we will use our own experience and intuition. For example, we suspect that interarrival times to a service system such as a recruiting station will be independent and identically distributed (IID) exponential random variables.

**Test Assumptions of Model.** The goal of this validation technique is to validate initial model assumptions. For our study, we have historical recruiting data that will show the seasonality effects we suspect in the DEP. From this data, we will propose various theoretical probability distributions for an applicant's time in the DEP. We will then access the validity of these probability distributions fitting our data through standard goodness-of-fit tests.

Another validation tool quite useful and intuitive is sensitivity analysis. With sensitivity analysis, we test the sensitivity of simulation output to small changes in input parameters. For example, we can perturb the arrival rates of walk-in applicants and check for reasonable changes in model output. When performing sensitivity analysis, it is important to reduce simulation variance through the use of common random numbers. Otherwise, changing one aspect of the model might be confounded with other changes that have occurred (Law and Kelton, 311). This idea calls for different random streams assigned to each of the recruiting processes. In our AweSim model, each of the recruiters will get the same streams; however, each separate recruiting process will get different streams.

**Compare Simulation Output with Recruiting Data.** This validation technique is very powerful and entails checking if the simulation output resembles the expected output from the system. The desired level of resemblance depends on the intended use of the simulation model. We hope that our simulation output matches actual recruiting station output with respect to seasonality trends. For example, our historical data shows higher numbers of recruits contracted during the summer months so we expect our model to show similar results. The validity of our model will be directly related to the level of correspondence between our recruiting simulation and the actual recruiting system.

A Turing test is another method of comparing simulation and system output. The test consists of asking system experts to examine sets of system output as well as sets of model output without knowing which sets are which. Both the system and simulation output data should be in the same format for standardization. If the system experts cannot distinguish between simulation and system output, the validity of our model is supported. If system experts are able to distinguish the simulation output, they should be asked why they were able to pinpoint the simulation output. Their explanations can be used to improve the simulation. We plan to conduct several Turing tests with local Army recruiters as early in the study as possible, so as to allow adequate time for simulation improvements.

**Summary**

This chapter described our research methodology. We discussed data analysis methods for interpreting seasonality effects from the USAREC recruiting data. Next, we quickly reviewed high-level SIMPROCESS constructs and also showed the high-level processes of the Army recruiting model within the SIMPROCESS environment. Then we introduced the AweSim simulation language as we planned to build a similar recruiting model for increased flexibility and speed. We also proposed simulation methodology to include random number generation and the various random variable distributions used within our models. The next section explained our proposed model enhancements. Finally, we discussed verification and validation issues utilized within this study.

The next chapter presents input analysis of the USAREC data along with the incorporation of the analysis results into our computer models.

## Chapter 4 – Input Analysis and Model Enhancements

### General

This chapter explains the input analysis and model enhancements of our study. The first section presents all input analysis results from our recruiting data. The next section covers the incorporation of the analysis results into the SIMPROCESS model. In the third section we explain our AweSim recruiting model, built to alleviate the limitations within the SIMPROCESS model. In addition, we will compare output from both recruiting models in an effort to show the similarities.

### Input Analysis

We intended to enhance a computer model through the analysis and subsequent incorporation of recruiting data results. The data we received from MAJ Fancher of USAREC detailed information on when each applicant was contracted along with when they shipped to basic training. The data represented recruiting from the Dayton Recruiting Company for FY95-99. This section presents our data analysis results and is broken into four subsections: Homogeneity of Recruiting Data, Prospect Proportions, Contract Seasonality, and DEP Seasonality.

**Homogeneity of Recruiting Data.** We had five years of recent recruiting data for our analysis. We wanted to test the homogeneity of our data in several areas: yearly contracts (FY95-99), monthly contracts, contracts by recruiting stations, monthly contract prospect proportions, and finally with respect to yearly DEP losses (FY95-98). These tests would enable us in the later subsections to merge entire data sets to better distinguish prospect proportions and determine seasonality characteristics. For each test we used a 90% confidence ($\alpha$=0.1).

**Yearly Contracts.** Before we could use our data for analysis, we needed to test whether we had the same contract distributions across the years FY95-99. Without such a determination we might find ourselves using data from an outlier year, thereby missing the true significance of the data. To set up the Kruskal-Wallis test we displayed the number of monthly contracts for each FY and then assigned appropriate rankings. For example, there were a total of 24 contracts from the Dayton Recruiting Company in October of FY95. The corresponding ranking is 10.5 for this number of contracts. The displayed data and rankings follow in Table 4.1.

Table 4.1 Test for Homogeneity – Yearly Contracts

| | FY95 | R1 | FY96 | R2 | FY97 | R3 | FY98 | R4 | FY99 | R5 |
|---|---|---|---|---|---|---|---|---|---|---|
| Oct | 24 | 10.5 | 20 | 4.5 | 31 | 37.5 | 37 | 52 | 29 | 32 |
| Nov | 24 | 10.5 | 20 | 4.5 | 36 | 49 | 27 | 24 | 26 | 18 |
| Dec | 34 | 45 | 26 | 18 | 24 | 10.5 | 27 | 24 | 26 | 18 |
| Jan | 27 | 24 | 18 | 2 | 26 | 18 | 33 | 43.5 | 37 | 52 |
| Feb | 28 | 29 | 29 | 32 | 29 | 32 | 27 | 24 | 33 | 43.5 |
| Mar | 31 | 37.5 | 32 | 41 | 25 | 14.5 | 25 | 14.5 | 41 | 56.5 |
| Apr | 30 | 34.5 | 24 | 10.5 | 23 | 7 | 24 | 10.5 | 26 | 18 |
| May | 27 | 24 | 20 | 4.5 | 17 | 1 | 20 | 4.5 | 24 | 10.5 |
| Jun | 35 | 46.5 | 43 | 58 | 28 | 29 | 36 | 49 | 30 | 34.5 |
| Jul | 31 | 37.5 | 39 | 54.5 | 37 | 52 | 28 | 29 | 41 | 56.5 |
| Aug | 53 | 60 | 32 | 41 | 52 | 59 | 27 | 24 | 31 | 37.5 |
| Sep | 32 | 41 | 27 | 24 | 39 | 54.5 | 35 | 46.5 | 36 | 49 |
| Rank Sums | | 400 | | 295 | | 364 | | 346 | | 426 |

Here we tested:

$H_0$: All five yearly contract distributions are identical
$H_1$: At least one year tends to yield more contracts than another year

From the rankings we computed a Kruskal-Wallis test statistic of 2.81. Since this value is less than the $\chi^2$ ($\alpha$=0.1, $k$-1=4) value of 7.78 we fail to reject Ho. In other words, we could now assume similar yearly contract distributions.

**Monthly Contracts.** We used the same data and rankings above to test monthly contract distributions. We needed only to calculate the Rank Sums horizontally across years FY95-99 for each month. Notice that there were still 24 contracts in October FY95 and this resulted in the same ranking of 10.5. The data is shown in Table 4.2.

Table 4.2 Test for Homogeneity – Monthly Contracts

| | FY95 | FY96 | FY97 | FY98 | FY99 | Rank Sums |
|---|---|---|---|---|---|---|
| **Oct** | 24 | 20 | 31 | 37 | 29 | |
| **R1** | 10.5 | 4.5 | 37.5 | 52 | 32 | 136.5 |
| **Nov** | 24 | 20 | 36 | 27 | 26 | |
| **R2** | 10.5 | 4.5 | 49 | 24 | 18 | 106 |
| **Dec** | 34 | 26 | 24 | 27 | 26 | |
| **R3** | 45 | 18 | 10.5 | 24 | 18 | 115.5 |
| **Jan** | 27 | 18 | 26 | 33 | 37 | |
| **R4** | 24 | 2 | 18 | 43.5 | 52 | 139.5 |
| **Feb** | 28 | 29 | 29 | 27 | 33 | |
| **R5** | 29 | 32 | 32 | 24 | 43.5 | 160.5 |
| **Mar** | 31 | 32 | 25 | 25 | 41 | |
| **R6** | 37.5 | 41 | 14.5 | 14.5 | 56.5 | 164 |
| **Apr** | 30 | 24 | 23 | 24 | 26 | |
| **R7** | 34.5 | 10.5 | 7 | 10.5 | 18 | 80.5 |
| **May** | 27 | 20 | 17 | 20 | 24 | |
| **R8** | 24 | 4.5 | 1 | 4.5 | 10.5 | 44.5 |
| **Jun** | 35 | 43 | 28 | 36 | 30 | |
| **R9** | 46.5 | 58 | 29 | 49 | 34.5 | 217 |
| **Jul** | 31 | 39 | 37 | 28 | 41 | |
| **R10** | 37.5 | 54.5 | 52 | 29 | 56.5 | 229.5 |
| **Aug** | 53 | 32 | 52 | 27 | 31 | |
| **R11** | 60 | 41 | 59 | 24 | 37.5 | 221.5 |
| **Sep** | 32 | 27 | 39 | 35 | 36 | |
| **R12** | 41 | 24 | 54.5 | 46.5 | 49 | 215 |

Here we tested:

$H_0$: All twelve monthly contract distributions are identical
$H_1$: At least one month tends to yield more contracts than another month

From the rankings we computed a Kruskal-Wallis test statistic of 26.07. Because this value is greater than the $\chi^2$ ($\alpha$=0.1, $k$-1=11) value of 17.275 we reject Ho. In other words, some months tend to yield more contracts than other months. This is exactly what we needed to support our notion of Contract Seasonality. Further analysis of this result will follow in the subsection Contract Seasonality.

**Contracts by Recruiting Station.** We suspected that different recruiting stations indeed performed differently. Reasons might be differences in regional demographics or the effectiveness of recruiters and station commanders. Since we had data available on six different recruiting stations (5D6A through 5D6S), we decided to test for contract differences between the stations. For a better comparison, we divided each station's total monthly contracts (for FY95-99) by its number of respective recruiters. The data and rankings follow in Table 4.3.

Table 4.3 Test for Homogeneity – Contracts by Recruiting Station

| | 5D6A | R1 | 5D6B | R2 | 5D6F | R3 | 5D6M | R4 | 5D6N | R5 | 5D6S | R6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Oct | 2.50 | 3 | 5.14 | 45 | 5.00 | 41.5 | 4.60 | 33 | 6.50 | 62.5 | 3.25 | 5 |
| Nov | 4.25 | 25 | 3.29 | 6 | 4.75 | 36 | 3.80 | 14.5 | 5.83 | 58 | 5.00 | 41.5 |
| Dec | 4.00 | 19 | 4.00 | 19 | 6.50 | 62.5 | 3.60 | 9 | 4.67 | 34 | 5.25 | 47 |
| Jan | 4.00 | 19 | 5.00 | 41.5 | 4.75 | 36 | 3.80 | 14.5 | 5.33 | 48 | 5.00 | 41.5 |
| Feb | 4.00 | 19 | 5.43 | 50.5 | 4.50 | 30 | 4.00 | 19 | 6.17 | 59 | 4.25 | 25 |
| Mar | 4.50 | 30 | 4.57 | 32 | 7.00 | 64.5 | 4.20 | 23 | 5.50 | 53.5 | 5.50 | 53.5 |
| Apr | 1.75 | 1 | 4.43 | 28 | 4.00 | 19 | 4.00 | 19 | 5.17 | 46 | 5.50 | 53.5 |
| May | 3.75 | 12 | 3.14 | 4 | 4.25 | 25 | 2.40 | 2 | 4.50 | 30 | 3.75 | 12 |
| Jun | 4.75 | 36 | 3.71 | 10 | 5.50 | 53.5 | 4.80 | 38 | 8.33 | 71 | 7.75 | 68 |
| Jul | 3.50 | 8 | 5.43 | 50.5 | 6.25 | 60 | 3.40 | 7 | 9.00 | 72 | 7.00 | 64.5 |
| Aug | 5.00 | 41.5 | 7.14 | 66 | 5.00 | 41.5 | 5.40 | 49 | 8.17 | 70 | 7.25 | 67 |
| Sep | 3.75 | 12 | 5.57 | 56 | 8.00 | 69 | 4.40 | 27 | 6.33 | 61 | 5.75 | 57 |
| **Rank Sums** | | 226 | | 409 | | 539 | | 255 | | 665 | | 536 |

Here we tested:

$H_0$: All six recruiting stations have the same contract distributions
$H_1$: At least one station tends to yield more contracts than another station

From the rankings we computed a Kruskal-Wallis test statistic of 28.66. Because this value is greater than the $\chi^2$ ($\alpha$=0.1, $k$-1=5) value of 9.24, we reject Ho. Thus, some stations tend to yield more contracts per recruiter than other stations, as we expected. We need not worry about this result since we modeled only a single recruiting station. Future researchers, however, should consider this result if modeling more than one station.

**Monthly Contract Prospect Proportions.** Later in this chapter we explain the prospect proportions we determined from our data, but first we must test the appropriate data for homogeneity during the course of the year. The data was grouped into total number of monthly prospects contracted and then appropriate rankings were assigned, as shown in Table 4.4.

Table 4.4 Test for Homogeneity – Monthly Contract Proportions

| | GMA | GMB | GFA | GFB | SMA | SMB | SFA | SFB | OTH | Rank Sums |
|---|---|---|---|---|---|---|---|---|---|---|
| **Oct** | 41 | 12 | 7 | 2 | 38 | 14 | 4 | 3 | 24 | |
| **R1** | 102.5 | 47 | 31.5 | 9 | 98 | 57 | 18 | 12.5 | 81 | 456.5 |
| **Nov** | 34 | 14 | 7 | 1 | 36 | 15 | 7 | 1 | 18 | |
| **R2** | 91.5 | 57 | 31.5 | 4.5 | 96 | 61 | 31.5 | 4.5 | 69 | 446.5 |
| **Dec** | 41 | 10 | 18 | 2 | 30 | 15 | 5 | 1 | 17 | |
| **R3** | 102.5 | 41.5 | 69 | 9 | 87.5 | 61 | 25 | 4.5 | 66 | 466 |
| **Jan** | 26 | 16 | 9 | 4 | 27 | 14 | 7 | 4 | 35 | |
| **R4** | 83 | 63.5 | 39 | 18 | 84 | 57 | 31.5 | 18 | 94 | 488 |
| **Feb** | 43 | 20 | 9 | 5 | 31 | 12 | 5 | 5 | 19 | |
| **R5** | 106 | 74 | 39 | 25 | 89 | 47 | 25 | 25 | 72 | 502 |
| **Mar** | 39 | 14 | 14 | 4 | 17 | 13 | 10 | 3 | 40 | |
| **R6** | 99.5 | 57 | 57 | 18 | 66 | 51.5 | 41.5 | 12.5 | 101 | 504 |
| **Apr** | 35 | 11 | 4 | 3 | 18 | 13 | 9 | 1 | 34 | |
| **R7** | 94 | 44 | 18 | 12.5 | 69 | 51.5 | 39 | 4.5 | 91.5 | 424 |
| **May** | 35 | 12 | 13 | 1 | 19 | 5 | 3 | 0 | 19 | |
| **R8** | 94 | 47 | 51.5 | 4.5 | 72 | 25 | 12.5 | 1 | 72 | 379.5 |
| **Jun** | 39 | 21 | 13 | 11 | 42 | 22 | 4 | 1 | 17 | |
| **R9** | 99.5 | 75.5 | 51.5 | 44 | 104.5 | 78.5 | 18 | 4.5 | 66 | 542 |
| **Jul** | 52 | 28 | 11 | 8 | 33 | 22 | 5 | 2 | 16 | |
| **R10** | 108 | 85 | 44 | 36 | 90 | 78.5 | 25 | 9 | 63.5 | 539 |
| **Aug** | 42 | 22 | 15 | 8 | 47 | 22 | 7 | 8 | 25 | |
| **R11** | 104.5 | 78.5 | 61 | 36 | 107 | 78.5 | 31.5 | 36 | 82 | 615 |
| **Sep** | 30 | 21 | 13 | 5 | 37 | 13 | 7 | 4 | 29 | |
| **R12** | 87.5 | 75.5 | 51.5 | 25 | 97 | 51.5 | 31.5 | 18 | 86 | 523.5 |

Here we tested:

$H_0$: All months have the same prospect proportions (with respect to contracts)
$H_1$: At least one month tends to yield different prospect proportions

From the rankings we computed a Kruskal-Wallis test statistic of 4.80. Because this value is less than the $\chi^2$ ($\alpha$=0.1, $k$-1=11) value of 17.275, we fail to reject Ho. In other words, we can use the same prospect proportions during the simulation year. This result will greatly simplify our modeling of prospect proportions.

**Yearly DEP Losses.** The last test involved whether our data showed similar patterns of DEP losses between the years FY95-98. We displayed our data to represent total DEP losses from those applicants contracted in each month. The reason for not including FY99 was that some contracts remain in the DEP for over a year and had we included FY99, we could miss future DEP losses. For example, Table 4.5 reveals six DEP losses from those applicants contracted in Oct FY95.

Table 4.5 Test for Homogeneity – Yearly DEP Losses

| | FY95 | R1 | FY96 | R2 | FY97 | R3 | FY98 | R4 |
|---|---|---|---|---|---|---|---|---|
| Oct | 6 | 32.5 | 2 | 9 | 3 | 13.5 | 3 | 13.5 |
| Nov | 4 | 20 | 5 | 27 | 0 | 2 | 1 | 5.5 |
| Dec | 4 | 20 | 0 | 2 | 3 | 13.5 | 0 | 2 |
| Jan | 3 | 13.5 | 3 | 13.5 | 7 | 35.5 | 1 | 5.5 |
| Feb | 2 | 9 | 6 | 32.5 | 4 | 20 | 4 | 20 |
| Mar | 5 | 27 | 4 | 20 | 1 | 5.5 | 5 | 27 |
| Apr | 5 | 27 | 6 | 32.5 | 5 | 27 | 4 | 20 |
| May | 4 | 20 | 2 | 9 | 11 | 41.5 | 1 | 5.5 |
| Jun | 5 | 27 | 15 | 44.5 | 11 | 41.5 | 14 | 43 |
| Jul | 15 | 44.5 | 17 | 46 | 19 | 47 | 23 | 48 |
| Aug | 8 | 37.5 | 8 | 37.5 | 6 | 32.5 | 9 | 39.5 |
| Sep | 7 | 35.5 | 9 | 39.5 | 3 | 13.5 | 5 | 27 |
| Rank Sums | | 314 | | 313 | | 293 | | 257 |

We tested:

$H_0$: All years (FY95-98) have identical DEP loss distributions
$H_1$: At least one year tends to yield more DEP losses than another year

From the rankings we computed a Kruskal-Wallis test statistic of 0.91. Because this value is less than the $\chi^2$ ($\alpha$=0.1, $k$-1=3) value of 6.25 we fail to reject Ho. Thus we can assume our DEP loss distributions are constant within our data.

This completes the testing for homogeneity of our data. We now use the results of these tests for the remainder of our input analysis.

**Prospect Proportions.** McLarney incorporated eight prospect types into the SIMPROCESS model. USAREC proposed the approximate proportions for his proposed eight prospect types, which he used in his study. We, however, had actual recruiting data over five statistically similar years with which to obtain our own prospect proportions. In our analysis we discovered another prospect group, the other (OTH) type, which was not represented in McLarney's study. Our data reflected this OTH type as accounting for 16.3% of all recruits, which we felt was substantial enough for incorporation into the recruiting model. In the previous section we determined that these contract proportions remained constant during the year. Therefore, we would create the same proportions of prospects during the year within our simulation model. We easily calculated each prospect type's contract proportion from our data (see Table 4.6).

Table 4.6 New Relative Contract Proportions

| Type | Proportion | Type | Proportion | Type | Proportion |
|---|---|---|---|---|---|
| GMA | 0.254 | GFB | 0.030 | SFA | 0.041 |
| GMB | 0.112 | SMA | 0.208 | SFB | 0.018 |
| GFA | 0.074 | SMB | 0.100 | OTH | 0.163 |

However, these proportions do not represent the proportions of applicants into the recruiting system. No such data was available at the time of our study. In Chapter 3 we proposed our methodology for computing approximate prospect input proportions. Here we present the complete analysis results.

We knew the average probabilities of each prospect type progressing through each recruiting stage (recall in Chapter 3 how we calculated the probability of making it from *Processing* to *DEP Sustainment*). The complete set of probabilities is displayed in Table 4.7. The last column shows each prospect type's total probability of becoming a contract. For example, 13.1% of GMA applicants (by multiplying each GMA stage probability together) make it through the recruiting process to *DEP Sustainment*.

Table 4.7 Recruiting Stage Probabilities

| **Type** | **Prospecting to Sales** | **Sales To Processing** | **Processing to DEP** | **Total Probability** |
|---|---|---|---|---|
| GMA | 0.65 | 0.28 | 0.720 | 0.131 |
| GMB | 0.65 | 0.28 | 0.325 | 0.060 |
| GFA | 0.65 | 0.28 | 0.720 | 0.131 |
| GFB | 0.65 | 0.28 | 0.325 | 0.060 |
| SMA | 0.65 | 0.20 | 0.661 | 0.086 |
| SMB | 0.65 | 0.20 | 0.333 | 0.043 |
| SFA | 0.65 | 0.20 | 0.661 | 0.086 |
| SFB | 0.65 | 0.20 | 0.333 | 0.043 |
| OTH | 0.65 | 0.24 | 0.510 | 0.080 |

Now that we had the total probability of each prospect type becoming contracts and the approximate contract proportions, we could determine approximate input proportions. For each prospect type we only had to solve a simple equation: $TotalProb_i * Input_i = ContractProp_i$, where the $i$ subscript represents each prospect type (GMA, GMB, ...). As an example, consider the GMA: $0.131 * Input_{GMA} = 0.254$ results in $Input_{GMA} = 1.94$. This tells us that to obtain 0.254 GMA contracts we should create 1.94 GMA applicants. However, we certainly do not want to create partial entities and we still do not know what proportions of each type to create. We can easily solve this by dividing each $Input_i$ by the sum of all $Input_i$'s. Our calculated input proportions are given in Table 4.8.

Table 4.8 Approximate Input Proportions

| Type | Proportion | Type | Proportion | Type | Proportion |
|---|---|---|---|---|---|
| GMA | 0.154 | GFB | 0.040 | SFA | 0.038 |
| GMB | 0.149 | SMA | 0.193 | SFB | 0.033 |
| GFA | 0.045 | SMB | 0.186 | OTH | 0.162 |

The only remaining determination was how to assign entities within our simulation to a particular prospect type. Table 4.9 shows how a *Unif(0,1)* random number draw and a cumulative probability table are used to assign prospect types within our models. For example, if a newly created entity draws $U = 0.23$ we see that it is assigned to type GMB. This construct is easily implemented in the model with conditional statements.

Table 4.9 Assignment of Prospect Types

| Prospect Type | Prospect Proportion | Cumulative Probability Values |
|---|---|---|
| SMB | 0.186 | $0.000 < U <= 0.186$ |
| SFB | 0.033 | $0.186 < U <= 0.219$ |
| GMB | 0.149 | $0.219 < U <= 0.368$ |
| GFB | 0.040 | $0.368 < U <= 0.408$ |
| SMA | 0.193 | $0.408 < U <= 0.601$ |
| SFA | 0.038 | $0.601 < U <= 0.639$ |
| GMA | 0.154 | $0.639 < U <= 0.793$ |
| GFA | 0.045 | $0.793 < U <= 0.838$ |
| OTH | 0.162 | $0.838 < U <= 1.000$ |

**Contract Seasonality.** Recall that the monthly contract test for homogeneity revealed significant contract differences between the months. Examination of the individual monthly Rank Sums suggests the summer months (June through September) produce significantly more contracts than non-summer months. In fact, the average number of contracts for summer months is 178/month, while the average number of contracts for non-summer months is 135.875/month. Thus, the summer months yield about 30% more contracts than non-summer months. Figure 4.1 shows the total monthly contracts for the Dayton Recruiting Company for FY95-99.

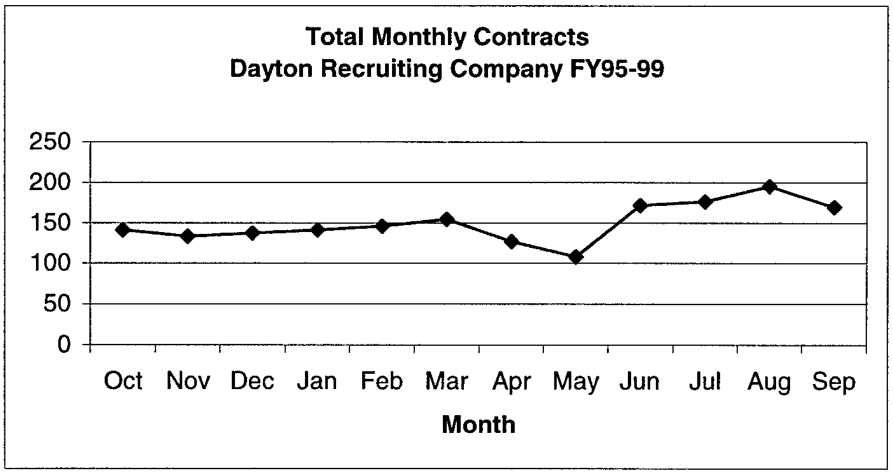



Figure 4.1 Monthly Contracts for Dayton Recruiting Company FY95-99

After discovering this seasonality effect, we needed to model this effect within our simulated recruiting process. It seems intuitive that to model such an effect we either have to create more applicants to the system or reduce the time needed to contract the applicant. We decided to use a combination of these ideas. The first thing we considered was the fact that a recruiter is already very busy in the current model. So adding more applicants to the system may not necessarily result in more contracts. Second, we have no supporting evidence suggesting it takes a recruiter more or less time during the year to complete many of the recruiting tasks. For example, it seems that processing paperwork will take the same amount of time during the year. These realizations steered us to consider changing only two recruiting processes to capture our seasonal behavior. First, we recognized walk-in applicants as being special, high priority applicants because they obviously show some desire to enter the service. Thus, we decided to shorten our walk-in interarrival rates during the summer months. This would result in easier contracting since the recruiter spends no energy getting the walk-in to agree to an initial meeting – the walk-in has already entered the station!

The second process we changed dealt with each recruiter's *Prospecting* stage. In this stage, the recruiter spends valuable time enticing potential applicants to agree to an initial meeting. Instead of creating more applicants in this stage we decided to shorten the time needed to get the applicant into the recruiting office. This captures the effect of easier prospecting and thus more time for actually contracting the applicant. Later we will show exactly how these ideas were incorporated into our computer model.

**DEP Seasonality.** Recall that the DEP loss test for homogeneity revealed similar distributions of DEP losses between FY95-98. The reason we did not look at the homogeneity between the months (as we did for Contract Seasonality) was because we felt the best way to model DEP Seasonality was to determine new DEP time distributions for each prospect type. Furthermore, these distributions would depend on when the prospect was contracted.

From our data we determined each contract's assigned DEP time (in hours). Note that this was the assigned DEP time, not the time they actually spent in DEP if they decided to drop. We then grouped the data according to contract type and in which season the recruit was contracted. Next we used Stat::Fit software to determine the appropriate distribution and parameters. Our goal was to find a single random distribution whose parameters could be changed to closely fit each of the DEP time data groups. We certainly had no desire to individually model each prospect type's DEP time with different random distributions. As it turned out, the Weibull distribution was the most appropriate single distribution, although in some cases other distributions also accurately fit the data. Figure 4.2 shows the Weibull fit to the DEP time distribution of GMA's contracted in the summer.

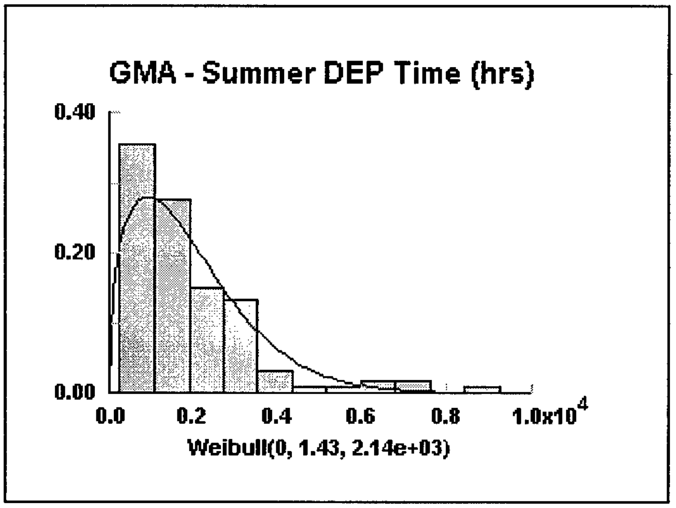



Figure 4.2 Stat::Fit Weibull Fit to GMA – Summer DEP Data

Before actually fitting the distributions to the data, we needed to decide how many bins should be used to represent the data. Simulation texts offer different rules to decide the number of appropriate bins. We decided to use the standard rule of thumb: # bins = square root of the number of available data points. For example, we had 127 sample points for GMA's contracted in the summer, which resulted in the data being put into 11 bins of equal length (see Figure 4.2).

We suspected extreme differences in the length of time spent in DEP between graduate and senior recruits. Intuitively, graduates can be shipped at almost any time of year while seniors usually must complete their high school education before shipping to basic training. As expected, our data supported this idea. Figure 4.3 shows the DEP time distribution (fit to the Weibull) for SMBs contracted in the summer. Contrast this senior's distribution shape to that of a graduate recruit in Figure 4.2.

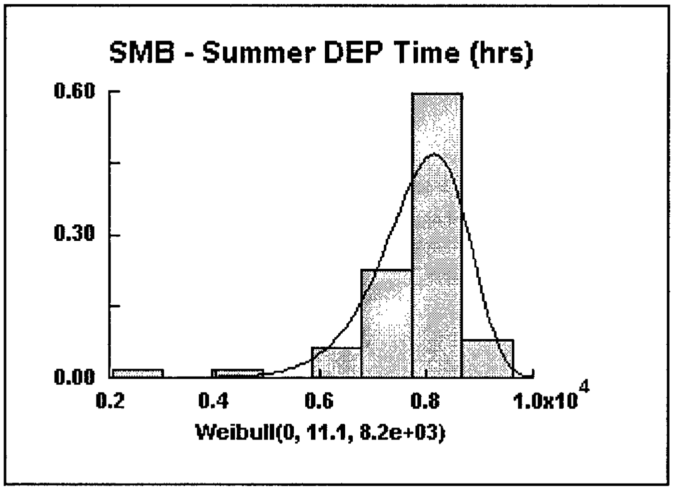



Figure 4.3 Stat::Fit Weibull Fit to SMB – Summer DEP Data

Furthermore, we expected to see differences in DEP time depending on whether the recruit was contracted during the summer or non-summer season. It turns out that the difference appears significant only between the senior recruits. This also seems intuitive. We would expect a senior contracted during the summer to spend more time in DEP than a senior contracted during his/her respective school year (a senior recruit typically does not attend basic training until after high school graduation). Tables 4.10 and 4.11 show each prospect type's Weibull parameters for the summer and non-summer season, respectively. Our data only included 24 SFB recruits, so separating their DEP times into two seasons would result in a poor representation. Instead, we combined all SFB DEP times and fit a single distribution, which we used in both seasons.

Table 4.10 DEP Time Weibull Parameters ~ Summer

| Type | $\alpha$ | $\beta$ | Type | $\alpha$ | $\beta$ |
|---|---|---|---|---|---|
| SMB | 11.06 | 8202.48 | SMA | 8.79 | 8115.46 |
| SFB | 3.59 | 6578.3 | SFA | 10.66 | 8175.11 |
| GMB | 1.47 | 2187.48 | GMA | 1.43 | 2139.35 |
| GFB | 1.81 | 2520.26 | GFA | 1.36 | 2410.76 |
| OTH | 1.45 | 1985.36 | | | |

Table 4.11 DEP Time Weibull Parameters ~ Non-Summer

| Type | $\alpha$ | $\beta$ | Type | $\alpha$ | $\beta$ |
|---|---|---|---|---|---|
| SMB | 3.4 | 4834.67 | SMA | 2.95 | 5364.94 |
| SFB | 3.59 | 6578.3 | SFA | 3.33 | 4834.67 |
| GMB | 1.51 | 1667.35 | GMA | 1.58 | 1821.75 |
| GFB | 1.3 | 2099.06 | GFA | 1.48 | 2309.0 |
| OTH | 1.36 | 1643.8 | | | |

For each Weibull fit, Stat:Fit conducted goodness-of-fit tests. Three tests were used to judge the accuracy of the fit: the chi-square test, the Kolmogorov-Smirnov test, and the Anderson-Darling test. The results of these tests can be found in Appendix D. The results support the appropriateness of using the Weibull distribution to model a recruit's DEP time.

### SIMPROCESS Model Modifications

In this section we incorporate the results of our input analysis into the SIMPROCESS model. We add a season control, the other prospect type, and constructs for Contract and DEP Seasonality.

**Season Control.** Our analysis results supported two different recruiting seasons: summer and non-summer. To keep track of the seasons within SIMPROCESS we added a season control loop at the highest level. Since our simulation was to begin on October 1$^{st}$, we initialized the global model variable *Season* to the non-summer value of 1.0. After a delay of eight months (5832 hours), we set *Season* to the summer value of 1.3.

These values introduced contract seasonality into the model, as discussed in the following subsection Contract Seasonality. The model user is free to experiment with different seasonality values.

**"Other" Type.** We encountered a few modeling problems when adding the other prospect type. First, we had no parameters values for this prospect type. As a quick fix, we assigned parameter values based on the average of the original eight prospect types. Future researchers may want to find better parameter estimates. These parameters are read in from the file "varvals1.txt" within the StartSimulation routine of our new season control loop's generate node. We had to read in the OTH parameter values separately because of memory limits within the StartSimulation routine of the Walk-in Generate node. The original eight prospect type's parameters are read in from the file "varvals2.txt".

We also had to declare a complete set of model variables for our new type. McLarney created seven duplicates of each model variable for each of his prospect types, then he appended a letter (from B-H) to each duplicate variable. We extended this meticulous process by creating a duplicate set of parameters and appending the letter I to the end to reference the parameter as belonging to the OTH prospect type.

**Contract Seasonality.** We made two model changes to allow for this seasonality. The first change involved how walk-ins arrive to the system. The second change was made within each recruiter's *Prospecting* stage.

We ran into another SIMPROCESS limitation when we tried to change the walk-in construct. We had hoped to simply change the previous walk-in interarrival rate of *Exp(72.0)* to *Exp(72.0/Season)*, giving the effect of faster walk-in arrivals during the summer (since Season = 1.3 during the summer). However, SIMPROCESS will not allow model variables as distribution variables within a generate node. Instead of manipulating a single generate node, we created another walk-in generator. Each generator (one for summer and the other for non-summer walk-ins) will produce walk-ins at their respective rates, but will only pass their walk-in applicants to recruiters depending on the current season.

Our second model change to facilitate Contract Seasonality takes place within each recruiter's *Prospecting* stage. Instead of creating more applicants within *Prospecting*, we simply reduced the amount of time needed by the recruiter to fully prospect a particular applicant (get him/her to the sales interview). We incorporated this change by adjusting the prospecting time based on the global variable *Season*. For example, an applicant is prospected either by telephone or face-to-face meetings and the model assigns the time needed (based on applicant type) to some variable, call it *ProspectT*. We simply adjusted this value to *ProspectT/Season*, which gives the desired effect of easier/faster prospecting during the summer season since *Season* = 1.3.

**DEP Seasonality.** This model change was the least cumbersome. Our DEP analysis revealed different seasonal Weibull parameters for each prospect type. We first needed to change the random variable draw within SIMPROCESS from the triangular to the Weibull. In addition, we needed to convert each prospect type's three previous triangular parameters into four Weibull parameters (two for summer and two for non-summer). We named the two summer parameters sumShapeDeptime and sumScaleDeptime corresponding to the Weibull shape and scale parameters, respectively. For the non-summer season, we used variables named nonShapeDeptime and nonScaleDeptime. Finally, we changed both parameter value files, "varvals1.txt" and "varvals2.txt", to correspond to the Weibull values calculated in the previous section. This completes our SIMPROCESS model enhancements. With all of our model enhancements added, the SIMPROCESS model runs extremely slowly. This result prompted us to consider porting the model into a different simulation language.

**AweSim Recruiting Model**

The previous thesis teams developed and enhanced a SIMPROCESS model. The model, although graphically elegant, runs very slowly. The primary reason is because the SIMPROCESS environment does not allow the use of arrays to store values. Instead the model must carry all parameters as distinct variables. For example, to determine the amount of time spent on a telephone DEP meeting, each of the three recruiters must have three parameters (to be used in the triangular distribution). This problem was amplified with the incorporation of nine different prospect types, because each prospect type could have different sets of values. We realized that the use of arrays could greatly reduce the model overhead associated with the large number of variables used in the model.

To alleviate the immense model overhead incurred by the SIMPROCESS model, we developed two AweSim models. The first model, Alpha Version, was a simple model with only a general prospect type and no seasonality. The second model, Beta Version, was more advanced using all nine prospect types and the seasonality characteristics we discovered in our data analysis. We now explain both AweSim models and compare each to their corresponding SIMPROCESS model.

**AweSim Model: Alpha Version.** AweSim supports the use of arrays and is also quite flexible. Graphically, AweSim seems inferior to SIMPROCESS; however, the reduced runtime more than compensates. We wanted to be able to build our AweSim model along the same logic as the SIMPROCESS model. As a basic AweSim model, we duplicated the general prospect type SIMPROCESS model developed by Cordeiro and Friend (1998) and then compared simulation outputs to test for differences.

We note here that we did not take full advantage of the power of AweSim. As noted in Chapter 3, SIMPROCESS does not support interrupts in the system (i.e. a recruiter will continue working with a lower priority task even if a higher priority task requests the recruiter resource). AweSim does, however, support interrupts through the use of PREEMPT nodes. However, we decided against using this construct in order to keep along the same programming logic as the SIMPROCESS model and to allow a better model comparison.

To validate the close resemblance of the two models we measured the mean number of contracts and the mean number of recruits shipped per replication. Each replication consisted of a standard one year model warm-up to reach steady state (with no statistics collected) followed by a one year model run. We ran 30 replications, enough to meet basic normality requirements, for our model comparison. To illustrate the runtime savings of our new model, the 30 replications using SIMPROCESS took about 100 real-time minutes versus the AweSim model completing in only 7 minutes (all runs were done on a Packard Bell 300MHz with a Pentium II Processor). Our AweSim model runs over 14 times faster than the SIMPROCESS model!

To compare the models we used four different methods to test for statistical differences in the output, each at a 90% confidence level ($\alpha$=0.1). The four methods were: normal theory assuming unequal variances (Welch method), the nonparametric Wilcoxon/Kruskal-Wallis Rank Sums test, simultaneous confidence intervals, and a multinomial ranking and selection procedure. The Welch and Wilcoxon/Kruskal-Wallis tests were conducted using the JMP statistical software package. Appendix D shows the simulation data used for the model comparisons.

**Welch Method Test.** Here we use normal theory and do not assume equal variances. Comparing average number of contracts, JMP computed an F ratio of 1.4877 and a p-value of 0.2276. This suggests no statistical difference between the models in terms of average contracts. Comparing average recruits shipped, JMP computed an F ratio of 0.6265 and a p-value of 0.4319. Likewise, there is no statistical difference between the models with respect to recruits shipped.

**Wilcoxon/Kruskal-Wallis Test.** For the contract comparison, JMP computed rank sums of 853.5 for the AweSim model and 976.5 for SIMPROCESS. This corresponds to a chi-square statistic of 0.8299 and an associated p-value of 0.3623. Thus, the models appear statistically similar. For recruits shipped, JMP computed rank sums of 970 for AweSim and 860 for SIMPROCESS. This resulted in a chi-square statistic of 0.6657 and a p-value of 0.4146. Again, our models appear similar.

**Simultaneous Confidence Intervals.** Following the Bonferroni approach on our confidence intervals for each model, we needed individual 95% confidence intervals for the mean performance of each model. This provides us a minimum 90% confidence that both intervals capture the true mean system performance for the respective model. For the mean number of contracts, we computed confidence intervals of (53.3 , 57.5) for the AweSim model and (54.9 , 59.8) for SIMPROCESS. For the mean number of recruits shipped, we computed confidence intervals of (49.1 , 53.1) and (47.8 , 52.1) for AweSim and SIMPROCESS, respectively. Since they overlap, we are 90% confident our models produce similar output.

**Ranking and Selection.** We used the Multinomial Selection Procedure and arbitrarily assumed the AweSim model produced more contracts and recruits shipped. Thus, we counted the number of times the AweSim output was greater than the SIMPROCESS output for the 30 replications. Ties were not considered. We hoped to be wrong about 50% of the time, which would support our models being similar. For contracts, AweSim had more contracts 11 out of 30 times. For recruits shipped, AweSim had more shipped 17 out of 30 times. These results further support our models as being similar.

**AweSim Model: Beta Version.** Now that we had a simple version of the recruiting model in AweSim, we wanted to extend the model to specifically include our proposed enhancements. Extending the AweSim model to accommodate the nine different prospect types was easily facilitated by the use of the ARRAY function. We simply reserved nine equal size blocks of memory (one block for each type) and referenced each prospect's parameters using the following scheme:

Suppose each applicant entity carries its type in the variable $T$: 0,1,...,8 with 0 corresponding to type SMB, 1 to SFB, ..., 8 to OTH. Also suppose each prospect type has 55 sets of parameters; thus, SMB's parameters are in array rows 1-55, SFB's parameters are in rows 56-110, and so on. An applicant can reference its parameters through ARRAY[55*$T$ + *row*, *col*] where *row* and *col* are dependent upon which process and parameters are being referenced. For example, the probability that an applicant will need a moral waiver resides in *row* = 29 and *col* = 1. Thus a SFB ($T$ = 1) applicant would reference ARRAY[55*$T$ + 29, 1] or ARRAY[84,1] for the value. There will typically be three *col* entries in each *row* corresponding to triangular distribution parameters min, mode, and max, respectively. For simplicity within our AweSim model, we assign to each applicant entity the variable B = 55*$T$ for faster array lookups. The model user could increase/decrease the parameter list by equally changing the size of each prospect's memory block (currently set to size 55).

To accommodate Contract Seasonality, we changed two recruiting processes. As noted in the previous section, we discovered two seasons in terms of contracting applicants: summer vs non-summer. To incorporate the season effects we made the walk-in arrival rate dependent upon the season, which is represented by the global variable *SeasonRate*. The previous interarrival rate for walk-ins was *Exp(72.0)*, which we changed to *Exp(72.0/SeasonRate)*. Thus a *SeasonRate* of 1.0 would have no effect on the walk-in arrival rate (this is the default setting of the non-summer season). However, a *SeasonRate* > 1.0 would cause a shorter time between arrivals to the system. As reported in the previous section, we estimated a *SeasonRate* of 1.3 (30% more recruits on average) during the summer months. This value of 1.3 is the default setting for the summer season. The determination of the current season is facilitated by a season control within the model, which begins on October 1st with the non-summer season (lasting for 5832 hours) then switches to the summer season (for 2928 hours).

In addition to changing the walk-in construct, we changed the *Prospecting* stages to further facilitate Contract Seasonality. These changes within the AweSim model were identical to those made within the SIMPROCESS model.

DEP Seasonality within the AweSim model was incorporated much the same as with the SIMPROCESS model. From our data analysis, we had determined the parameters from *Weibull*($\alpha,\beta$) for each prospect type to be used in assigning DEP time (in hours). We discovered that AweSim has a small quirk regarding the weibull parameters $\alpha$ and $\beta$. AweSim uses a different parameter scheme; therefore, the parameters must first be adjusted accordingly. The differences reside in two areas. First, AweSim takes the Weibull parameters in reverse order so the first parameter is the scale and the second parameter is the shape. Second, the scale parameter is a manipulation of $\alpha$ and $\beta$ by the equation $\chi = \exp(\alpha^*\ln(\beta))$. Thus, AweSim must take the standard *Weibull*($\alpha,\beta$) as WEIBL($\chi,\alpha$). To further complicate matters, some of our present values of $\alpha$ and $\beta$ make this conversion difficult. For example, a SMB recruited in the summer will use standard Weibull parameters $\alpha$=11.06 and $\beta$=8202.48 (from Table 4.10). This makes the AweSim WEIBL parameter $\chi$ about $1.94^*10^{43}$, which is a bit ridiculous.

We discovered that our problem developed when we calculated the $\beta$ (scale) parameters using the DEP time in hours. This caused our $\beta$ parameter to be rather large. It turns out that for the Weibull distribution: *Weibull*($\alpha,\beta$) = C**Weibull*($\alpha,\beta$/C) for some positive constant C. To make our Weibull parameters within AweSim manageable, we used C equal to 3000. After adjusting all the $\beta$'s and then computing the $\chi$'s we obtained the AweSim parameters shown in Table 4.12 (summer parameters) and Table 4.13 (non-summer parameters). Within our model we must remember to multiply our Weibull random draw by C to get the correct distribution.

Table 4.12 AweSim DEP Scaled Weibull Parameters ~ Summer

| Type | $\chi$ | $\alpha$ | Type | $\chi$ | $\alpha$ |
|---|---|---|---|---|---|
| SMB | 67806.70 | 11.06 | SMA | 6294.58 | 8.79 |
| SFB | 16.756 | 3.59 | SFA | 43759.19 | 10.66 |
| GMB | 0.629 | 1.47 | GMA | 0.617 | 1.43 |
| GFB | 0.730 | 1.81 | GFA | 0.743 | 1.36 |
| OTH | 0.550 | 1.45 | | | |

Table 4.13 AweSim DEP Scaled Weibull Parameters ~ Non-Summer

| Type | $\chi$ | $\alpha$ | Type | $\chi$ | $\alpha$ |
|---|---|---|---|---|---|
| SMB | 5.066 | 3.4 | SMA | 5.555 | 2.95 |
| SFB | 16.756 | 3.59 | SFA | 4.899 | 3.33 |
| GMB | 0.412 | 1.47 | GMA | 0.455 | 1.58 |
| GFB | 0.629 | 1.3 | GFA | 0.679 | 1.48 |
| OTH | 0.441 | 1.36 | | | |

This completes the changes to our AweSim Beta Version. Now we wished to compare this model to the SIMPROCESS model we enhanced in the last section. We encountered a serious problem when running the updated SIMPROCESS model. Adding our enhancements drastically degraded model performance with 30 replications taking approximately 18 hours. The corresponding AweSim model (Beta Version) ran the entire 30 replications in just under eight minutes! This made comparing these two models nearly impossible.

However, our AweSim Beta Version was a simple extension of the AweSim Alpha Version. And since our AweSim Alpha Version compared favorably with the Cordeiro and Friend (1998) SIMPROCESS model, we feel justified in using our AweSim Beta Version for our simulation experimentation and analysis.

## Summary

This chapter represented our input analysis results and our model modifications. We also showed that our new AweSim model was statistically similar to the previous SIMPROCESS model. In the next chapter we design a simulation experiment and analyze the output. We will use our AweSim Beta model for all simulation runs.

# Chapter 5 - Experimental Designs and Simulation Results

## General

In this chapter, we complete the analysis of our study. The first section explains our simulation experiments to test different recruiting aspects and policies. In the final section, we analyze and interpret the simulation output.

## Experimental Designs

With our enhanced model in hand, we set out to experiment with different aspects of recruiting. Certainly, we could design a number of experiments with our flexible and efficient AweSim model. We were interested in three specific recruiting experiments. The first dealt with seasonal applicant flow, which would involve giving higher priorities to certain applicants at different times of the year. The second experiment tested the effects of reducing each recruit's DEP time by some standard percentage. The third experiment involved varying each recruiter's skill level and examining the effects on station performance. Each of our three experiments was conducted separately to avoid confounding results. In this section, we explain our simulation experiments. First, however, we need some baseline results with which to compare our experimental results. We begin with an explanation of this baseline design.

**Baseline Design.** The basic recruiting model, AweSim Beta Version, assigns the same priorities to applicants and uses three station recruiters. One recruiter is representative of a "poor" recruiter (meaning ineffective at his/her job), another recruiter is defined as an "average" recruiter, and the third recruiter is "good". Two recruiter-dependent characteristics help distinguish between the three recruiter types: the probabilities of prospects leaving the recruiting process at various stages and the time the recruiter needs to complete recruiting tasks. As an example of the first characteristic, our model's first recruiter, defined as "poor", expects SMB applicants to drop from the sales stage with a probability of 0.87. However, the third recruiter, defined as "good", expects SMB applicants to drop from the sales stage with a probability of only 0.66.

Our baseline model, stored in AweSim network file "FINAL" and using control file "BASE", uses the three station recruiters (poor, average, and good) and assigns each prospect type the same priority. As explained in Chapter 4, we set the seasonality multiplier to 1.0 in the non-summer months and 1.3 in the summer months to incorporate recruiting seasonality. With our baseline model defined, we now explain each of our simulation experiments.

**Experiment #1: Seasonal Applicant Priorities.** Here we tested the effects of giving certain applicants priority during different times of the year. It makes intuitive sense that a recruiter should give priority to graduate prospects, especially during the summer months. First of all, graduates have already demonstrated some intellectual ability by graduating from high school. Secondly, graduates are typically not constrained by when they can ship to basic training, whereas a senior will have to wait until graduation. Thus, a contracted graduate recruit will have a lower probability of dropping from the DEP than a senior (a senior could wait in the DEP for up to a year).

The argument could be made to give graduates priority all year long. However, many graduates will probably be looking at other career fields following the first few months after high school graduation. In addition, the recruiter must not forget about the senior market. These seniors will be looking for career options following their summer break and the recruiter must take advantage. These interesting intuitions provided the motivation for our first experiment: give graduates priority during the summer months and seniors priority during the non-summer months.

This experimental idea presupposes the notion of many applicant types to choose from for prospecting. Our prospecting stage is set up so applicants arrive often and wait for the recruiter resource. We maintain a pool of approximately 10 prospects for each recruiter. Thus, each recruiter has an adequate number of prospects waiting and can thus discriminate between prospects. Note that walk-ins of all types still arrive to the system and wait in the sales stage.

To assign prospect priorities within our model, we utilized two new ARRAY rows. The first row, array row 496, holds nine priority values for prospects contracted during the non-summer months. The second row, array row 497, holds the nine priority values for prospects contracted during the summer. The priority values are either 1,2, or 3, with higher values meaning higher priority. Each applicant references it's appropriate column in these arrays using the local applicant type variable *T* (0,1,...8). Thus, every newly created applicant gets a priority (stored in local variable *Pri*) based on the season and prospect type. We added a global flag variable, *SummerFlag*, to help access the correct seasonal row. *SummerFlag* was set to 0 during the non-summer months and to 1 during the summer months.

Next, we needed to decide how to handle the OTH prospect type with our rankings. The OTH type includes neither graduates nor seniors. We decided to give all OTH prospects a constant ranking of 2 (middle priority). Thus, we declared our experimental priorities within our AweSim control file as:

ARRAY row 496: 3, 3, 1, 1, 3, 3, 1, 1, 2 /*non-summer priorities*/
ARRAY row 497: 1, 1, 3, 3, 1, 1, 3, 3, 2 /*summer priorities*/

And each applicant would set its priority upon creation with:

$$Pri = \text{ARRAY}[ExpDesign{+}SummerFlag,\ T{+}1]$$

with *ExpDesign* a global variable set at value 496.

Finally, we needed to instruct the recruiters to give priorities to those applicants with higher priority values. This was quite simple, because AweSim allows one to declare file rankings through the PRIORITY statement within the control file. Applicants have to wait in various files (according to various recruiting stages and tasks) for a recruiter resource within our model, so we set each file's ranking according to each applicant's priority value (1,2, or 3). This moves higher priority applicants to the top of each file, thereby simulating applicant priorities. This experiment uses the AweSim network file "FINAL" and control file "GRADSEN".

**Experiment #2: Reduced DEP Times.** Once a recruit is contracted, he/she waits in the DEP until shipped to basic training. The amount of time spent in the DEP depends on the recruit's type and the season when contracted (summer or non-summer), as uncovered in our input data analysis. Clearly, the longer the recruit waits in DEP the higher the probability of dropping from military service. The obvious question we wanted to explore was: "What are the effects of reducing the DEP time?"

We first thought to simply decrease each recruit's DEP time by some standard value, say one month. However, we noticed some problems with this idea. First, we know that graduates typically spend much less time in DEP than seniors. Thus, decreasing every recruit's DEP time by some standard value might not capture the effects we wished to capture. It seemed more intuitive to decrease each recruit's DEP time by some percentage of the assigned DEP time. We decided to test a DEP time reduction of 25%.

One possible problem with this approach is that most seniors are constrained by when they can ship to basic training. A 25% DEP time reduction for a senior might suggest the senior must ship to basic training before high school graduation. Since we were only interested in the effects of the DEP time reduction, we chose to neglect this factor and proceeded with our experiment.

To facilitate this experiment, we declared a global variable *DepAdjust* set to 0.75. After a recruit is assigned a DEP time, we simply multiply the DEP time by *DepAdjust*. This results in a DEP time reduction of 25%. This experiment uses the AweSim network file "FINALDEP" and control file "DEP-25".

**Experiment #3: Recruiter Skill Levels.** Here we wanted to measure the station effects of changing recruiter skill levels. As noted previously, our baseline model consists of a poor, an average, and a good recruiter. We wanted to run our model with all combinations of these skill levels. Such an experiment could provide insight into a question such as: "What happens to our station contract and shipping averages if we can replace an average recruiter with a good recruiter?"

This experiment involved the most simulation work. With three recruiters and three possible skill levels, and assuming recruiter order is of no importance, we are left with 10 total designs. Therefore, we needed to make nine different simulation runs, since we already had the baseline design. Table 5.1 shows the designs involved with this experiment.

Table 5.1 Experiment #3 - Design Description

| Design | Description | Design | Description |
|---|---|---|---|
| GAP | Baseline design | GPP | One good, two poor |
| PPP | All poor recruiters | GAA | One good, two average |
| PAP | Two poor, one average | GGP | Two good, one poor |
| AAP | Two average, one poor | GAG | Two good, one average |
| AAA | All average recruiters | GGG | All good recruiters |

To incorporate the different recruiter skill levels, we changed all recruiter dependent input parameters accordingly. For instance, to go from our baseline design of GAP to the design of GAA we changed all applicable input parameters for the poor recruiter to that of an average recruiter. All these changes were done within AweSim's control files; thus, we used a different control file for each design. The control file for design PPP was named "RECRPPP", the control file for design PAP was named "RECRPAP", and so on. We made sure to use the appropriate control file for each design point. The AweSim network for this experiment is "FINAL".

### Simulation Results

In the previous section, we explained our baseline model and experiments, now we present the simulation results. From these results, we hoped to gain further insight into the recruiting process. The complete results are given in Appendix E, Simulation Results.

**Baseline Results.** We first ran the baseline model for 30 replications and recorded the results using MS Excel. Each replication consisted of a one year warm-up, with no statistics collected, followed by one year of recruiting activities. In terms of model output, we were interested in when each recruit was contracted and when each recruit shipped to basic training (if they shipped at all). In addition, we kept track of the recruit's type along with which recruiter (1,2, or 3) contracted them into the Army.

For simplicity in presentation, we displayed results in three categories: seniors, graduates, and total. The total category included seniors, graduates, and the OTH prospect type. Furthermore, each category was broken into contracts and recruits shipped. The simulation results for the baseline model are shown in Table 5.2, with a 90% confidence interval on the averages. Note that these are yearly station averages.

Table 5.2 Baseline Simulation Results

| | Seniors | | Graduates | | Total | |
|---|---|---|---|---|---|---|
| | **Contracts** | **Shipped** | **Contracts** | **Shipped** | **Contracts** | **Shipped** |
| **Upper** | 19.92 | 17.28 | 24.23 | 23.50 | 50.82 | 48.34 |
| **Average** | 18.73 | 16.10 | 23.17 | 22.40 | 49.23 | 46.40 |
| **Lower** | 17.55 | 14.92 | 22.11 | 21.30 | 47.64 | 44.46 |

With seasonality effects built into our model, we were also interested in the monthly averages for both contracts and recruits shipped. Figures 5.1 and 5.2 display the baseline model's monthly contract and shipping averages, respectively.

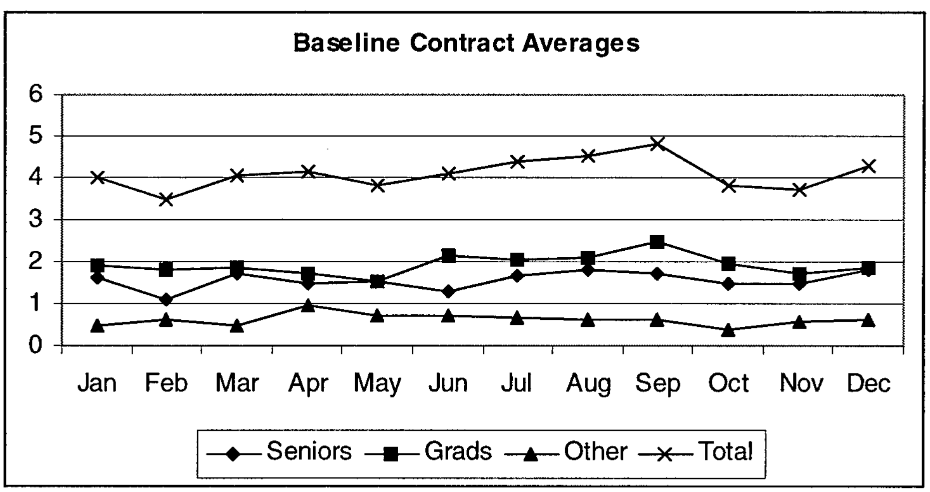



Figure 5.1 Monthly Contract Averages – Baseline Model

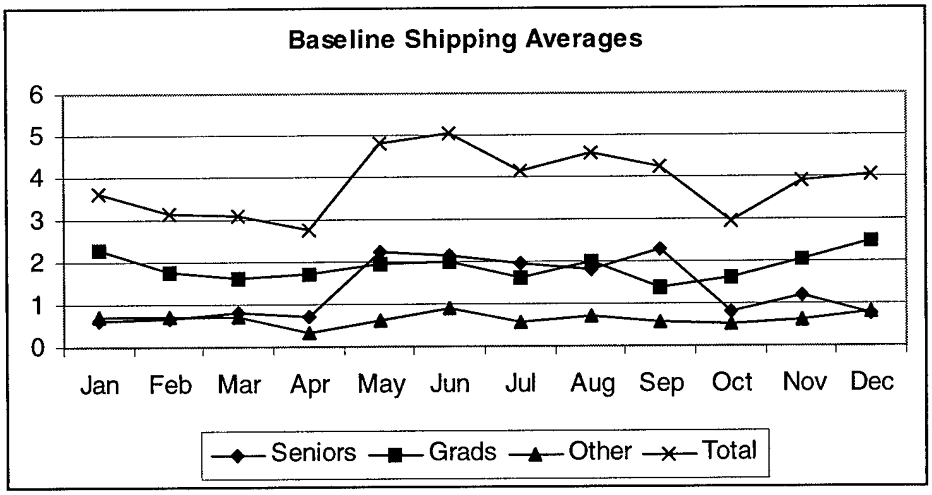



Figure 5.2 Monthly Shipping Averages – Baseline Model

**Experiment #1 Results.** This experiment assigned graduates priority during the summer months and seniors priority during the non-summer months. We then ran the simulation for 30 replications and recorded the results.

The simulation results showed this policy resulting in statistically less seniors shipped and less total recruits shipped. This may seem disconcerting; however, this policy was not simply intended to increase the number of recruits contracted or shipped. We were also interested in examining the effects on seasonal trends in contracting and shipping. This required an examination of the monthly contracts and recruits shipped. Figure 5.3 shows the average graduates contracted during the year, comparing the baseline results to the results for Experiment #1.

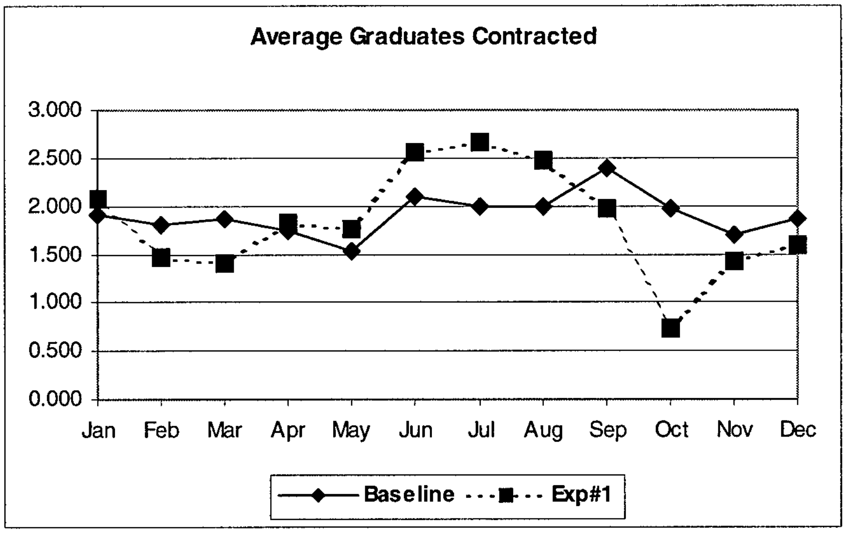



Figure 5.3 Average Graduates Contracted – Baseline versus Experiment #1

Figure 5.3 makes intuitive sense. Notice that during the summer months, more graduates were contracted. Also notice the decline in graduates contracted during the non-summer months. Overall, no statistical difference existed in yearly graduates contracted, but we certainly noticed some seasonal differences. Reference Appendix E for further seasonal comparisons.

**Experiment #2 Results.** In this experiment, we were only interested in the effects on the number of recruits shipped (not contracted), since a reduction in the DEP time should have little effect on contracts. We ran the simulation for 30 replications and noticed only slight increases in the number of seniors shipped and the total number of recruits shipped, reference Appendix E for complete results. However, the results were not statistically significant. Thus, our model appears insensitive to a 25% reduction in assigned DEP times.

**Experiment #3 Results.** With this experiment, we were primarily interested in the effects of different recruiter skill levels on station performance. For each design point, defined in Table 5.1, we ran 30 replications. The results were put into tabular form for comparison, reference Appendix E. Most of the results made intuitive sense. For example, design GGG (three good recruiters) resulted in statistically significant increases in each contracting and shipping category, design PPP (three poor recruiters) resulted in statistically significant decreases in each contracting and shipping category, and design AAA (three average recruiters) resulted in no statistically significant differences. The other designs are more complicated to compare. For example, should the results for design AAP be similar to the results for design GPP. For an easier visualization of the results, we ranked the design points and plotted their respective results.

We can assign a design point a ranking based on each recruiter's skill level. For our ranking, we assigned a poor recruiter 1 point, an average recruiter 2 points, and a good recruiter 3 points. Thus, the design point GGP would have a ranking of 7. Figure 5.4 shows the plot of total contract averages for each ranked design point, each displayed with a 90% confidence interval about the mean.

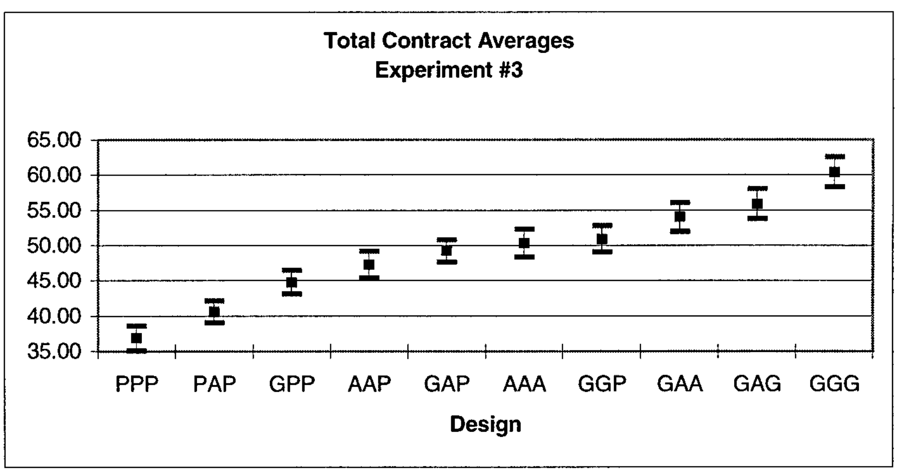



Figure 5.4 Total Contracts by Ranked Recruiter Design Points

With the confidence intervals displayed, one can visually extract the designs statistically different from the baseline design GAP. This provides insight into the effects of recruiter skills on station performance. For example, Figure 5.4 shows no significant total contract differences between designs GAP and GPP; thus, replacing an average recruiter with a poor recruiter (GAP, switch the A to a P, leads to GPP) results in no statistical difference in total contracts. However, we do see a statistical difference in total contracts by replacing a good recruiter with a poor recruiter (GAP to PAP). Consult Appendix E for further comparisons.

The results obtained from our recruiter experiment were very interesting. After further examination of the results, we began to wonder what factors were most important in distinguishing the success of our recruiters within the model. Each recruiter type (poor, average, good) had different task durations and associated probabilities of prospects leaving the recruiting process. After some preliminary sensitivity analysis, we noticed that the number of contracts and recruits shipped remained nearly constant when just varying the task durations. On the other hand, model output varied greatly as we changed the probabilities of prospects leaving the recruiting process.

This suggested an additional experimental design to find the primary success factors for our simulated recruiters. We decided to vary three recruiter type dependent variables. These variables were *TelePr* (the probability a specific prospect drops between telephone prospecting and sales), *FacePr* (the probability a specific prospect drops between face-to-face prospecting and sales), and *SalesPr* (the probability a specific prospect drops between sales and processing). We adjusted each factor between low and high levels. The low level corresponded to that of a good recruiter and the high level corresponded to that of a poor recruiter. For example, a SMB prospect would have a *SalesPr* value of 0.73 for a good recruiter and 0.87 for a poor recruiter. Note that the average recruiter would have a value approximately midway between the two. Thus, we could run a factorial design with three factors and two levels each. This resulted in $2^3 = 8$ simulation runs. The complete experimental design with the factor settings and results are included in Appendix E. The experiment uses the AweSim network file "FINAL" and control files "DES1", "DES2",...,"DES8", corresponding to the eight design points.

The results of this additional experiment were very interesting. We first computed the three factor effects with respect to both total contracts and total recruits shipped. In terms of total contracts, *SalesPr* had an effect of -7.942, *TelePr* had an effect of +0.158, and *FacePr* had an effect of -0.358. The interaction effects were negligible. In terms of total recruits shipped, *SalesPr* had an effect of -7.883, *TelePr* had an effect of +0.517, and *FacePr* had an effect of -0.933. The interaction effects were negligible here as well. The sign of the effect also makes intuitive sense, since our low level represents a lower probability of dropping and our high level represents a higher probability of dropping. Thus, it appears that the factor *SalesPr* is the dominating factor with respect to recruiting success (at least within our model).

Next, we set out to verify this discovery within our model. The idea was to vary only the *SalesPr* parameter for each recruiter type in our simulation and compare the results to those obtained in Experiment #3. First, we assigned each recruiter type the exact same parameters (dependent upon the prospect types, of course). We used the average recruiter type's values for these parameters. Then we reran the design points of Experiment #3, varying only the *SalesPr* values for each design point (GAP, GGG, ...).

The results were astounding, with nearly the same results in model output! Figure 5.5 shows how closely the two experiments aligned with respect to total contracts.

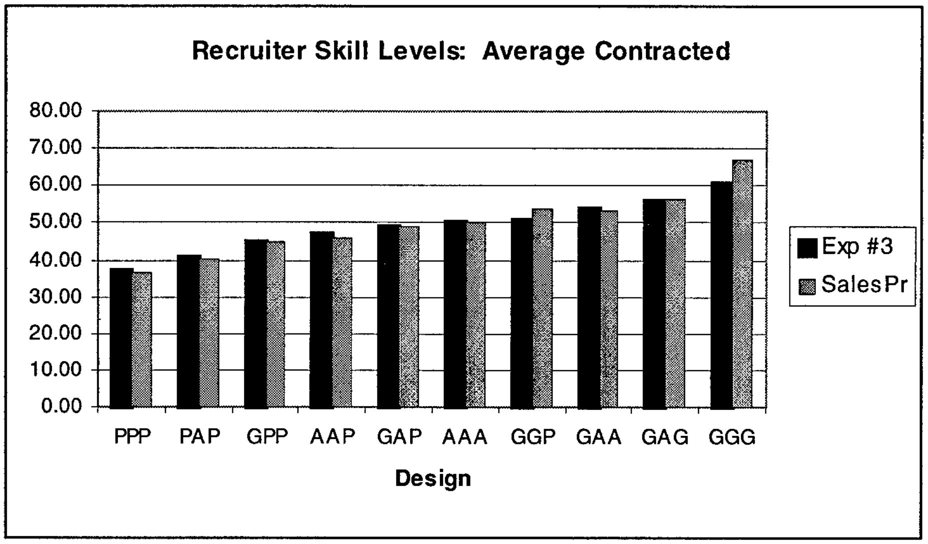



Figure 5.5 Total Contract Comparison – Experiment #3 and *SalesPr* Experiment

Thus, the most important parameter for distinguishing recruiter success appears to be *SalesPr*. This extra endeavor leads to some interesting insights. First, recruiter performance appears insensitive to changes in recruiter task durations. Second, the dominating factor for recruiter performance appears to be how effectively the recruiter is at "selling" the Army to the prospect. This makes intuitive sense, and also suggests the need for accurate values for *SalesPr* when modeling the recruiting process.

**Summary**

This chapter first explained our three experimental designs. Then we presented our simulation results based on these experiments. We were able to run many different designs because of the efficiency of our new AweSim model. The complete simulation results are included in Appendix E. In the next chapter, we give our research conclusions and recommendations for future work in this area.

# Chapter 6 – Conclusions and Recommendations

## General

Army recruiters have a very difficult job. They face long hours, frequent rejections, and strong pressure to meet recruiting missions. Simulation can be a powerful aid to USAREC, allowing analysts to better understand the key factors in recruiting success. Simulation also allows the testing of various recruiting policies, with no affect on actual recruiting stations.

In previous years, AFIT researchers had developed and enhanced a computer simulation with the goal of gaining insight into the workings of an Army recruiting station. Our research set out to discover suspected recruiting seasonality effects: the idea that the number of prospects contracted and shipped to basic training varies during the year. The hope was to incorporate these effects into the previous recruiting model and conduct simulation experiments to gain further insight. However, the model was pushed to its limits in terms of efficiency. Thus, further enhancements drastically increased model runtime, hindering our simulation experiments. To fix this problem, we built a similar recruiting model in a more powerful and efficient simulation language, using the previous model processes and interactions as a template. Our new model compared favorably with the previous model and ran in only a fraction of the time. With this new model, we were able to conduct a number of interesting experiments, which provided some key insight into the recruiting process. This chapter contains a research summary and recommendations for future research.

## Summary

With our study topic in mind, we researched the previous work conducted in recruiting. Since our study was a follow-on to previous AFIT researchers, we started with the work of Cordeiro and Friend (1998) and then McLarney (1999). We were able to get a firm hold on the recruiting process by studying their work, consulting with a recruiting expert, and attending a symposium dedicated to the current recruiting problems. Then we set out to conduct our own research.

First, we decided what data we would need to uncover our seasonality effects and then requested the data from USAREC. After testing the data for homogeneity, we began analyzing the data. Right away we noticed a new prospect group accounting for 16% of all recruits, which we named the "Other" group and incorporated into our analysis. Furthermore, we found seasonality effects in prospect contracting. The data showed about 30% more prospects being contracted during the summer months, June-September. In addition, we found seasonality effects in recruit shipping, with a large distinction between the amount of time graduates spend in the DEP versus the time seniors spend in the DEP. The time of year in which the prospect was contracted also played a role in the time spent in DEP. We fit the data to different distributions and ultimately the Weibull distribution proved the best overall fit. This was advantageous, since we could model very different DEP times with the single Weibull distribution (giving each prospect group different parameters). In the previous model, all recruits were assigned a DEP time based on the same Triangular distribution parameters, independent of recruit type and season contracted.

With our input data analysis complete, we wanted to incorporate our results into the current SIMPROCESS recruiting model. Very quickly we noticed the inefficiency of the SIMPROCESS language. The primary reason for the slow runtimes was SIMPROCESS's inability to support the use of arrays. Each model parameter had to be stored in global or local variables; thus, the nine different prospect types, each with over 50 sets of parameters, required an immense amount of model overhead in storage. The use of arrays could greatly reduce the overhead by requiring less memory and allowing quick references. The AweSim simulation language, however, supports the use of arrays and is also quite flexible in terms of network design. So we began the painstaking voyage of building a similar recruiting model in the AweSim environment. We followed the basic logic of the previous model and then formally compared model output. The results were favorable, so we assumed our AweSim model was representative of the previous model.

Next, we wanted to incorporate the results of our input analysis into our AweSim model. USAREC was still interested in the SIMPROCESS model, so we decided to make appropriate enhancements to that model as well. However, all of our simulation experiments would be conducted using our AweSim model. Adding the "Other" prospect type proved simple. We added a new set of model parameters to distinguish the "Other" type. However, we lacked adequate data to determine the approximate values for the "Other" type, so we simply used the averages of the original eight prospect types. Future researchers should collect appropriate data to determine better values. Incorporating the seasonality in terms of recruit shipping was also straightforward. The previous model assigned the DEP time using the Triangular distribution (with minimum, mode, and maximum parameters). We determined the Weibull distribution (with shape and scale parameters) was more appropriate, so we changed the Triangular random draw within the model to a Weibull random draw (based on the prospect type and season contracted).

Incorporating contract seasonality proved a bit more difficult. From our input analysis, we determined a 30% boost in contracting during the summer months. We changed two model constructs to facilitate this seasonality: the walk-in applicant arrival rate and the prospecting time needed to get an applicant to sales. The previous walk-in interarrival rate was Exponential with a mean of 72 hours. We changed the mean to *72/Season*, with *Season* set to 1.0 during the non-summer months and 1.3 during the summer months (the value 1.3 was chosen based on an approximate 30% increase in contracts). For the reduced prospecting time, we applied the same principle: reduce the time needed to prospect based on a seasonality factor (i.e. *ProspectT/Season*). These model changes gave recruiting a boost during the summer months, just as we had discovered in our data analysis. The model user is free to vary these seasonality factors.

Finally, we conducted different simulation experiments using our enhanced model. We ran 30 replications for each simulation run, with each replication consisting of a one year model warm-up with not statistics collected followed by one year of simulated recruiting activities. We were able to conduct a number of experiments because of the flexibility and efficiency of our AweSim model. Each run of 30 replications took only about 8 minutes on a 300 MHz Pentium II machine, whereas a SIMPROCESS run of 30 replications would have taken about 18 hours. For our first experiment, we wanted to test the effects of giving different prospects priority during different times of the year. We chose to give graduates priority during the summer months and seniors priority during the non-summer months. Our results showed statistical decreases in the number of seniors shipped to basic training and in the number of total recruits (graduates, seniors, and other) shipped to basic training. But more importantly, the results showed significant changes to the monthly contracting and shipping patterns. Thus, this policy does in fact change the contracting and shipping patterns, which certainly provides valuable insight.

Our second experiment tested the effects of reducing each recruit's DEP time by 25%. This was of interest because reducing DEP times might significantly reduce the probability of recruits dropping out of the DEP. However, our results showed no significant differences in the number of recruits shipped to basic training. Thus, our model appears insensitive to a 25% reduction in DEP time.

Our final experiment tested the effects of varying the recruiter skill levels. The baseline model consisted of a recruiting station with a good (G), an average (A), and a poor (P) recruiter. The skill level of a recruiter is defined by various model parameters: task durations and prospect-dependent dropout probabilities. We tested all combinations of the three skill levels (PPP, PAP, ..., GGG). The results made intuitive sense in that stations with better recruiters performed better; however, we were interested in what model factors were most important in determining recruiter success. Preliminary sensitivity analysis uncovered three recruiter parameters impacting the level of success. We used these three parameters/variables, with low and high values, in a full factorial experimental design. The factor effects pointed to only one variable as being significant to recruiter success - the probability of a prospect dropping from the recruiting process between sales and processing. This parameter is really just a measure of the recruiter's salesmanship. To check this result, we reran our recruiter skill level experiment, just varying this sales probability parameter. The model output corresponded nearly exactly with the output from the original experiment; thus, recruiter salesmanship appears to be the dominant factor attributing to success or failure as a recruiter.

**Future Research**

Many of our model parameters are "best" guesses. More data needs to be collected for better parameter estimates. If recruiters were able to accurately record various task durations and prospect-dependent drop probabilities, future analysts could have access to more accurate model parameter estimates. In addition, a survey could be administered to provide more accurate estimates. We showed in our experimentation that our model is very sensitive to the estimate of recruiter salesmanship; thus, efforts should be made to accurately gauge this parameter.

Presently, our simulation models station level recruiting. It would be interesting to aggregate our model to the company level or higher. Such an endeavor could provide insight into effects of larger policy decisions. However, modeling higher echelons of recruiting would have to also take into account differences between recruiting stations and companies due to demographic and/or leadership effects.

Future research could also model the recruiting processes of different military services. It is well known that the services recruit differently. Some services are more successful than others, and it would be interesting to discover the reasons.

## Final Thoughts

Our research resulted in a flexible, yet powerful, Army recruiting simulation model. The simulation models three recruiters and is capable of handling nine different prospect types. In addition, both contracting and shipping seasonality have been incorporated into the model. We were able to conduct a number of recruiting experiments with the model and gain valuable insight into the workings of Army recruiting. We hope future researchers will continue the efforts already begun in this interesting area. Finally, we sincerely hope this research will assist USAREC in their efforts to halt the recent recruiting problems and make the recruiter's job easier.

## Appendix A- Recruiter Leadership and Personality Survey

### Purpose and Techniques

The primary goal of Edward McLarney's survey (1999) was to study leadership and personality traits of recruiters in hopes of relating these factors to success as a recruiter. We conducted a multivariate analysis of the survey responses and present the main results in this appendix. We demonstrated two analysis techniques for our analysis.

**Principal Component Analysis (PCA).** We performed a dimensionality assessment on the survey data with the hopes of reducing the variable space as much as possible, while still explaining a majority of the total variance in the data set. Component scores were then calculated for each of the survey respondents. Finally, we offered an interpretation of these new component scores.

**Discriminant Analysis (DA).** Using the component scores from our PCA, we wanted to both predict membership in various recruiting groups (Gender, Career Recruiter, Station Commander, and Low/High Recruit Production) along with explain the important variables for predicting group membership. Of considerable importance was discovering the leadership and personality characteristics of those recruiters who produce a high number of recruits.

### Database/Survey Description

The survey was first administered to Army recruiters in the local Dayton, OH area. In addition, the survey was sent to other recruiting stations around the country. These stations were part of the 3$^{rd}$, 5$^{th}$, and 6$^{th}$ Army Recruiting Brigades. Five hundred surveys were sent out with an expected return rate of about 55%. However, only 142 survey responses were returned.

The survey consisted of various forms of questions. The questions were asked to provide variable scores for four categories: general information, leadership characteristics, personality traits, and outcomes. For a complete description of the survey, reference the thesis by CPT Edward McLarney (see bibliography section).

The survey database was incomplete in two areas: dependent variables (outcomes) and independent variables (general & leadership/personality). For the dependent variables (Gender, Career Recruiter, Station Commander, Low/High Recruit Production), six of the 142 entries were lacking values. We needed to know these values for our prediction within Discriminant Analysis; therefore, we decided to discard these responses entirely. This left us with a total of 136 responses.

For the independent variables (general & leadership/personality), there were also gaps in our database because of unanswered questions. If the recruiter failed to give answers to some of the questions, they did not receive a score for the affected variable. In these cases (approximately ten of the entries), we assigned a score based on the average of the remaining entries for that particular variable score.

Another database manipulation involved a scaling of certain variable scores. The scores affected were those pertaining to the 5-tiered responses. The answers were coded as -2, -1, 0, 1, 2 corresponding to Strongly Disagree to Strongly Agree, respectively. We wanted to scale these variables to be all positive values and thereby easier to interpret. To accomplish this we added a discrete value to each variable.

The last database manipulation we made involved how we grouped a recruiter into the outcome category of low or high number of recruits produced. This grouping was of primary interest to our analysis. We were just given the number of recruits signed in the last six months. As a simple rule, we used the average number of recruits contracted as the divider between the two groups. The average was about 8.5 recruits per recruiter (in six months). If a recruiter contracted less than 8.5 recruits he/she was in the low group, and if they signed more than 8.5 recruits he/she was in the high group.

**Variable Description**

The survey variables are related to four categories. Below we display the categories and their respective variables.

1) **General** – Direct questions relating to various recruiting aspects
   - Interv — Number of applicant interviews each week
   - Hrs — Hours worked in a typical workweek
   - Wkend — Frequency of weekends worked
   - Mission — Frequency of recruiting station meeting missions
   - Train — Level of training received
   - Social — Level of recruiter-recruiter social interactions
   - Effic — Efficacy level of recruiter
   - Months — Months as a recruiter
   - PayGr — Pay Grade of recruiter

2) **Leadership** – Various goal setting and leadership markers were measured
   - KSD — I **K**now what I'm **S**upposed to **D**o
   - RFG — I have **R**esources **F**or my **G**oals
   - ACC — I **ACC**ept my goals as important
   - RWV — I am **R**ewarded **W**ith things of **V**alue
   - CSG — I have **C**hallenging and **S**pecific **G**oals
   - FBK — I receive **F**eed**B**ac**K** on my goals
   - SUP — I have a **SUP**portive boss
   - GSM — Deals with setting own schedule

3) **Personality** – Measures of recruiter personality
   - Agree — Level of Agreeableness (friendliness with others)
   - Consc — Level of Conscientiousness (dedicated to work and timely)

- Extra	Level of Extraversion (outgoingness of recruiter)

4) **Outcome**
   - M/F	Male or Female recruiter
   - 79R	An Army career recruiter is designated as a 79R
   - SC	Whether the recruiter is a Station Commander
   - Lo/Hi	Whether the recruiter contracts low/high number of recruits

**Special Problems Encountered**

We encountered several problems during our analysis. First, we received only a mere 28% return rate on the survey (as opposed to the expected return rate of 55%). In addition, 93 of the 136 responses were from recruiting station commanders. Typically, an Army recruiting station will have one station commander and three or four subordinate recruiters (non-station commanders). Thus, our data might be biased towards station commander responses.

Another problem we encountered involved interpreting the PCA loadings matrix. The PCA loadings matrix consisted of poorly arranged clusters. We saw no specific patterns or groupings and we also witnessed very few high values. In addition, many variables were represented by several components. Luckily, the JMP software package could rotate the loadings matrix for an easier interpretation. The rotated loadings matrix showed higher values and a much more structured pattern. A word of caution: JMP rotates the factor loadings matrix and not the PCA loadings matrix. However, we were simply interested in a better interpretation of component scores and the JMP rotation was an invaluable aid. Using the JMP rotated loadings matrix, each variable was represented exactly once by a principal component.

## Analysis Results

We will present our analysis results in two sections: PCA and DA.

**PCA.** We had 20 independent variables within our survey and we wanted to reduce this set to something more manageable. We decided to examine the correlation matrix, as opposed to the covariance matrix, due to the survey responses having different variable units and large variances. From the correlation matrix, we extracted the eigenvalues. Now we needed to decide how many principal components to keep. Different rules suggested keeping different numbers of components. For example, Kaiser's rule suggested keeping the first seven components and Cattell's Scree test suggested keeping anywhere from four to nine components. In the end, we kept nine principal components, which explained 72% of the total variance in the survey responses. Thus, instead of carrying 20 variables we only had to carry nine.

Next, we calculated nine new component scores for each survey respondent. After rotating the PCA loadings matrix within JMP, we were able to offer an interpretation of the nine component scores. Let $Y_i$ represent the $i^{th}$ component score.

| | |
|---|---|
| Y1 | Measures (+) accept goals as important, rewarded with valuables, and level of supportive boss |
| Y2 | Compares (+) agreeableness and conscientiousness of recruiter against (-) setting own schedule |
| Y3 | Measures (+) experience as recruiter: months and pay grade |
| Y4 | Measures (-) extraversion (outgoingness) of the recruiter |
| Y5 | Measures (+) level of training and social skills of recruiter along with the degree to which the recruiter's station meets mission requirements |
| Y6 | Measures (+) number of applicant interviews conducted |
| Y7 | Measures (-) hours worked during the week and weekends |
| Y8 | Measures (+) challenging and specific goals |
| Y9 | Measures (+) resources for goals, know what to do as a recruiter, and recruiter efficacy (ability to produce the desired outcomes) |

To see whether these scores made intuitive sense, we examined the average component scores of the Low/High recruit production category. For example, those recruiters producing a high number of recruits had an average Y3 (experience as a recruiter) score of 0.26, while those recruiters producing a low number of recruits had an average Y3 score of -0.17. Intuitively, this tells us that the more experienced recruiters tend to contract more recruits. Two other average component scores added further insight for low/high recruit production.

**Low:** Average Y1 = -0.45
Average Y5 = -0.17

**High:** Average Y1 = 0.71
Average Y5 = 0.27

**DA**. With our reduced variable space, we now wanted to predict membership in the different recruiter groups and determine the important variables for predication in these groups. We will present the main steps we took in our analysis.

**Data Splitting**. We wanted to be able to validate our grouping schemes, so we pulled between 20% and 25% of the data from each group for later validation. This data splitting was done arbitrarily. One note of exception: we were unable to pull data from the female recruiter subset due to the small number of female survey responses.

**Test for Normality, Outliers, and Correlations**. DA assumes normality of the data. We tested normality, the presence of outliers, and data correlations between the nine component scores (which made up our new set of variables for DA) within JMP. To sum up our results, we noticed no strong normality violations and no strong correlations (which might have suggested dependence among our new data set). As far as outliers, JMP identified a few outliers from each group. However, we had no reason to exclude these sample points so we pressed on with our data set.

**Test for Equal Covariance Structures**. Looking at the covariance structures for each of the subgroups, we noticed strong differences in most cases. Since we would later determine discriminant scores using dQ, we went ahead and assumed unequal covariance structures (we did not pool the covariance matrices).

**Obtain Discriminant Scores with dQ**. We calculated the discriminant scores and, subsequently, classified the responses into groups.

**Error Assessment (using APER – apparent error rate)**. Next we wanted to assess our prediction error rates using both our validation data and our test data. We came up with two different APERs for each grouping, given below:

**Validation Data:**

***Gender***

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Male | Female | Total | | |
| Actual | Male | 26 | 0 | 26 | | |
| | Female | 0 | 0 | 0 | APER | 0 |

***Career Recruiter***

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Career | NonCareer | Total | | |
| Actual | Career | 18 | 2 | 20 | | |
| | NonCareer | 5 | 6 | 11 | APER | 0.226 |

***Station Commander***

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | SC | NonSC | Total | | |
| Actual | SC | 15 | 4 | 19 | | |
| | NonSC | 5 | 4 | 9 | APER | 0.321429 |

***Low/High Recruit Production***

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Low | High | Total | | |
| Actual | Low | 15 | 3 | 18 | | |
| | High | 5 | 6 | 11 | APER | 0.275862 |

**Test Data:**

### *Gender*

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Male | Female | Total | | |
| Actual | Male | 100 | 0 | 100 | | |
| | Female | 0 | 10 | 10 | **APER** | 0 |

### *Career Recruiter*

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Career | NonCareer | Total | | |
| Actual | Career | 62 | 3 | 65 | | |
| | NonCareer | 7 | 33 | 40 | **APER** | 0.095 |

### *Station Commander*

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | SC | NonSC | Total | | |
| Actual | SC | 70 | 4 | 74 | | |
| | NonSC | 8 | 26 | 34 | **APER** | 0.111 |

### *Low/High Recruit Production*

| | | Predicted with dQ | | | | |
|---|---|---|---|---|---|---|
| | | Low | High | Total | | |
| Actual | Low | 55 | 10 | 65 | | |
| | High | 14 | 28 | 42 | **APER** | 0.276 |

Finally, we joined the APERs for the validation and test data for a combined APER.

| | |
|---|---|
| **Gender:** | APER = 0.0 |
| **Career:** | APER = 0.125 |
| **SC:** | APER = 0.154 |
| **Low/High:** | APER = 0.235 |

These values seemed reasonable. We at first were disappointed in the relatively high APER for Low/High Recruit Production. However, based on our simple classification rule (Low < 8.5 recruits in six months vs High > 8.5 recruits in six months) we expected more errors because the groupings were obviously not widely separated.

**DA Insights**. The second goal of our DA was to explain the important predictors of certain recruiter group membership. Using the factor loadings matrix, we are able to deduce the important group predictors. The variables and the average component scores for each subgroup are presented below.

- **Gender**

Y2 – Measure of recruiter personality (Females -0.88, Males 0.07)
Y6 – Number of interviews conducted (Females 0.76, Males -0.06)
Y8 – Having challenging and specific goals as a recruiter (Females -0.33, Males 0.33)

- **Career Recruiter**

Y3 – Experience as a recruiter (Career -0.52, NonCareer 0.86)
Y7 – Number of hours worked each week (Career -0.24, NonCareer 0.40)

- **Station Commander**

Y2 – Measure of recruiter personality (SC -0.35, NonSC 0.76)
Y3 – Experience as a recruiter (SC -0.31, NonSC 0.67)

- **Low/High Recruit Production**

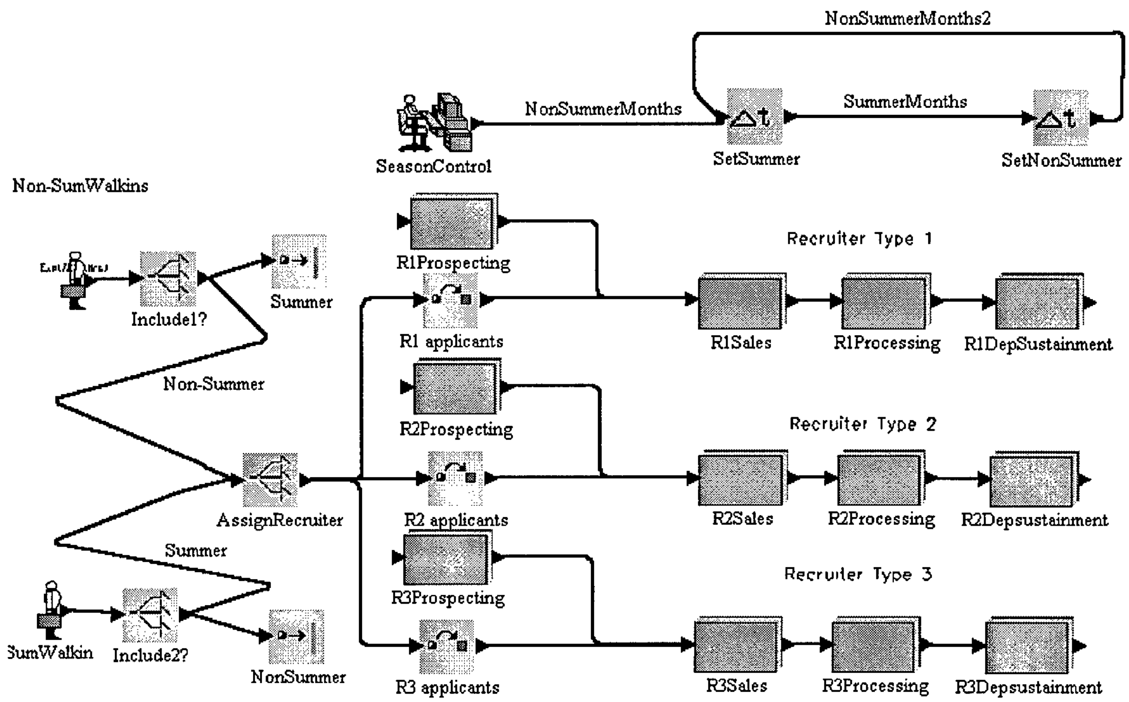
Y1 – Measure of leadership traits and goal markers (Low -0.45, High 0.71)
Y5 – Level of training received (Low -0.17, High 0.27)
Y6 – Number of interviews conducted (Low -0.15, High 0.23)

Thus, for low/high recruit production (our most important group) it seems that those recruiters who accept their goals as important, feel they are rewarded with things of value, and have a supportive boss will tend to produce a high number of recruits (in accordance with the average Y1 scores). Also, recruiters with more training and more applicant interviews held tend to produce a high number of recruits (Y5 and Y6 scores).

This completes our analysis of McLarney's survey. While the results were not important for our research, they were interesting and provided keen insight into how recruiter leadership and personality traits affected recruiting success.

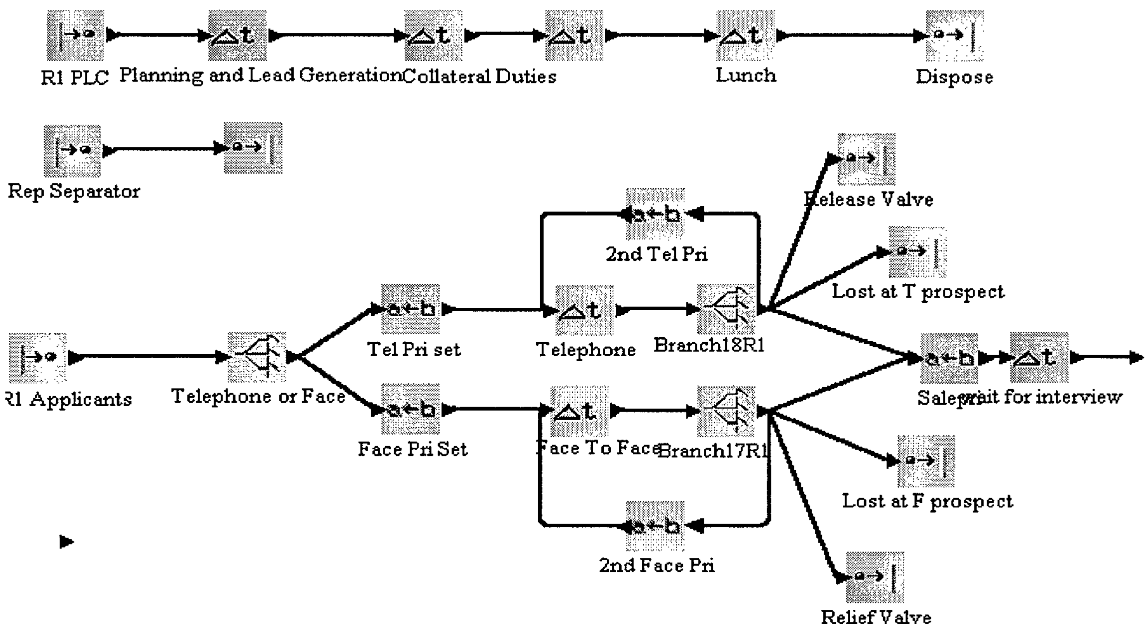
## Appendix B- SIMPROCESS Model

# High Level Processes

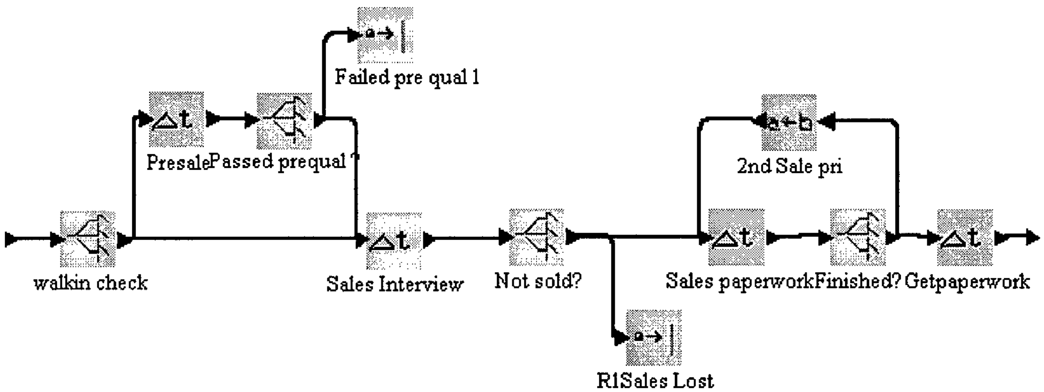


# Recruiter 1 Prospecting

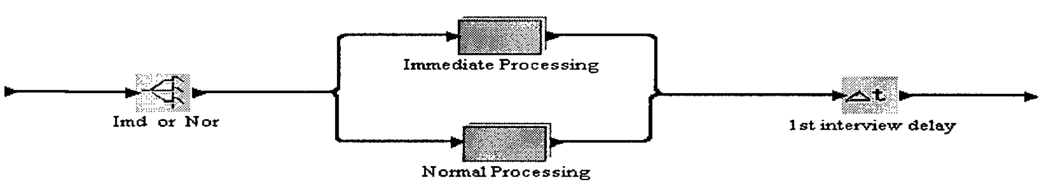
Note: we will only show the SIMPROCESS model's processes for Recruiter 1



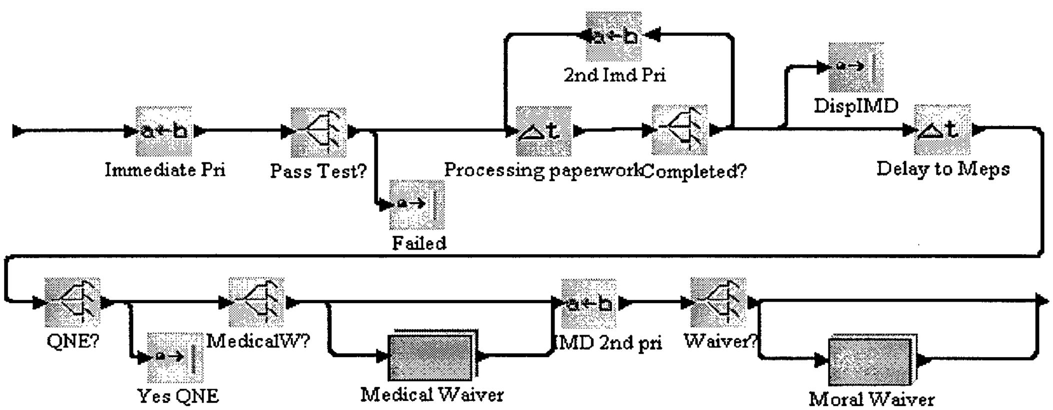
## Recruiter 1 Sales



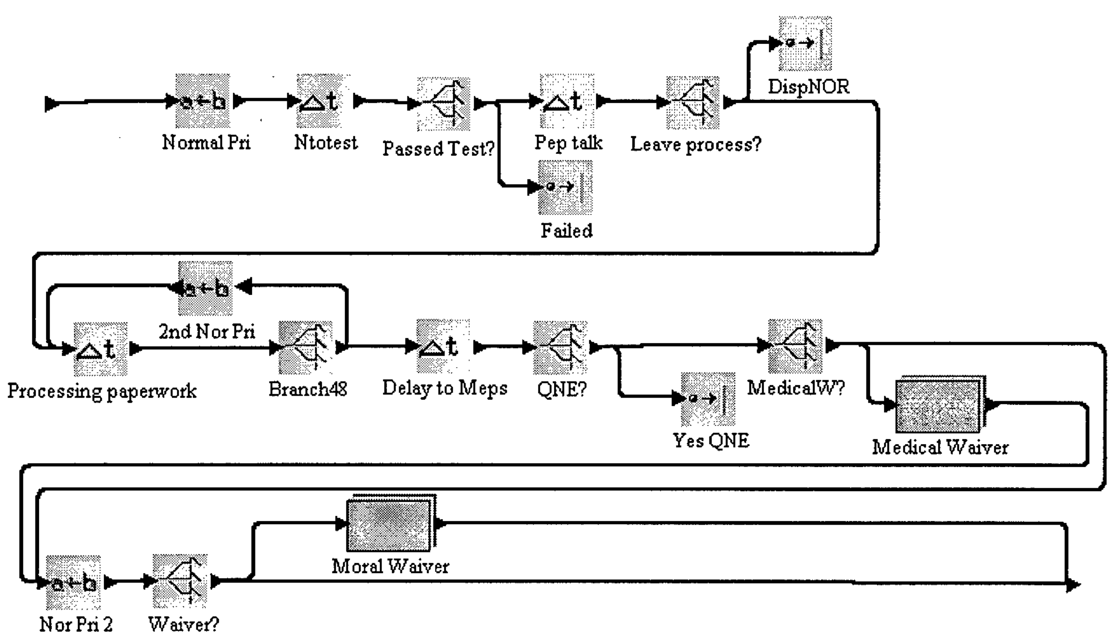

## Recruiter 1 Processing



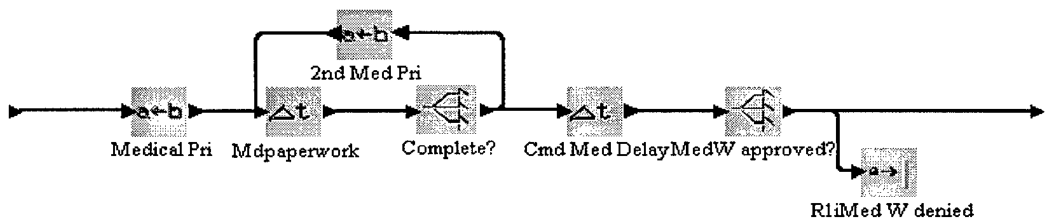
# Recruiter 1 Immediate Processing



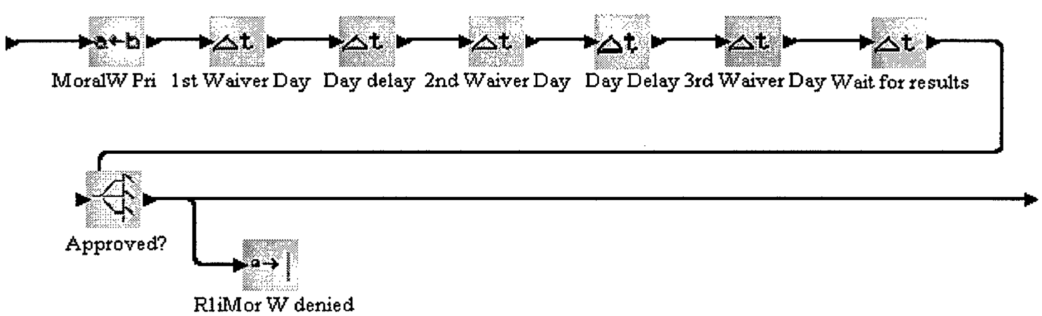

# Recruiter 1 Normal Processing



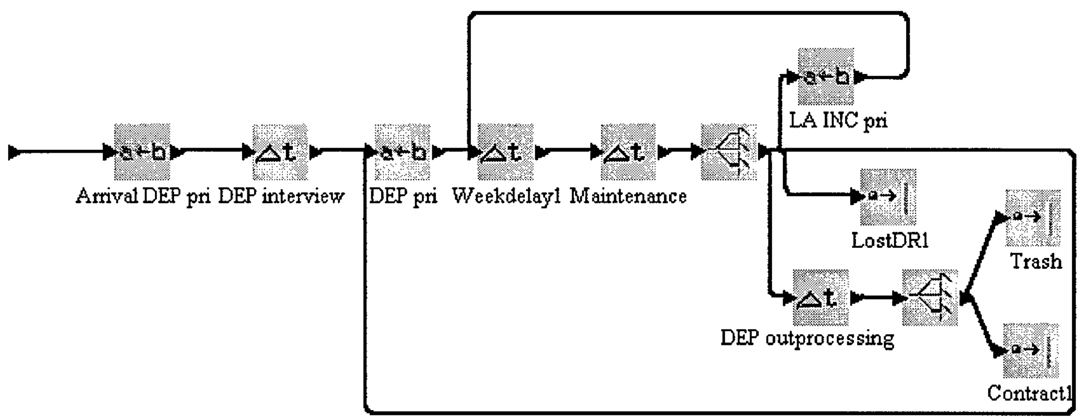
## Recruiter 1 Medical Waiver




## Recruiter 1 Moral Waiver



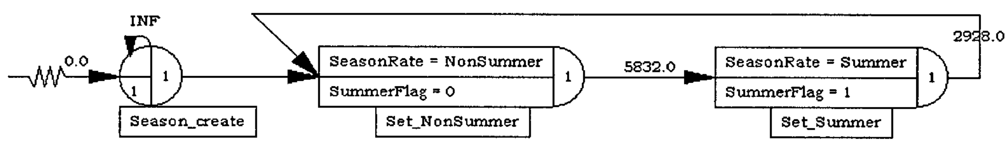
# Recruiter 1 DEP Sustainment

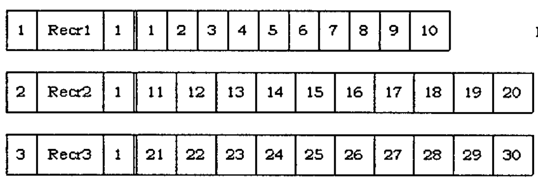


## Appendix C- AweSim Model (Beta Version)

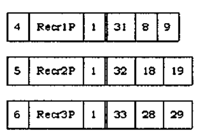
# Season Control and Prospecting Schedules

Season Control (assume year begins on Oct 1 (8am) and summer begins on Jun 1, time in Hours)



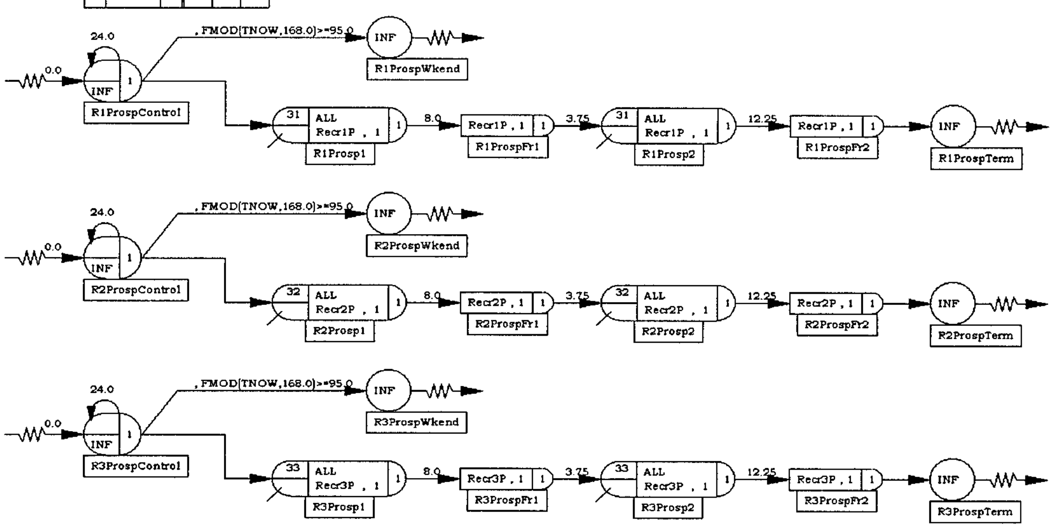




Declaration of 3 Army station recruiters along with their respective priority files

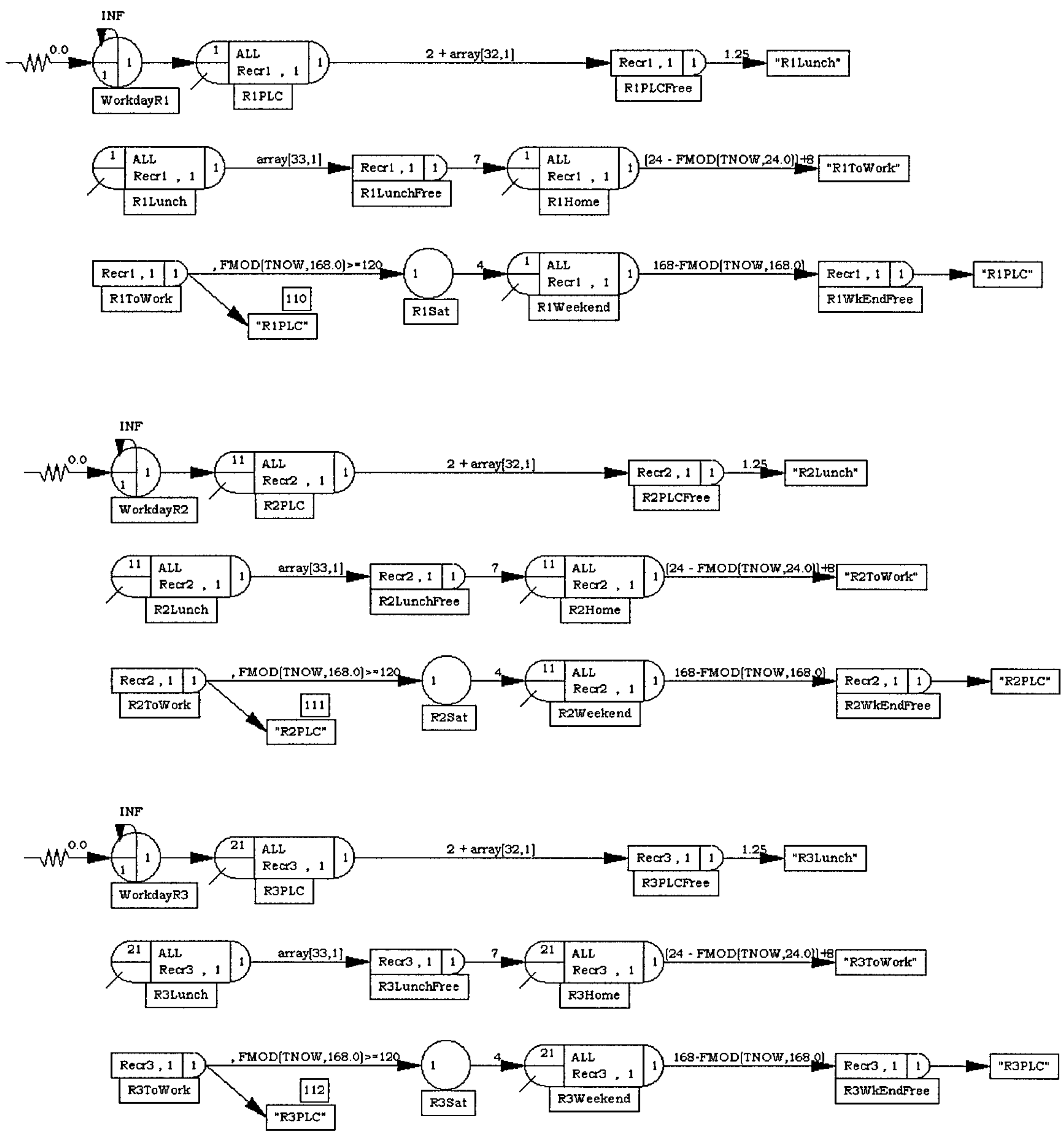



Allow recruiters to Prospect applicants only at selected times

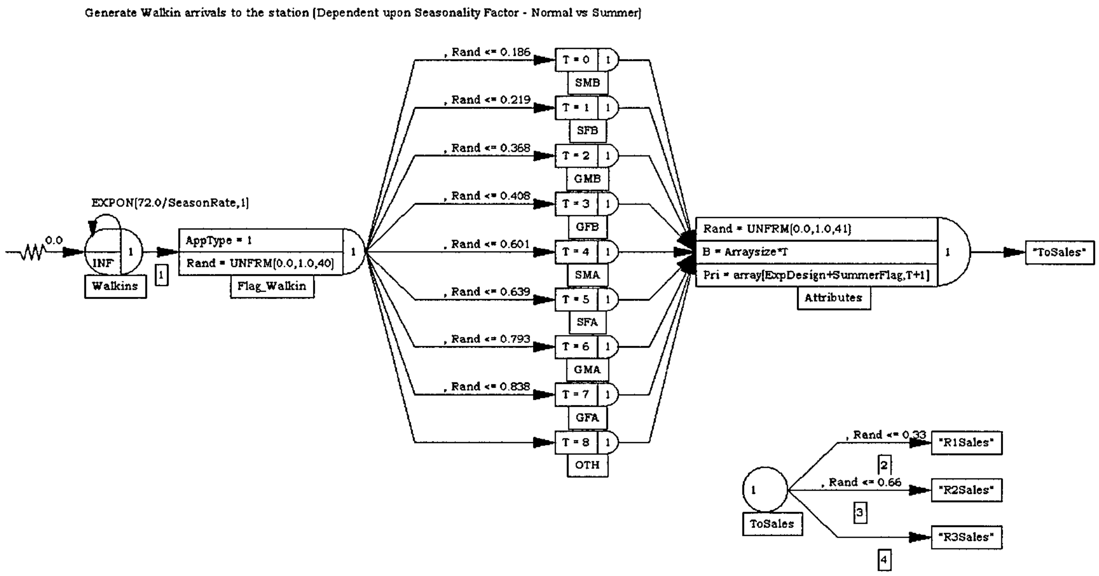
Current Schedule: M-Th Prospecting from 4pm to 7:45pm



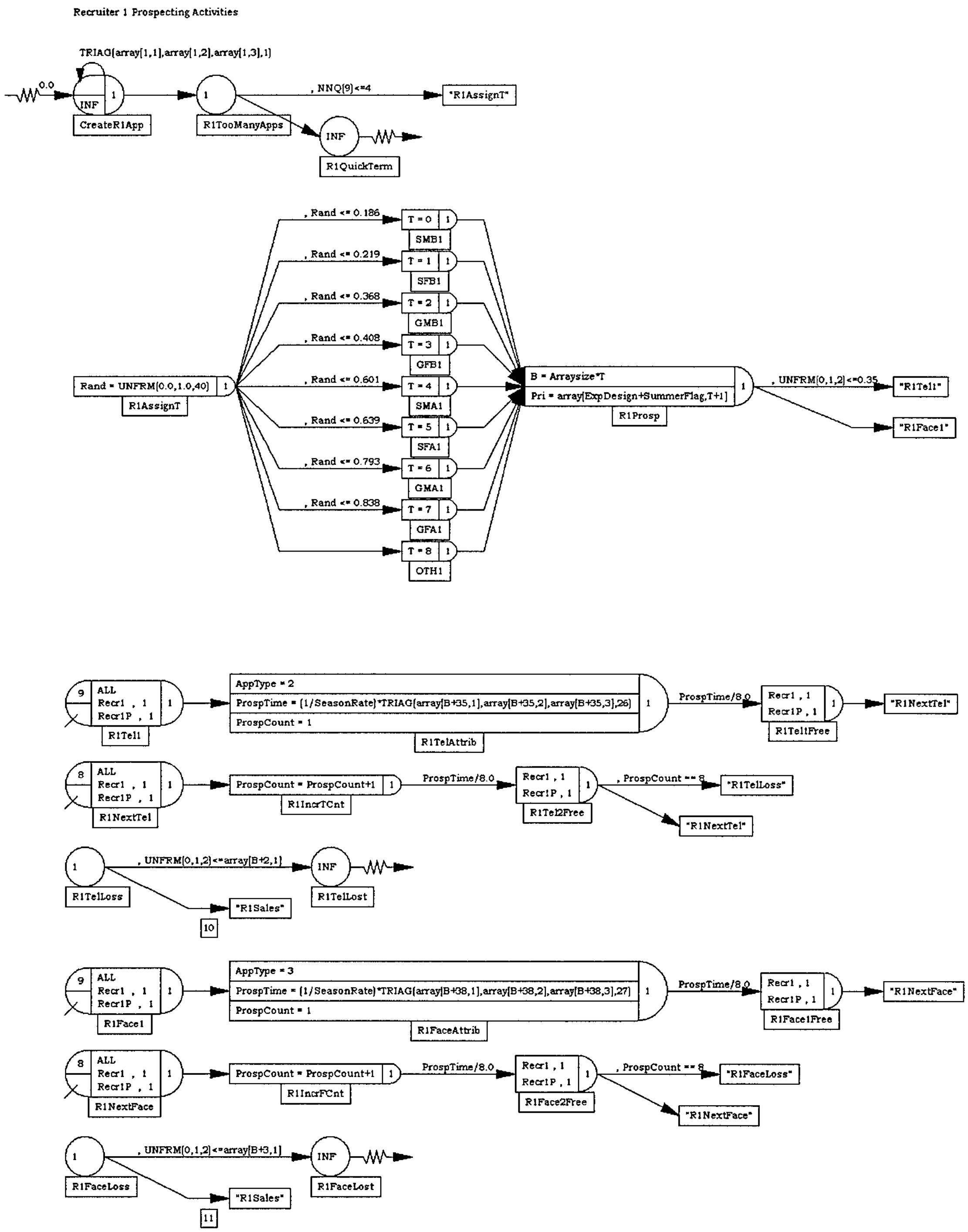
# Recruiter Daily/Weekly Schedules



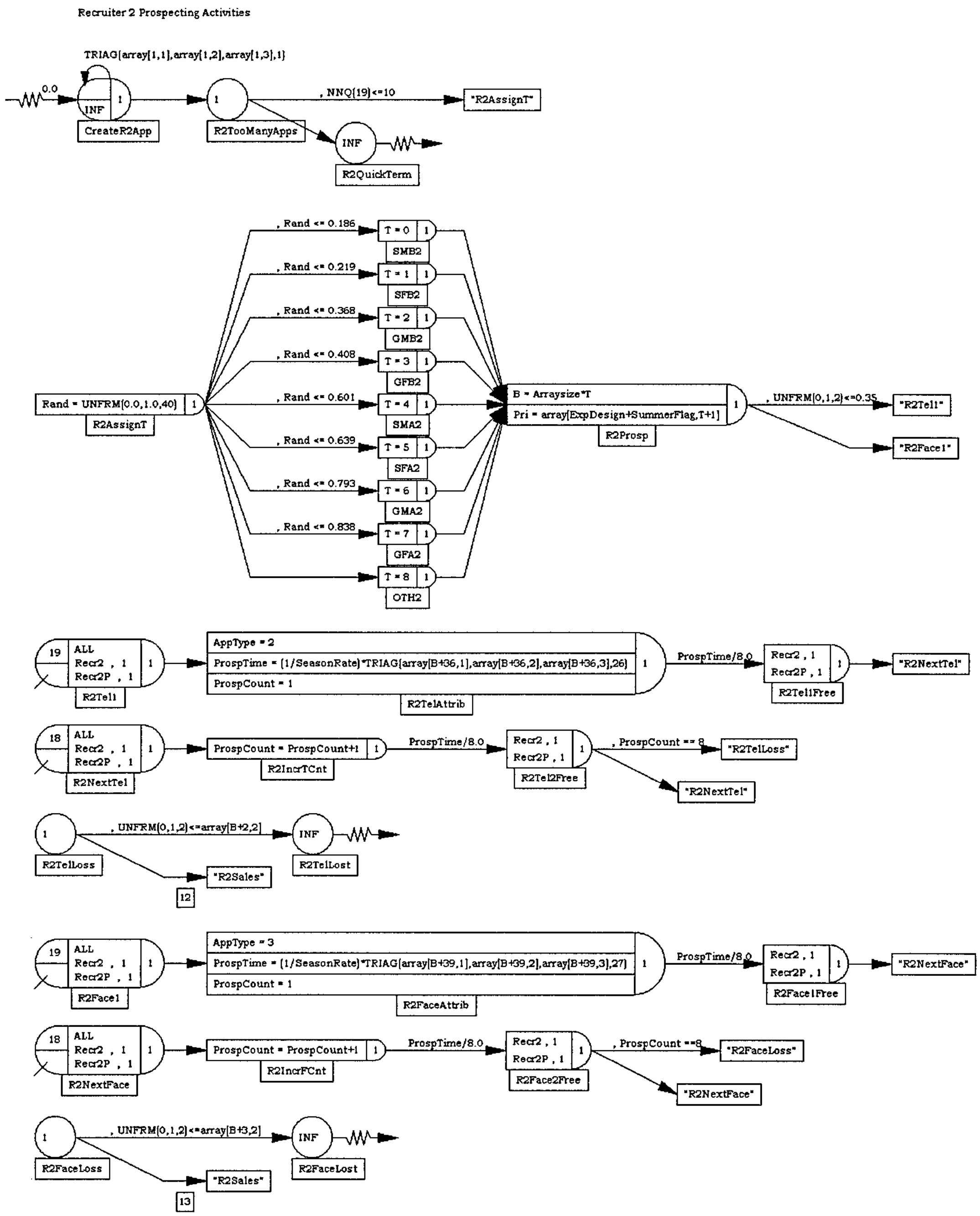
# Walk-in Generation



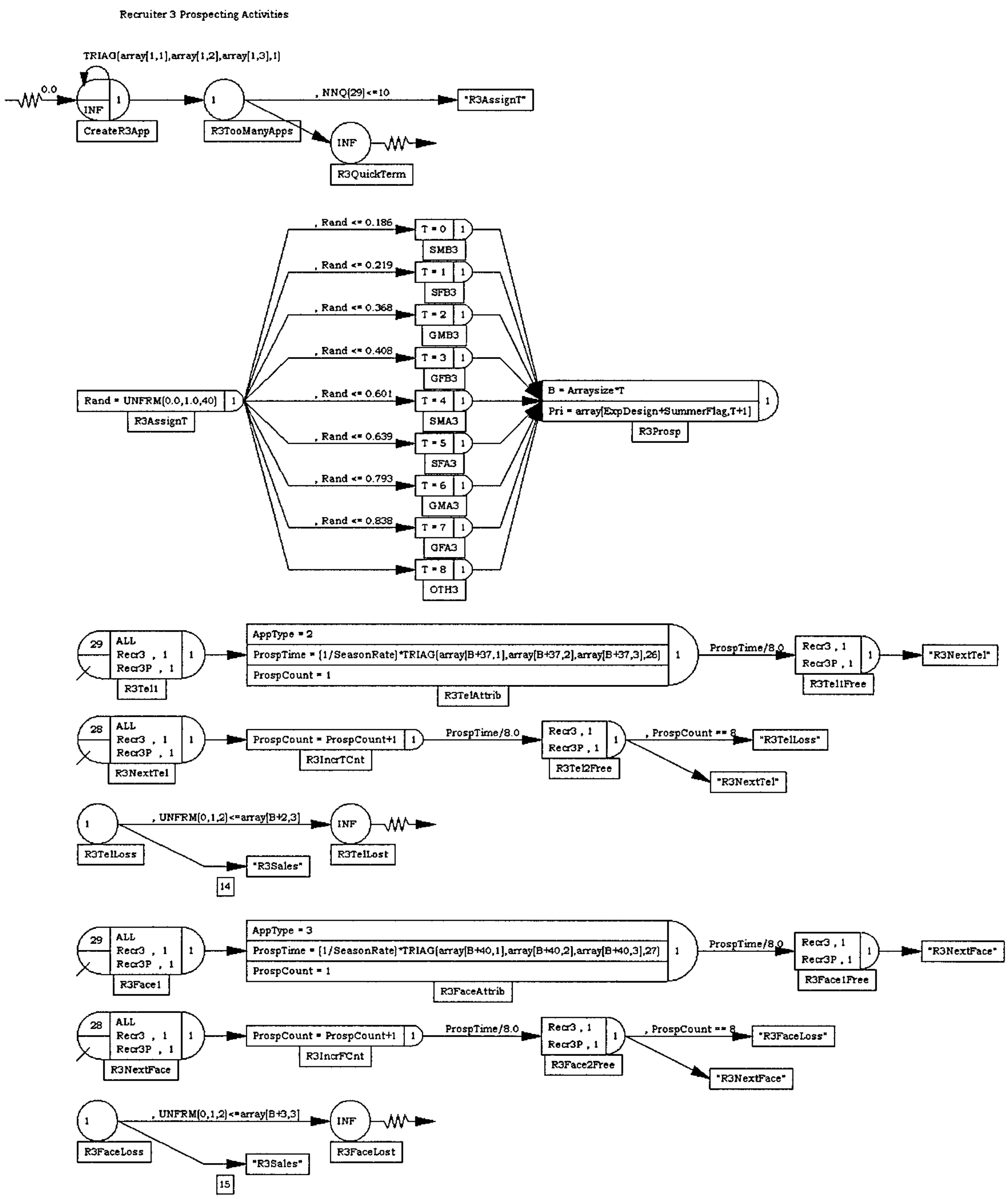
# Recruiter 1 Prospecting Activities



# Recruiter 2 Prospecting Activities

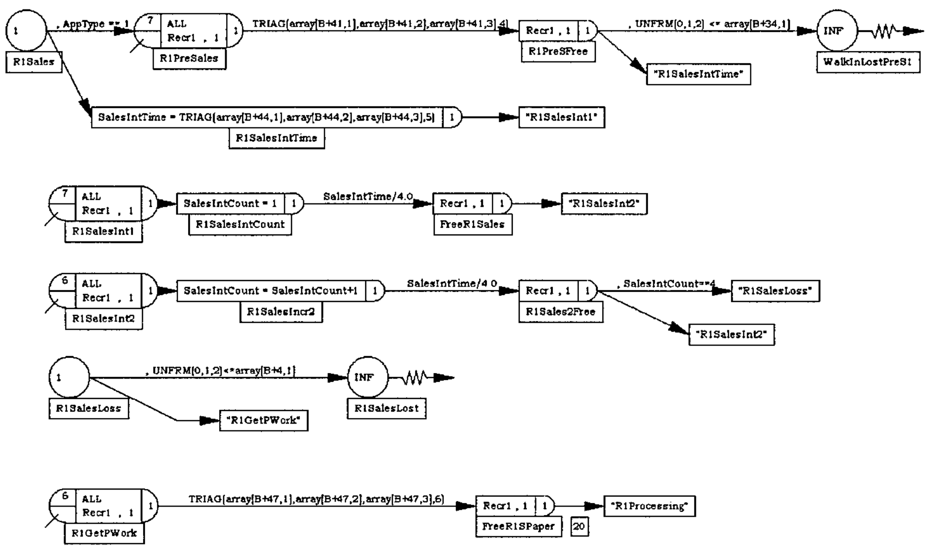


# Recruiter 3 Prospecting Activities

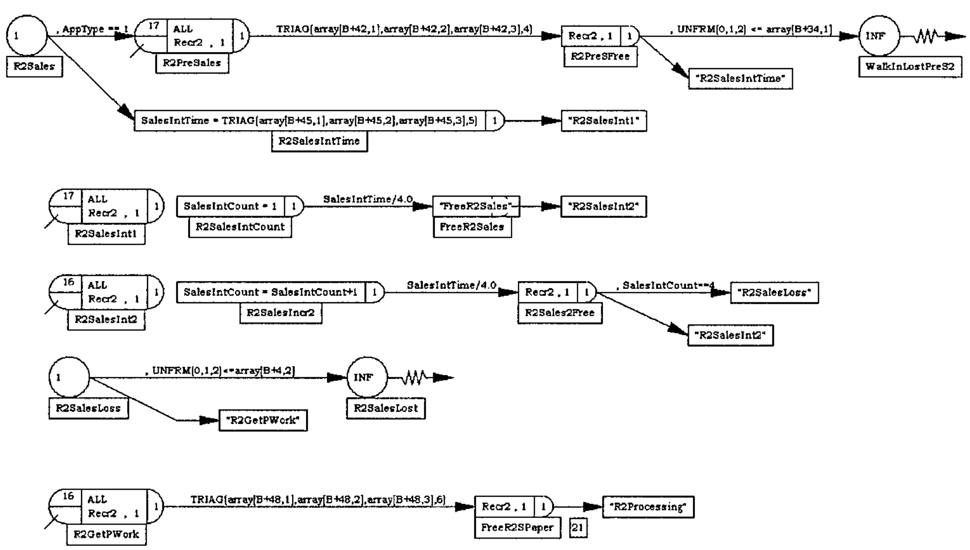


# Recruiter 1 and 2 Sales Activities

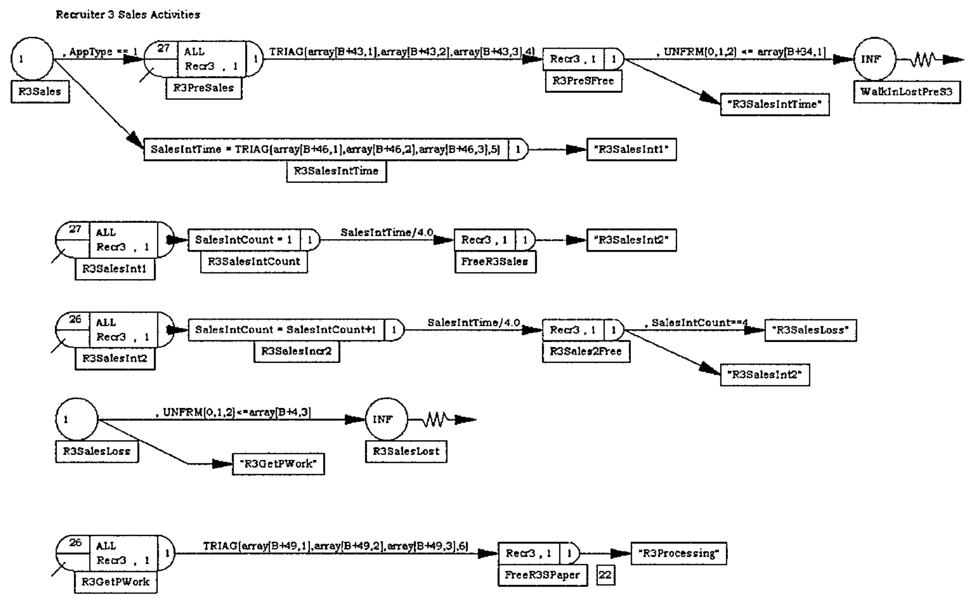
Recruiter 1 Sales Activities



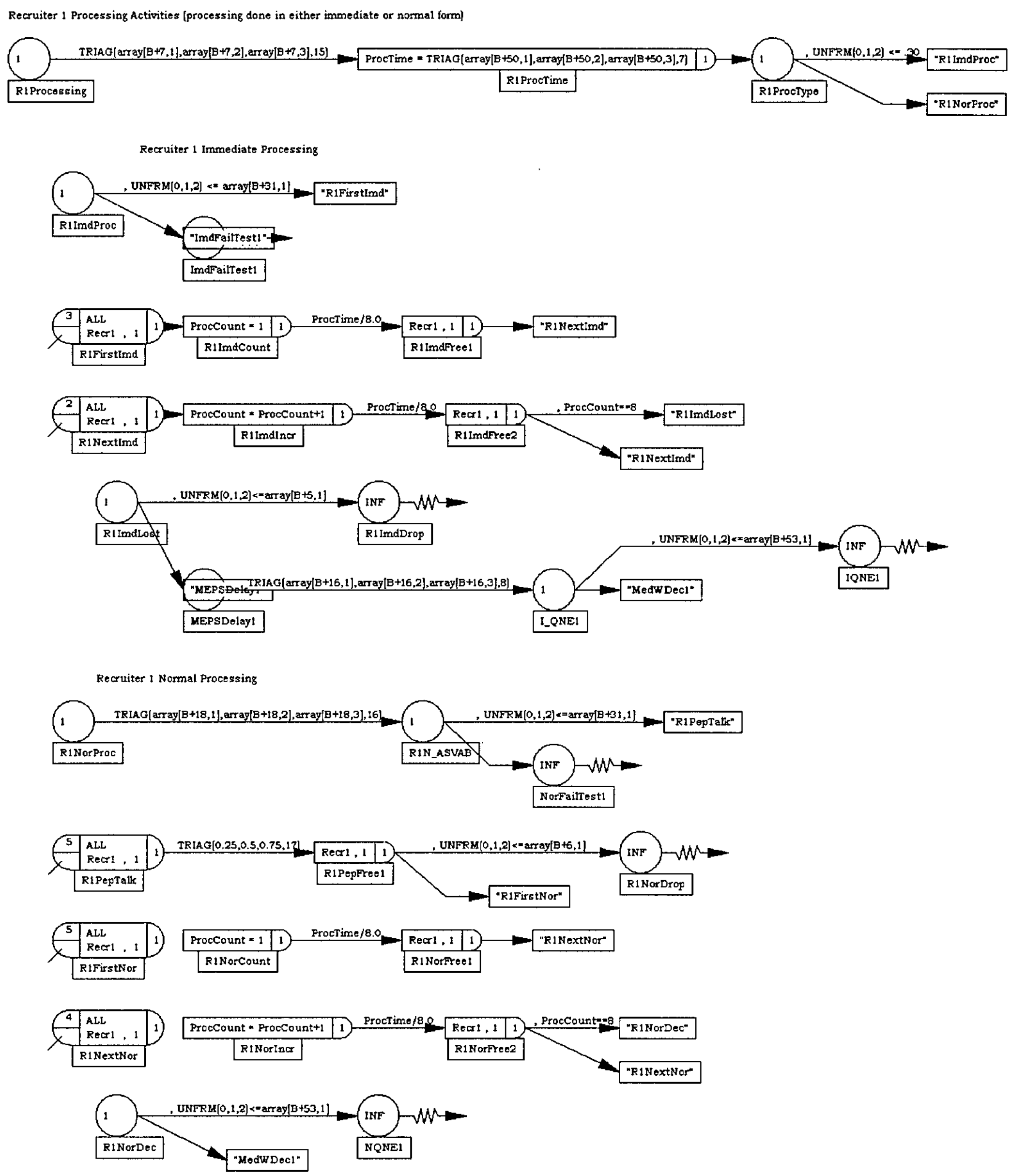

Recruiter 2 Sales Activities



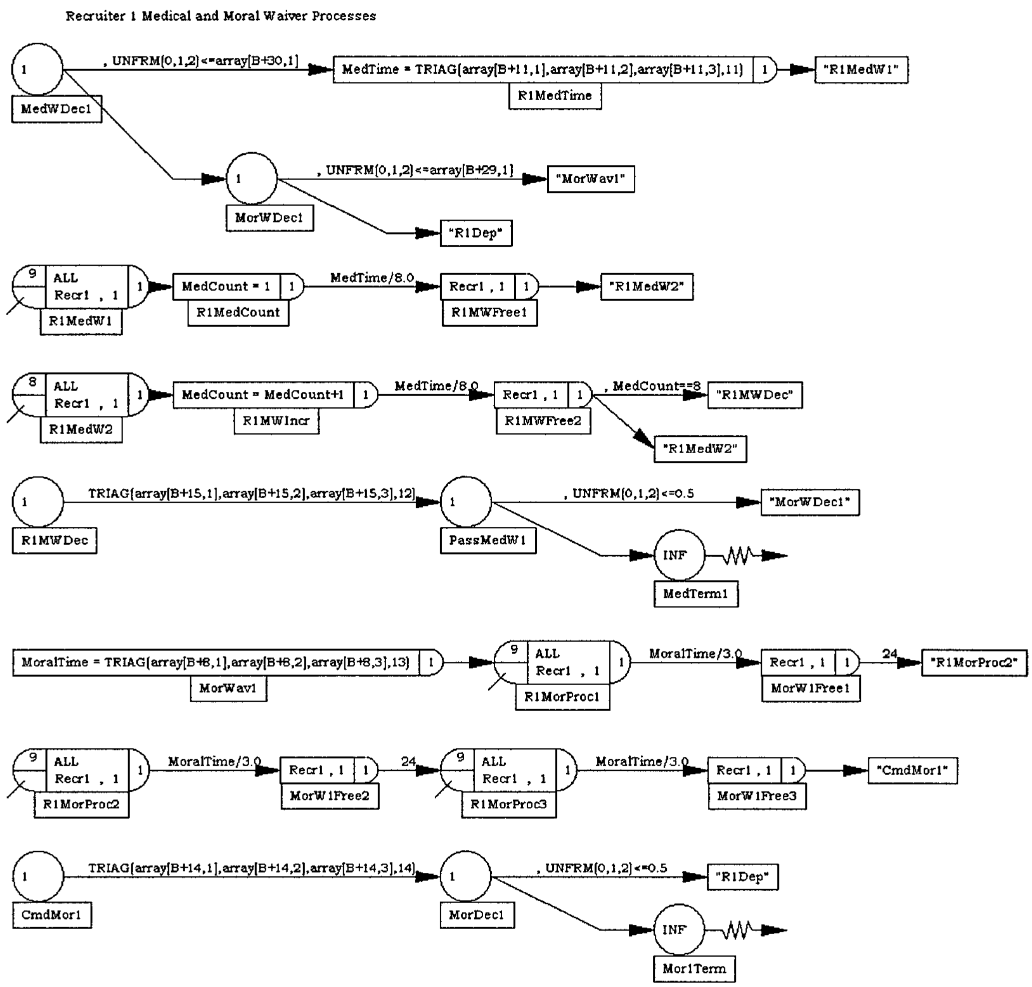
# Recruiter 3 Sales Activities



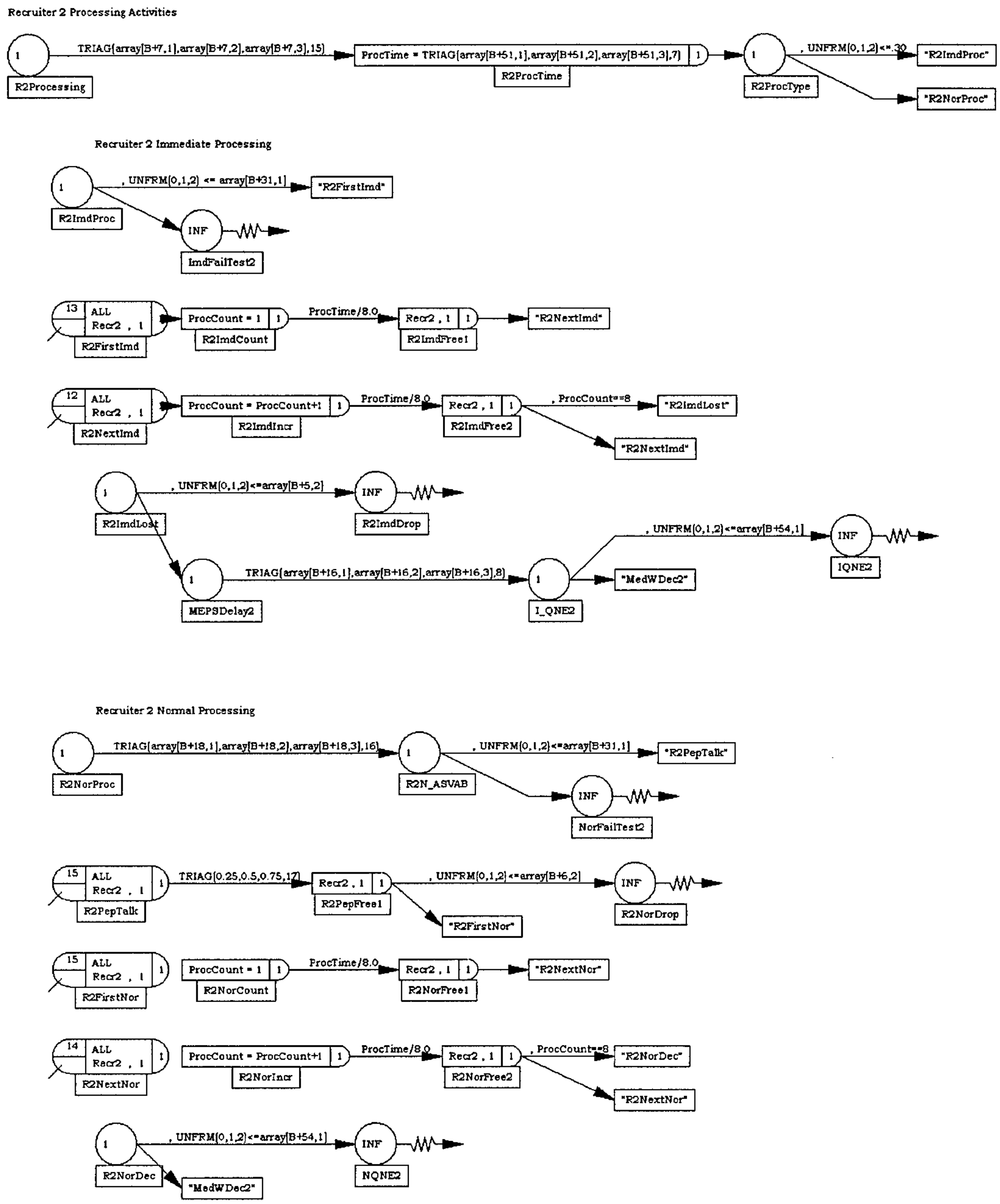
# Recruiter 1 Processing



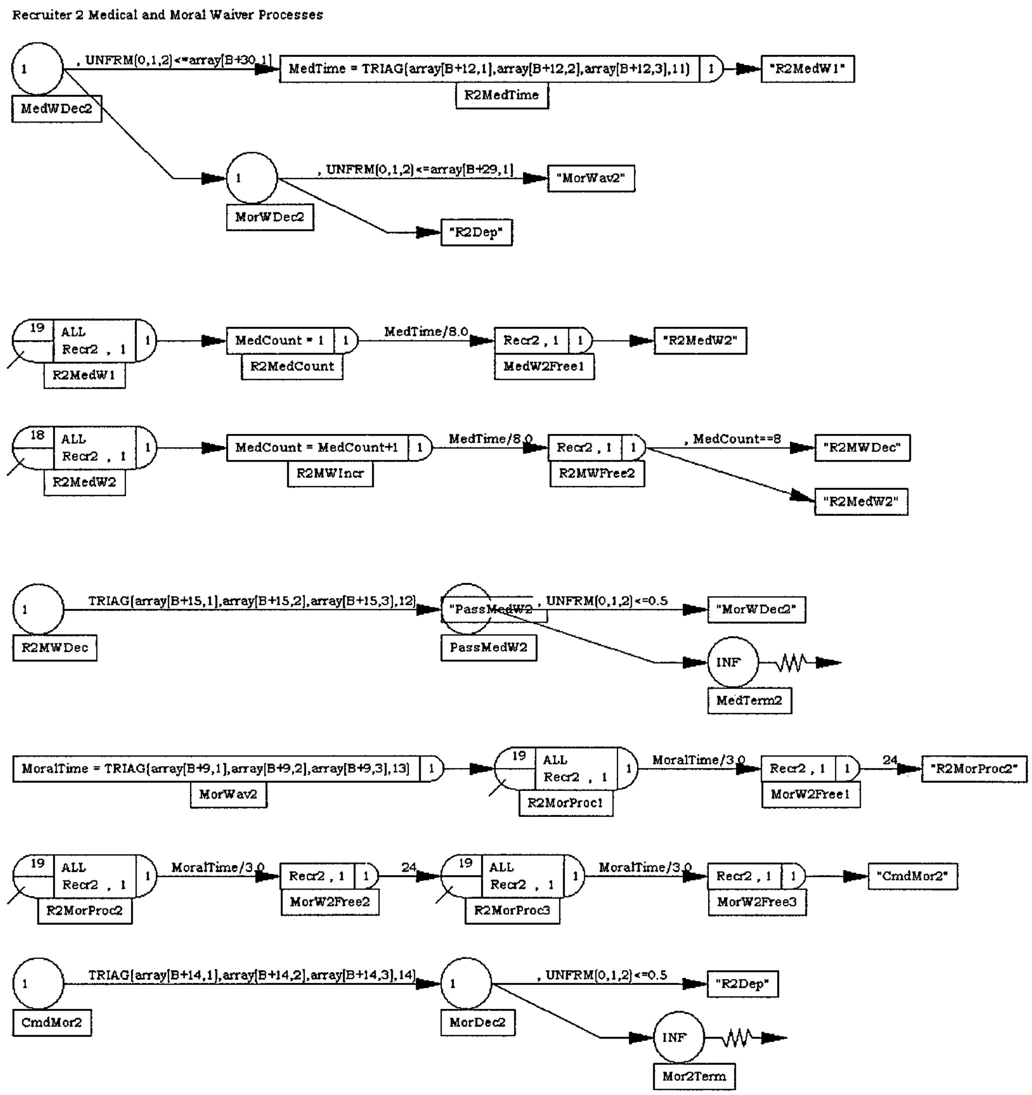
# Recruiter 1 Medical and Moral Waivers



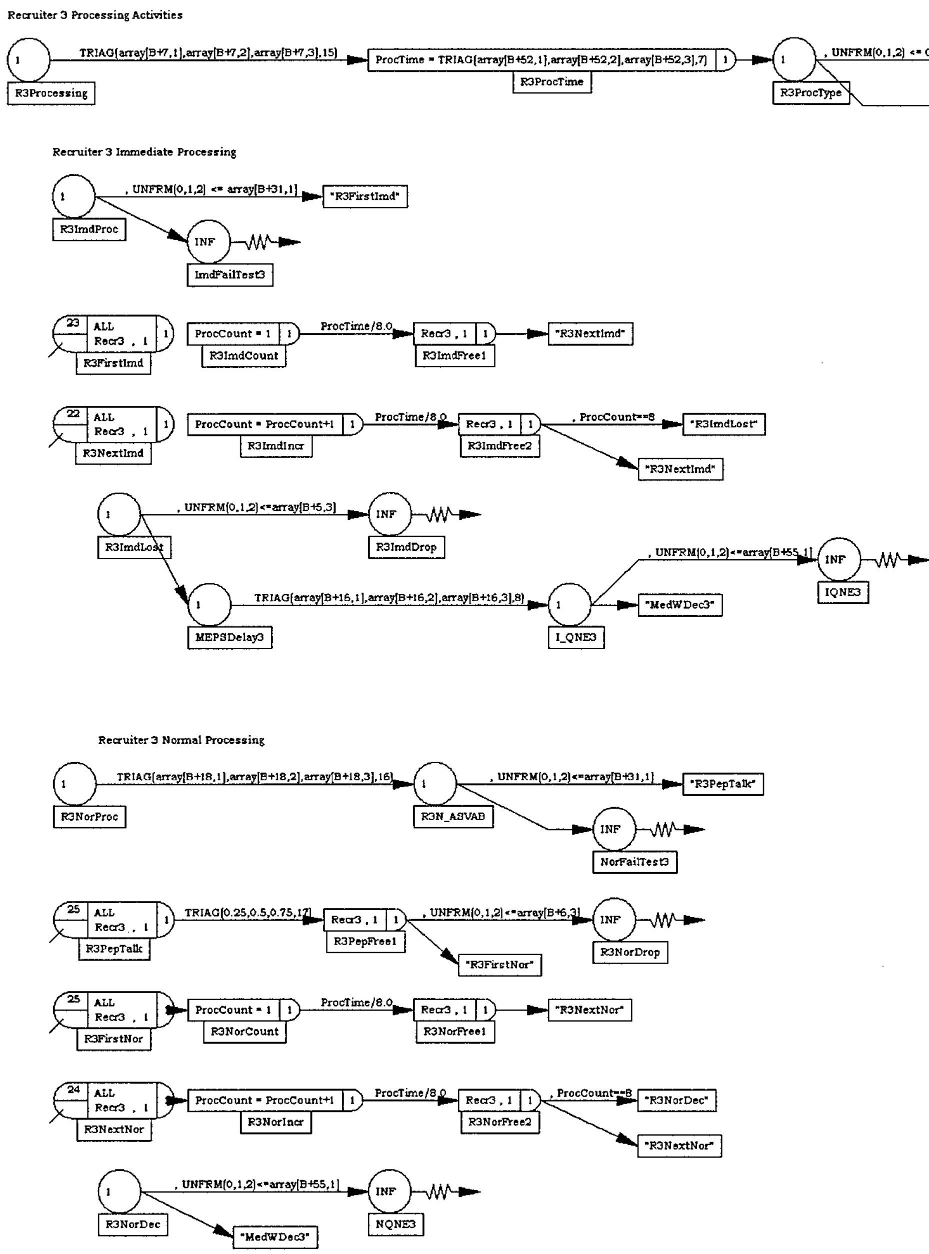
# Recruiter 2 Processing



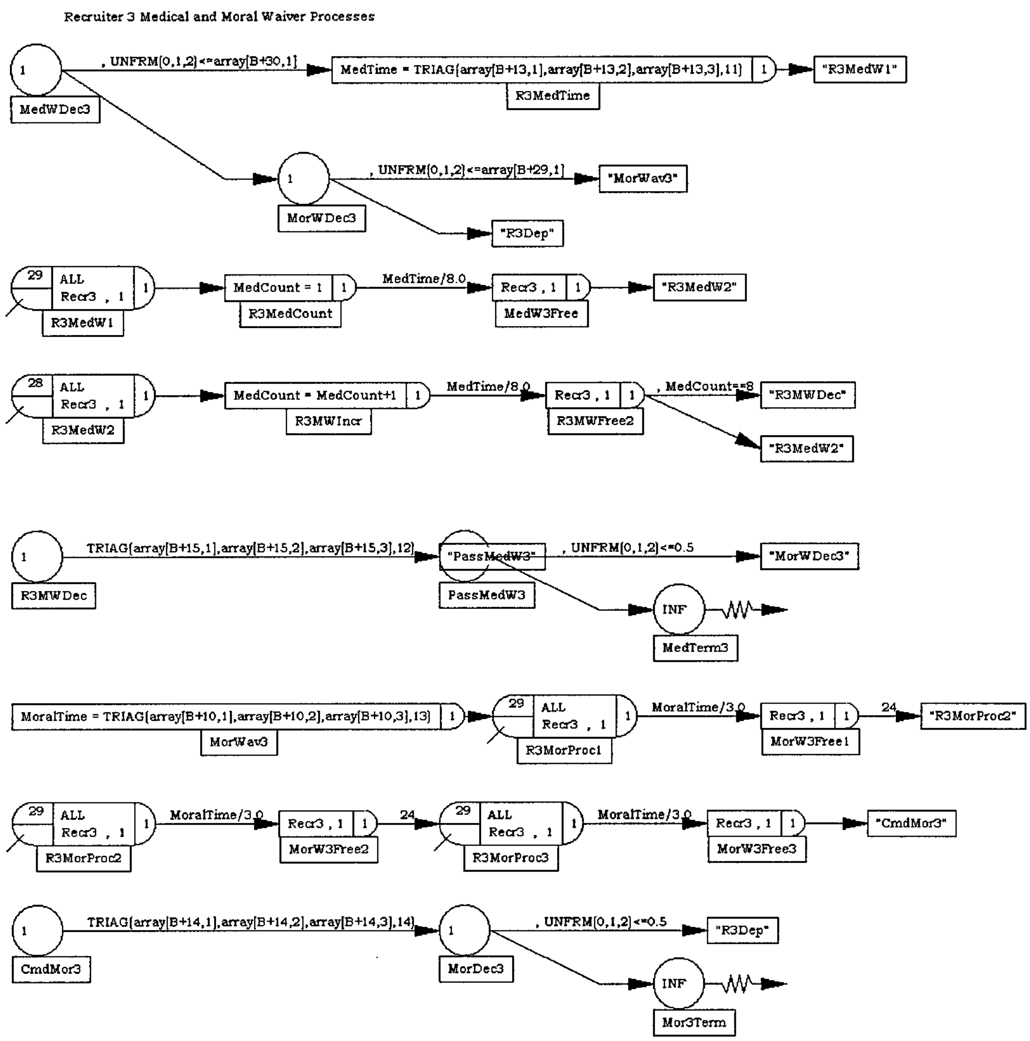
# Recruiter 2 Medical and Moral Waivers



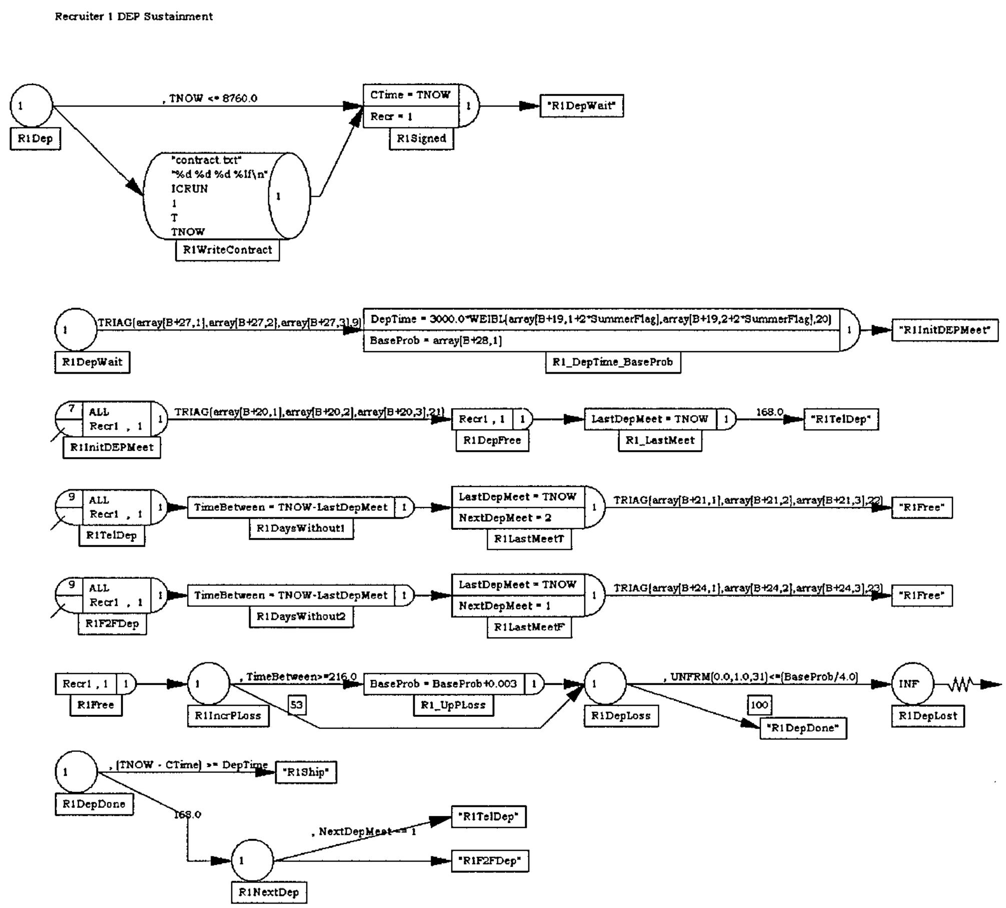
# Recruiter 3 Processing



# Recruiter 3 Medical and Moral Waivers

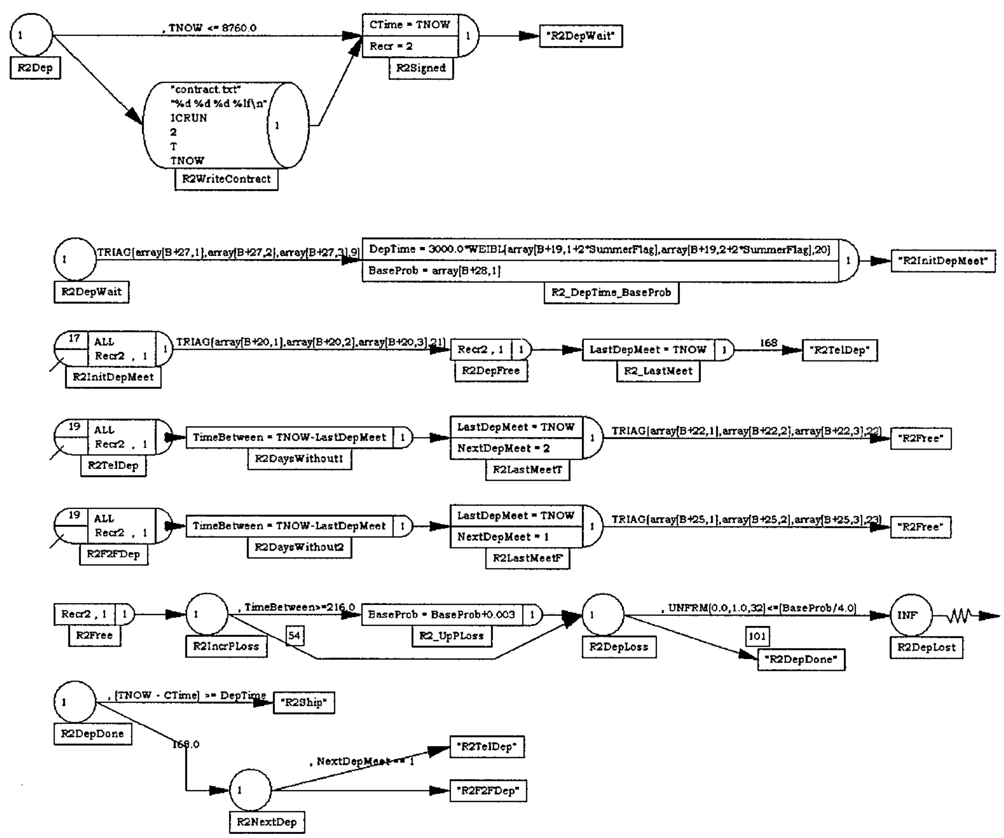


# Recruiter 1 DEP Sustainment

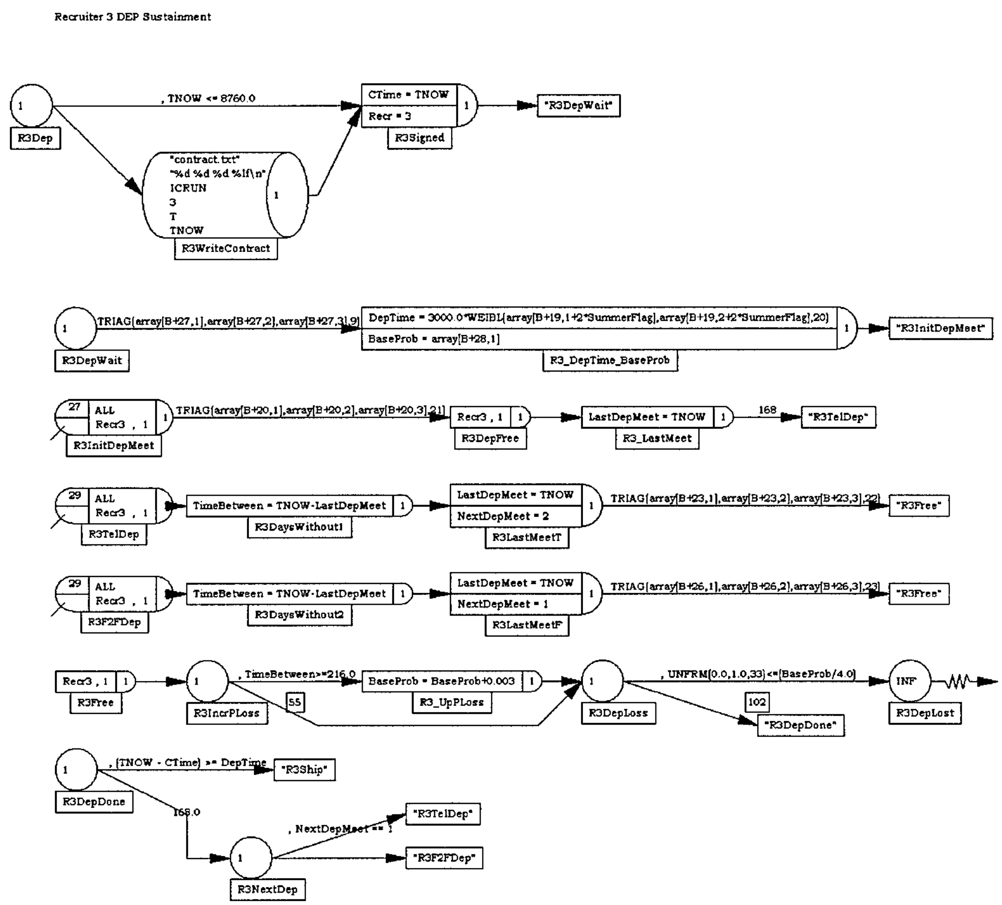


# Recruiter 2 DEP Sustainment

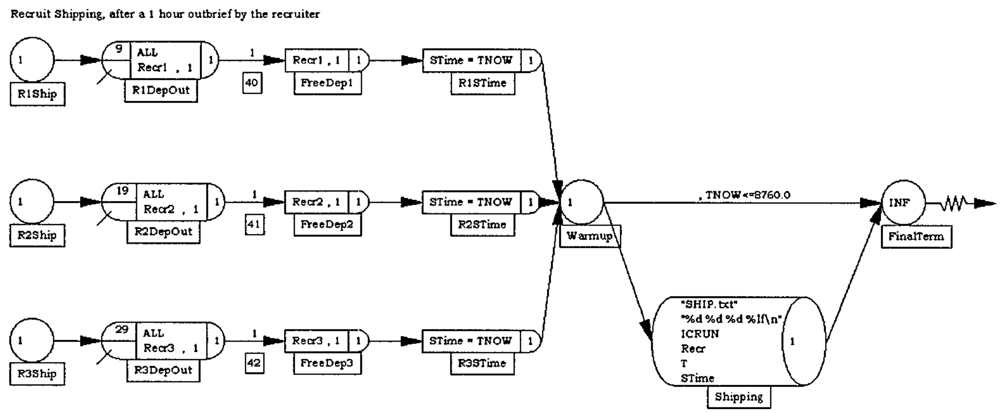
Recruiter 2 DEP Sustainment



# Recruiter 3 DEP Sustainment



# DEP Outprocessing



## AweSim Random Number Stream Assignments

| Stream | Process Description |
|---|---|
| 1 | Walk-in interarrivals |
| 2 | General decisions *Unif(0,1)* |
| 4 | Walk-in PreSales time delay |
| 5 | Sales interview time |
| 6 | Sales paperwork time |
| 7 | Processing time |
| 8 | MEPS delay (for immediate processing) |
| 9 | Delay until initial DEP interview |
| 11 | Medical waiver time |
| 12 | Delay for medical waiver |
| 13 | Moral waiver time |
| 14 | Delay for command decision regarding moral decision |
| 15 | Delay from sales to processing stages |
| 16 | Delay for ASVAB test (for normal processing) |
| 17 | Pep talk time (for normal processing) |
| 20 | Dep time |
| 21 | Time of initial DEP meeting |
| 22 | Time of telephone DEP meeting |
| 23 | Time of face-to-face DEP meeting |
| 26 | Telephone prospecting time |
| 27 | Face-to-face prospecting time |
| 31 | Recruiter 1 DEP loss decision |
| 32 | Recruiter 2 DEP loss decision |
| 33 | Recruiter 3 DEP loss decision |
| 40 | Assignment of prospect type (walk-in and prospecting) |
| 41 | Assignment of walk-in to a recruiter |

# AweSim Equivalence Variables

## Global Variables

Reals (AweSim's XX variables)

| | |
|---|---|
| SeasonRate | Seasonality rate multiplier, set to either Summer or NonSummer |
| Summer | Summer rate multiplier, default at 1.3 |
| NonSummer | NonSummer rate multiplier, default at 1.0 |

Integers (AweSim's LL variables)

| | |
|---|---|
| ArraySize | Array block for each prospect type, default at 55 |
| SummerFlag | Flag representing season (0 ~ non-summer, 1 ~ summer) |
| ExpDesign | Experimental design array index, default at 496 |

## Entity Variables

Reals (AweSim's ATRIB variables)

| | |
|---|---|
| CTime | Time of contracting into the Army |
| STime | Time of shipping to basic training |
| MoralTime | Total time spent processing moral waiver package |
| DepTime | Time assigned to spend in DEP |
| BaseProb | Base probability of dropping from DEP in any given month |
| LastDepMeet | Time of last DEP meeting |
| TimeBetween | Time between consecutive DEP meetings |
| ProcTime | Total time needed for processing |
| MedTime | Total time spent processing medical waiver package |
| SalesIntTime | Time spent on sales interview |
| ProspTime | Time spent on prospecting (either telephone or face-to-face) |

Integers (AweSim's LTRIB variables)

| | |
|---|---|
| T | Prospect type (0-8) |
| B | Array block index for this applicant type |
| NextDepMeet | Flag representing next DEP meeting (0 ~ telephone, 1 ~ face) |
| SalesIntCount | Counter for sales interview loops (4 segments) |
| ProspCount | Counter for prospecting loops (8 segments) |
| AppType | Flag representing applicant type (0 ~ walk-in, 2 ~ telephone, 3 ~ face) |
| Recr | References the applicant's recruiter (1 ~ R1, 2 ~ R2, 3 ~ R3) |
| Pri | Priority of applicant (depends on season and design) |
| ProcCount | Counter for processing loops (8 segments) |
| MedCount | Counter for medical waiver loops (8 segments) |

# AweSim Array Description

As noted in Chapter 4, each prospect type's parameters are stored in an array. Each type has 55 rows within the array. Here we explain these entries. Note: R1 represents recruiter 1, R2 represents recruiter 2, and R3 represents recruiter 3

| Row | Col | Description |
|---|---|---|
| 1 | 1,2,3 | Applicant entity generation, triangular |
| 2 | 1,2,3 | % of applicants lost from telephone prospecting to sales (R1, R2, and R3) |
| 3 | 1,2,3 | % of applicants lost from face prospecting to sales (R1, R2, and R3) |
| 4 | 1,2,3 | % of applicants lost from sales interview to processing (R1, R2, and R3) |
| 5 | 1,2,3 | % of applicants lost from immediate processing to DEP (R1, R2, and R3) |
| 6 | 1,2,3 | % of applicants lost from normal processing to DEP (R1, R2, and R3) |
| 7 | 1,2,3 | Time for applicants to bring in processing paperwork, triangular |
| 8 | 1,2,3 | Time R1 spends on moral waiver package, triangular |
| 9 | 1,2,3 | Time R2 spends on moral waiver package, triangular |
| 10 | 1,2,3 | Time R3 spends on moral waiver package, triangular |
| 11 | 1,2,3 | Time R1 spends on medical waiver package, triangular |
| 12 | 1,2,3 | Time R2 spends on medical waiver package, triangular |
| 13 | 1,2,3 | Time R3 spends on medical waiver package, triangular |
| 14 | 1,2,3 | Time waiting for moral waiver command decision, triangular |
| 15 | 1,2,3 | Time waiting for medical waiver command decision, triangular |
| 16 | 1,2,3 | Immediate processing delay until MEPS appointment, triangular |
| 17 | 1,2,3 | Normal processing delay until MEPS appointment, triangular |
| 18 | 1,2,3 | Delay in normal processing to schedule ASVAB test, triangular |
| 19 | 1,2,3,4 | Non-summer (1,2) and summer (3,4) DEP time parameters, weibull |
| 20 | 1,2,3 | Time spent on initial DEP interview, triangular |
| 21 | 1,2,3 | Time R1 spends on one telephone DEP meeting, triangular |
| 22 | 1,2,3 | Time R2 spends on one telephone DEP meeting, triangular |
| 23 | 1,2,3 | Time R3 spends on one telephone DEP meeting, triangular |
| 24 | 1,2,3 | Time R1 spends on one face-to-face DEP meeting, triangular |
| 25 | 1,2,3 | Time R2 spends on one face-to-face DEP meeting, triangular |
| 26 | 1,2,3 | Time R3 spends on one face-to-face DEP meeting, triangular |
| 27 | 1,2,3 | Delay from contracting to first DEP interview, triangular |
| 28 | 1 | DEP loss probability in any given month |
| 29 | 1 | Probability the applicant needs a moral waiver |
| 30 | 1 | Probability the applicant needs a medical waiver |
| 31 | 1 | Probability the applicant will pass the ASVAB test |
| 32 | 1 | Time spent on collateral duties (all recruiters), set to 0.75 hours |
| 33 | 1 | Time spent on lunch (all recruiters), set to 1.0 hour |
| 34 | 1 | Probability a walk-in applicant will fail pre-qualification |

| | | |
|---|---|---|
| 35 | 1,2,3 | Time R1 spends telephone prospecting to get an interview, triangular |
| 36 | 1,2,3 | Time R2 spends telephone prospecting to get an interview, triangular |
| 37 | 1,2,3 | Time R3 spends telephone prospecting to get an interview, triangular |
| 38 | 1,2,3 | Time R1 spends face-to-face prospecting to get an interview, triangular |
| 39 | 1,2,3 | Time R2 spends face-to-face prospecting to get an interview, triangular |
| 40 | 1,2,3 | Time R3 spends face-to-face prospecting to get an interview, triangular |
| 41 | 1,2,3 | Time R1 spends on presales interview for walk-in, triangular |
| 42 | 1,2,3 | Time R2 spends on presales interview for walk-in, triangular |
| 43 | 1,2,3 | Time R3 spends on presales interview for walk-in, triangular |
| 44 | 1,2,3 | Time R1 spends on sales interview, triangular |
| 45 | 1,2,3 | Time R2 spends on sales interview, triangular |
| 46 | 1,2,3 | Time R3 spends on sales interview, triangular |
| 47 | 1,2,3 | Time R1 spends on sales interview paperwork, triangular |
| 48 | 1,2,3 | Time R2 spends on sales interview paperwork, triangular |
| 49 | 1,2,3 | Time R3 spends on sales interview paperwork, triangular |
| 50 | 1,2,3 | Total time R1 spends on enlistment package, triangular |
| 51 | 1,2,3 | Total time R2 spends on enlistment package, triangular |
| 52 | 1,2,3 | Total time R3 spends on enlistment package, triangular |
| 53 | 1 | Probability R1 applicant will qualify, but not enlist |
| 54 | 1 | Probability R2 applicant will qualify, but not enlist |
| 55 | 1 | Probability R3 applicant will qualify, but not enlist |

We now show the array listing for the SMB prospect type. These descriptions are within the AweSim control files.

```
;Recruit Prospect Parameter Values
;
;SMB (Senior Male Beta)
ARRAY,1,3,{0.5,0.75,1.0};
ARRAY,2,3,{0.39,0.35,0.31};
ARRAY,3,3,{0.39,0.35,0.31};
ARRAY,4,3,{0.87,0.8,0.73};
ARRAY,5,3,{0.05,0.07,0.09};
ARRAY,6,3,{0.07,0.08,0.09};
ARRAY,7,3,{9,19,44};
ARRAY,8,3,{6,9,17};
ARRAY,9,3,{7,10,18};
ARRAY,10,3,{8,10,18};
ARRAY,11,3,{7,14,36};
ARRAY,12,3,{8,15,38};
ARRAY,13,3,{9,16,40};
ARRAY,14,3,{120,240,720};
ARRAY,15,3,{528,720,1440};
```

```
ARRAY,16,3,{24,96,144};
ARRAY,17,3,{48,168,240};
ARRAY,18,3,{48,96,168};
; Weibull parameters:  first two are nonsummer (alpha,beta), last two are summer
ARRAY,19,4,{5.066,3.4,67806.7,11.06};
ARRAY,20,3,{0.9,1.5,2.15};
ARRAY,21,3,{0.5,1.1,2.9};
ARRAY,22,3,{0.6,1.2,3.0};
ARRAY,23,3,{0.7,1.3,3.2};
ARRAY,24,3,{1.0,2.25,4.8};
ARRAY,25,3,{1.25,2.5,5.0};
ARRAY,26,3,{1.5,3.0,5.5};
ARRAY,27,3,{72,168,240};
ARRAY,28,1,{0.035};
ARRAY,29,1,{0.05};
ARRAY,30,1,{0.07};
ARRAY,31,1,{0.4};
ARRAY,32,1,{0.75};
ARRAY,33,1,{1.0};
ARRAY,34,1,{0.6};
ARRAY,35,3,{1.0,2.5,4.8};
ARRAY,36,3,{1.2,3.0,5.0};
ARRAY,37,3,{1.5,3.3,5.5};
ARRAY,38,3,{1.0,2.75,4.4};
ARRAY,39,3,{1.1,3.0,4.6};
ARRAY,40,3,{1.25,3.3,5.0};
ARRAY,41,3,{0.5,0.75,1.1};
ARRAY,42,3,{0.55,0.8,1.2};
ARRAY,43,3,{0.6,0.85,1.25};
ARRAY,44,3,{1.0,1.5,2.25};
ARRAY,45,3,{1.1,1.6,2.4};
ARRAY,46,3,{1.2,1.75,2.5};
ARRAY,47,3,{0.6,0.85,1.5};
ARRAY,48,3,{0.6,0.9,1.75};
ARRAY,49,3,{0.6,1.1,2.0};
ARRAY,50,3,{1.8,3.2,7.0};
ARRAY,51,3,{1.9,3.3,7.2};
ARRAY,52,3,{2.0,3.5,7.5};
ARRAY,53,1,{0.045};
ARRAY,54,1,{0.04};
ARRAY,55,1,{0.035};
;
;SMB (Senior Male Beta)
ARRAY,56,3,{0.5,0.75,1.0};
.
```

The remaining prospect parameters continue through ARRAY row 495

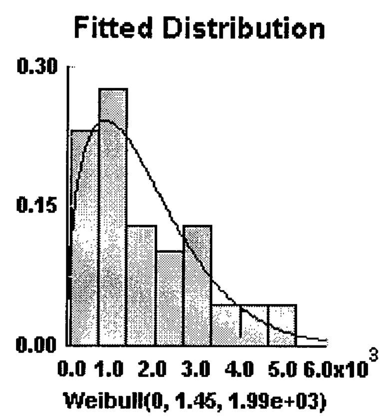
## Appendix D- Analysis Support

### DEP Distributions

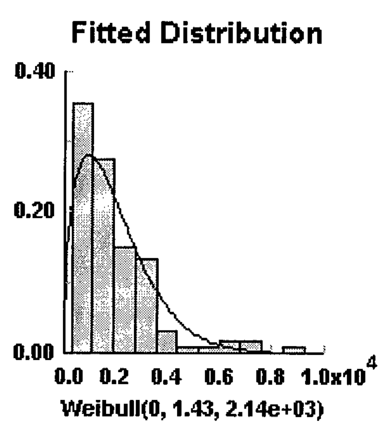
In Chapter 4 we presented the results of our new DEP distributions (fit to the Weibull random distribution). Here we show each prospect type's distribution fit along with the chi-square, Kolmogorov-Smirnov (KS), and Anderson-Darling (AD) goodness-of-fit test results. Recall we did not break up the SFB (Senior-Female-Beta) data into summer and non-summer distributions because of the low number of sample points.

### Summer DEP Distributions

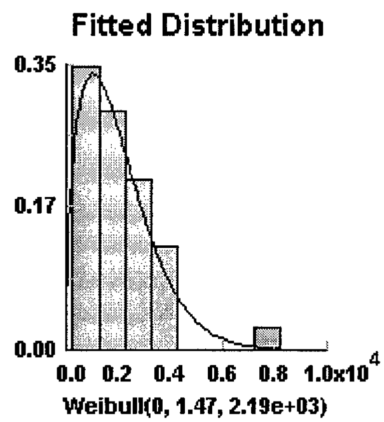
| Other Type - Summer | | |
|---|---|---|
| Sample Points | | 69 |
| Number of Bins | | 8 |
| | Weibull | |
| Alpha | | 1.45 |
| Beta | | 1985.36 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.3 |
| KS | | 0.83 |
| AD | | 0.78 |



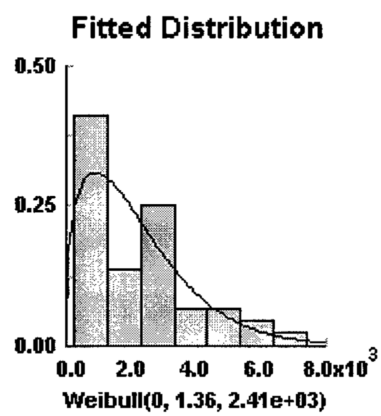

| Grad Male Alpha - Summer | | |
|---|---|---|
| Sample Points | | 127 |
| Number of Bins | | 11 |
| | Weibull | |
| Alpha | | 1.43 |
| Beta | | 2139.35 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.07 |
| KS | | 0.24 |
| AD | | 0.13 |



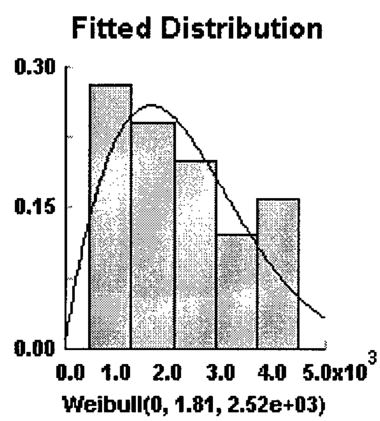
| Grad Male Beta - Summer | | |
|---|---|---|
| Sample Points | | 72 |
| Number of Bins | | 8 |
| | Weibull | |
| Alpha | | 1.47 |
| Beta | | 2187.48 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.3 |
| KS | | 0.8 |
| AD | | 0.48 |



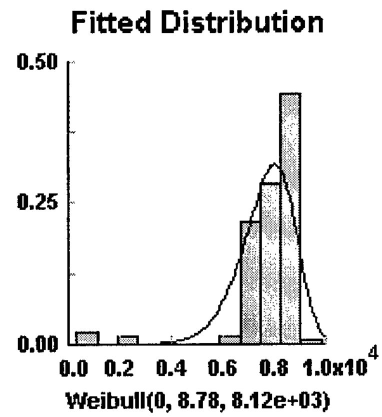

| Grad Female Alpha - Summer | | |
|---|---|---|
| Sample Points | | 44 |
| Number of Bins | | 7 |
| | Weibull | |
| Alpha | | 1.36 |
| Beta | | 2410.76 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.01 |
| KS | | 0.41 |
| AD | | 0.64 |



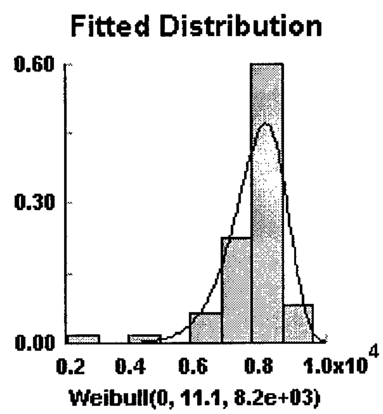

| Grad Female Beta - Summer | | |
|---|---|---|
| Sample Points | | 25 |
| Number of Bins | | 5 |
| | Weibull | |
| Alpha | | 1.81 |
| Beta | | 2520.26 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.36 |
| KS | | 0.94 |
| AD | | 0.85 |



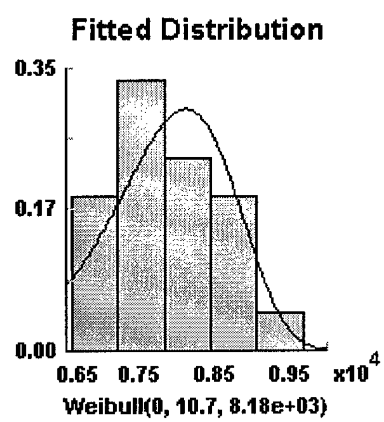
| Senior Male Alpha - Summer | | |
|---|---|---|
| Sample Points | | 138 |
| Number of Bins | | 12 |
| | Weibull | |
| Alpha | | 8.79 |
| Beta | | 8115.46 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0 |
| KS | | 0 |
| AD | | 0 |




| Senior Male Beta - Summer | | |
|---|---|---|
| Sample Points | | 62 |
| Number of Bins | | 8 |
| | Weibull | |
| Alpha | | 11.06 |
| Beta | | 8202.48 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0 |
| KS | | 0.14 |
| AD | | 0.1 |

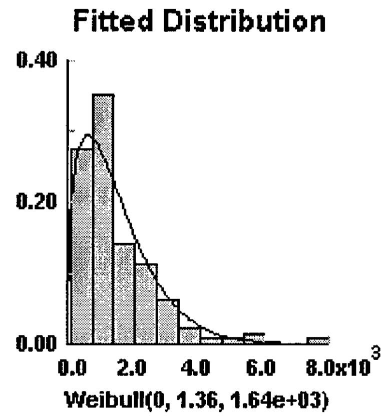



| Senior Female Alpha - Summer | | |
|---|---|---|
| Sample Points | | 21 |
| Number of Bins | | 5 |
| | Weibull | |
| Alpha | | 10.66 |
| Beta | | 8175.11 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.49 |
| KS | | 0.8 |
| AD | | 0.76 |

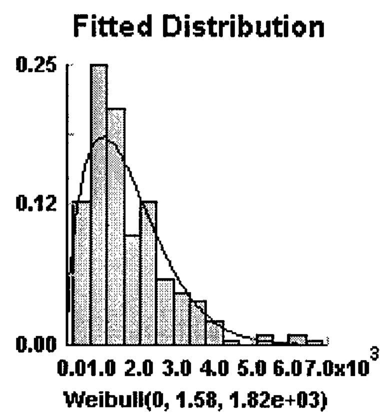


## Non-summer DEP Distributions

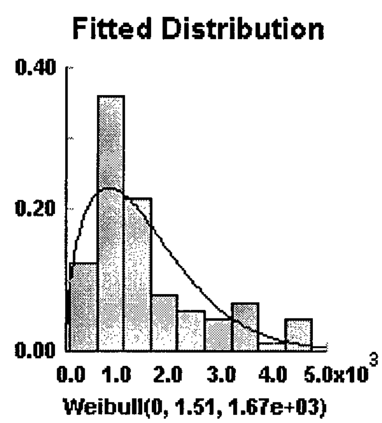
| Other Type - NonSummer | | |
|---|---|---|
| Sample Points | | 142 |
| Number of Bins | | 12 |
| | Weibull | |
| Alpha | | 1.36 |
| Beta | | 1643.8 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.12 |
| KS | | 0.19 |
| AD | | 0.24 |



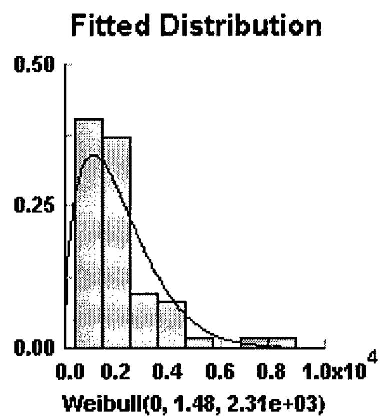

| Grad Male Alpha - NonSummer | | |
|---|---|---|
| Sample Points | | 237 |
| Number of Bins | | 15 |
| | Weibull | |
| Alpha | | 1.58 |
| Beta | | 1821.75 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.21 |
| KS | | 0.13 |
| AD | | 0.17 |



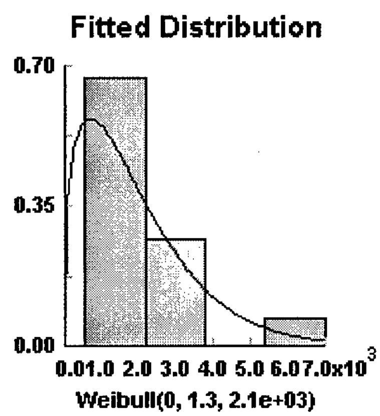

| Grad Male Beta - NonSummer | | |
|---|---|---|
| Sample Points | | 89 |
| Number of Bins | | 9 |
| | Weibull | |
| Alpha | | 1.51 |
| Beta | | 1667.35 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0 |
| KS | | 0.09 |
| AD | | 0.09 |



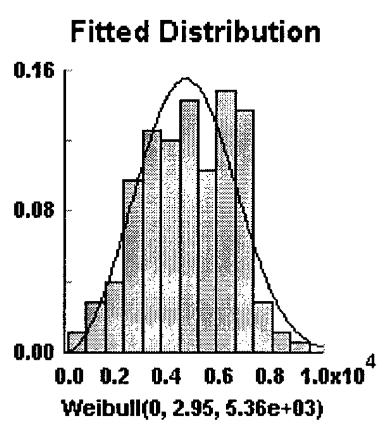
| Grad Female Alpha - NonSummer | | |
|---|---|---|
| Sample Points | | 62 |
| Number of Bins | | 8 |
| | Weibull | |
| Alpha | | 1.48 |
| Beta | | 2309 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.13 |
| KS | | 0.54 |
| AD | | 0.43 |



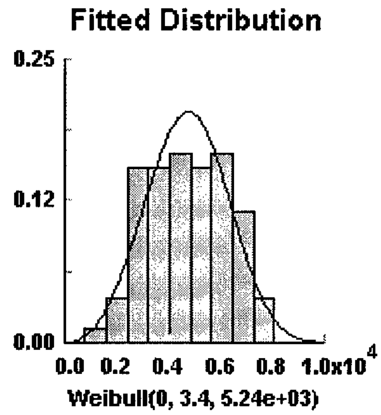

| Grad Female Beta - NonSummer | | |
|---|---|---|
| Sample Points | | 15 |
| Number of Bins | | 4 |
| | Weibull | |
| Alpha | | 1.3 |
| Beta | | 2099.06 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.17 |
| KS | | 0.4 |
| AD | | 0.6 |



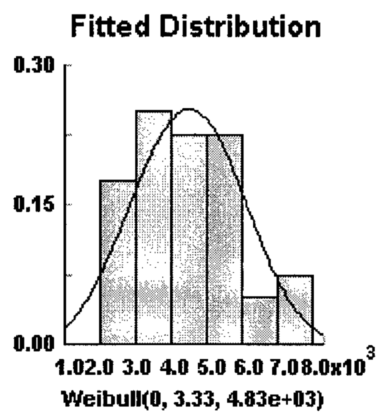

| Senior Male Alpha - NonSummer | | |
|---|---|---|
| Sample Points | | 175 |
| Number of Bins | | 13 |
| | Weibull | |
| Alpha | | 2.95 |
| Beta | | 5364.94 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.03 |
| KS | | 0.16 |
| AD | | 0.27 |



| Senior Male Beta - NonSummer | | |
|---|---|---|
| Sample Points | | 78 |
| Number of Bins | | 9 |
| | Weibull | |
| Alpha | | 3.4 |
| Beta | | 4834.67 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.6 |
| KS | | 0.79 |
| AD | | 0.7 |

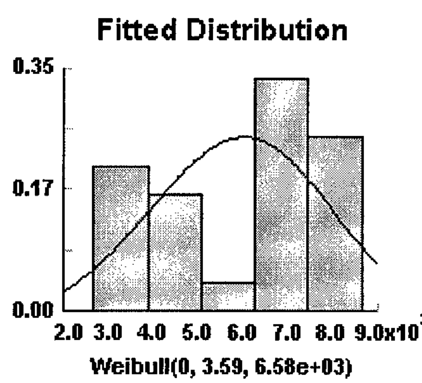



| Senior Female Alpha - NonSummer | | |
|---|---|---|
| Sample Points | | 40 |
| Number of Bins | | 6 |
| | Weibull | |
| Alpha | | 3.33 |
| Beta | | 4834.67 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.62 |
| KS | | 0.95 |
| AD | | 0.93 |




## Combined Distribution for SFB Data

| Senior Male Beta - Combined | | |
|---|---|---|
| Sample Points | | 24 |
| Number of Bins | | 5 |
| | Weibull | |
| Alpha | | 3.59 |
| Beta | | 6578.3 |
| | | |
| GOF Tests: | | p value |
| Chi_square | | 0.06 |
| KS | | 0.22 |
| AD | | 0.24 |



## AweSim/SIMPROCESS Model Comparison

In Chapter 4 we presented our model comparison results. Here we give the comparison data from the general prospect SIMPROCESS model and our AweSim Alpha Version. We have listed both the number of contracts and recruits shipped.

**Simulation Results (30 reps)**

| | AweSim Alpha | | SIMPROCESS | |
|---|---|---|---|---|
| **Run** | **Contracts** | **Shipped** | **Contracts** | **Shipped** |
| 1 | 65 | 54 | 53 | 48 |
| 2 | 48 | 39 | 55 | 47 |
| 3 | 54 | 50 | 51 | 41 |
| 4 | 65 | 58 | 48 | 35 |
| 5 | 61 | 52 | 55 | 51 |
| 6 | 51 | 56 | 54 | 46 |
| 7 | 64 | 51 | 64 | 58 |
| 8 | 46 | 47 | 55 | 54 |
| 9 | 52 | 43 | 52 | 42 |
| 10 | 48 | 55 | 44 | 50 |
| 11 | 55 | 54 | 60 | 49 |
| 12 | 59 | 54 | 56 | 45 |
| 13 | 61 | 61 | 68 | 50 |
| 14 | 54 | 52 | 55 | 50 |
| 15 | 49 | 49 | 58 | 48 |
| 16 | 44 | 44 | 57 | 51 |
| 17 | 51 | 54 | 56 | 52 |
| 18 | 59 | 58 | 54 | 46 |
| 19 | 60 | 45 | 59 | 52 |
| 20 | 54 | 52 | 60 | 54 |
| 21 | 57 | 48 | 61 | 45 |
| 22 | 56 | 46 | 68 | 63 |
| 23 | 58 | 50 | 64 | 62 |
| 24 | 57 | 48 | 50 | 49 |
| 25 | 63 | 56 | 54 | 46 |
| 26 | 57 | 49 | 66 | 52 |
| 27 | 56 | 46 | 68 | 56 |
| 28 | 59 | 62 | 56 | 53 |
| 29 | 51 | 48 | 70 | 52 |
| 30 | 48 | 52 | 49 | 52 |
| | | | | |
| **Totals** | 1662 | 1533 | 1720 | 1499 |

## Appendix E- Simulation Results

Chapter 5 presents the main results from our simulation experiments. Here we include the resulting data from our experiments.

### Baseline Results

We will present our baseline results in a high level of detail (contract percentages, individual replication results, etc), since they are of prime interest.

| Total Contracts | | | | Rep | Seniors | Grads | Other | Total |
|---|---|---|---|---|---|---|---|---|
| Recr1 | 360 | | | 1 | 14 | 25 | 3 | 42 |
| Recr2 | 505 | | | 2 | 17 | 22 | 3 | 42 |
| Recr3 | 612 | | | 3 | 25 | 22 | 9 | 56 |
| Total | 1477 | | | 4 | 16 | 23 | 9 | 48 |
| | | | | 5 | 11 | 19 | 10 | 40 |
| | | | | 6 | 22 | 17 | 11 | 50 |
| | | | | 7 | 23 | 20 | 4 | 47 |
| Prospecting Category | | % | | 8 | 14 | 25 | 7 | 46 |
| Walkins | 179 | 0.12 | | 9 | 18 | 23 | 6 | 47 |
| Telephone | 457 | 0.31 | | 10 | 27 | 22 | 6 | 55 |
| Face2Face | 841 | 0.57 | | 11 | 19 | 18 | 11 | 48 |
| | | | | 12 | 17 | 20 | 9 | 46 |
| | | | | 13 | 18 | 26 | 7 | 51 |
| | | | | 14 | 23 | 19 | 5 | 47 |
| | | | | 15 | 19 | 23 | 9 | 51 |
| | | | | 16 | 16 | 27 | 8 | 51 |
| | | | | 17 | 17 | 28 | 10 | 55 |
| | | | | 18 | 20 | 27 | 10 | 57 |
| Awesim Total Prospects | | | | 19 | 16 | 22 | 12 | 50 |
| | Count | Proportion | | 20 | 15 | 29 | 6 | 50 |
| SMB | 155 | 0.105 | | 21 | 17 | 19 | 7 | 43 |
| SFB | 23 | 0.016 | | 22 | 17 | 20 | 11 | 48 |
| GMB | 169 | 0.114 | | 23 | 21 | 26 | 9 | 56 |
| GFB | 52 | 0.035 | | 24 | 25 | 25 | 10 | 60 |
| SMA | 320 | 0.217 | | 25 | 22 | 30 | 4 | 56 |
| SFA | 64 | 0.043 | | 26 | 22 | 20 | 4 | 46 |
| GMA | 370 | 0.251 | | 27 | 17 | 24 | 7 | 48 |
| GFA | 104 | 0.07 | | 28 | 15 | 23 | 2 | 40 |
| OTH | 220 | 0.149 | | 29 | 23 | 24 | 4 | 51 |
| | | | | 30 | 16 | 27 | 7 | 50 |
| | | | | High | 19.92 | 24.23 | 8.2 | 50.82 |
| | | | | Avg | 18.73 | 23.17 | 7.33 | 49.23 |
| | | | | Low | 17.55 | 22.11 | 6.47 | 47.64 |

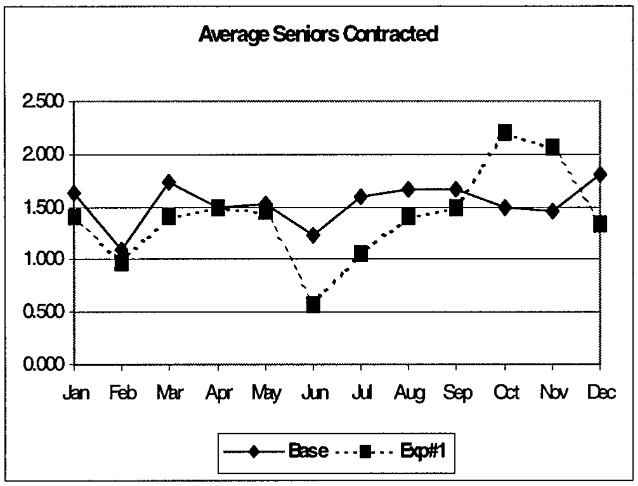
| **Total Shipped** | | | | Rep | Seniors | Grads | Other | Total |
|---|---|---|---|---|---|---|---|---|
| Recr1 | 343 | | | 1 | 15 | 26 | 4 | 45 |
| Recr2 | 472 | | | 2 | 22 | 18 | 6 | 46 |
| Recr3 | 577 | | | 3 | 21 | 18 | 13 | 52 |
| Total | 1392 | | | 4 | 17 | 26 | 13 | 56 |
| | | | | 5 | 15 | 16 | 9 | 40 |
| | | | | 6 | 25 | 21 | 9 | 55 |
| | | | | 7 | 8 | 18 | 4 | 30 |
| Prospecting Category | | % | | 8 | 12 | 23 | 8 | 43 |
| Walkins | 169 | 0.12 | | 9 | 13 | 23 | 9 | 45 |
| Telephone | 435 | 0.31 | | 10 | 13 | 20 | 7 | 40 |
| Face2Face | 788 | 0.57 | | 11 | 16 | 21 | 8 | 45 |
| | | | | 12 | 12 | 19 | 6 | 37 |
| | | | | 13 | 17 | 18 | 9 | 44 |
| | | | | 14 | 17 | 24 | 5 | 46 |
| | | | | 15 | 13 | 28 | 11 | 52 |
| | | | | 16 | 18 | 23 | 10 | 51 |
| | | | | 17 | 16 | 28 | 8 | 52 |
| | | | | 18 | 12 | 24 | 10 | 46 |
| Awesim Total Shipped | | | | 19 | 15 | 20 | 12 | 47 |
| | Count | Proportion | | 20 | 16 | 28 | 5 | 49 |
| SMB | 132 | 0.095 | | 21 | 16 | 20 | 6 | 42 |
| SFB | 22 | 0.016 | | 22 | 16 | 26 | 11 | 53 |
| GMB | 166 | 0.119 | | 23 | 18 | 26 | 10 | 54 |
| GFB | 52 | 0.037 | | 24 | 17 | 25 | 12 | 54 |
| SMA | 272 | 0.195 | | 25 | 19 | 28 | 4 | 51 |
| SFA | 57 | 0.041 | | 26 | 14 | 18 | 4 | 36 |
| GMA | 352 | 0.253 | | 27 | 12 | 22 | 7 | 41 |
| GFA | 102 | 0.073 | | 28 | 22 | 23 | 5 | 50 |
| OTH | 237 | 0.170 | | 29 | 23 | 21 | 5 | 49 |
| | | | | 30 | 13 | 21 | 7 | 41 |
| | | | | High | 17.28 | 23.50 | 8.77 | 48.34 |
| | | | | Avg | 16.10 | 22.40 | 7.90 | 46.40 |
| | | | | Low | 14.92 | 21.30 | 7.03 | 44.46 |

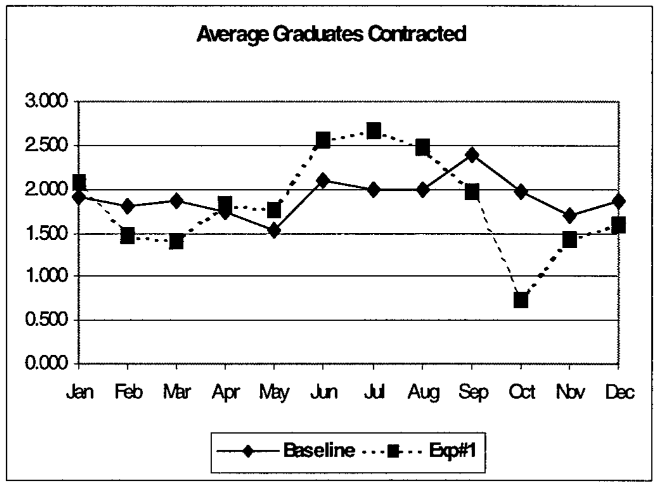
## Experiment #1 Results

**Yearly Averages**

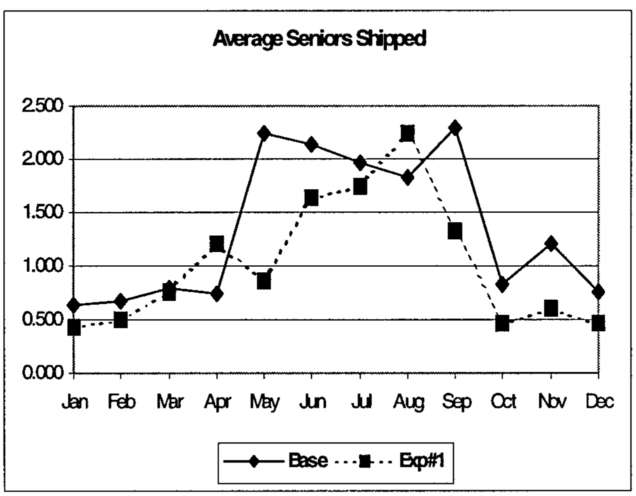
| | | Seniors | | Grads | | Total | |
|---|---|---|---|---|---|---|---|
| | | Contracts | Shipped | Contracts | Shipped | Contracts | Shipped |
| | Upper | 19.92 | 17.28 | 24.23 | 23.50 | 50.82 | 48.34 |
| Baseline | Average | 18.73 | 16.10 | 23.17 | 22.40 | 49.23 | 46.40 |
| | Lower | 17.55 | 14.92 | 22.11 | 21.30 | 47.64 | 44.46 |
| | | | | | | | |
| Experiment #1 | Upper | 18.47 | 13.26 | 25.00 | 22.23 | 49.69 | 42.17 |
| Grad in Sum | Average | 17.17 | 12.23 | 23.73 | 20.67 | 48.23 | 40.47 |
| Sen in NonSum | Lower | 15.87 | 11.21 | 22.47 | 19.10 | 46.77 | 38.77 |

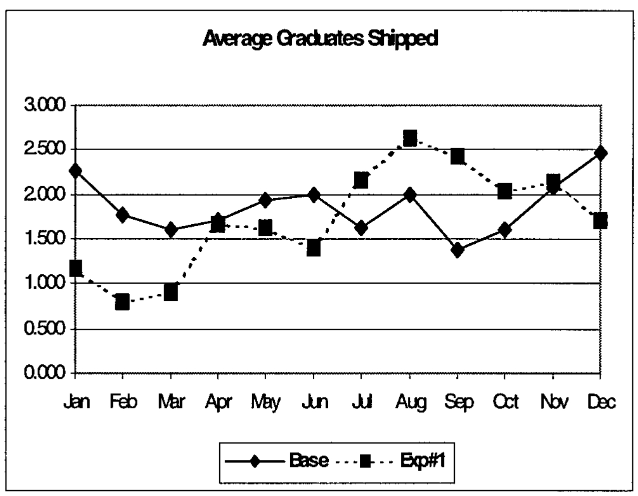
### Experiment #1 Monthly Contract Patterns




### Experiment #1 Monthly Shipping Patterns



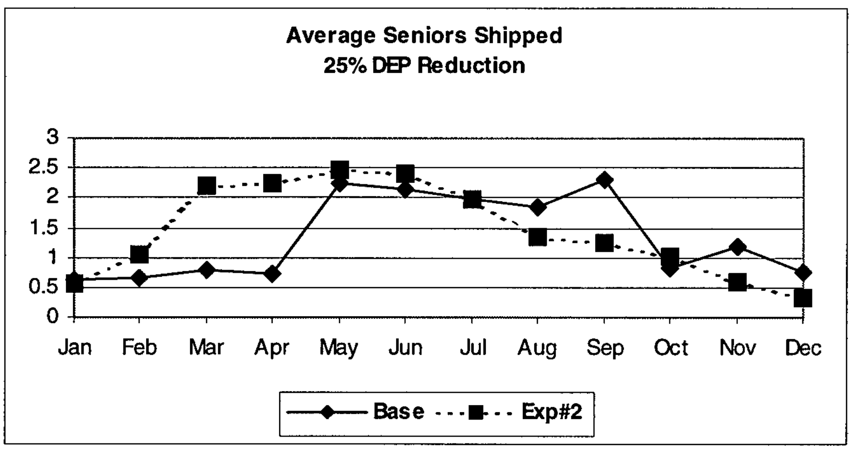



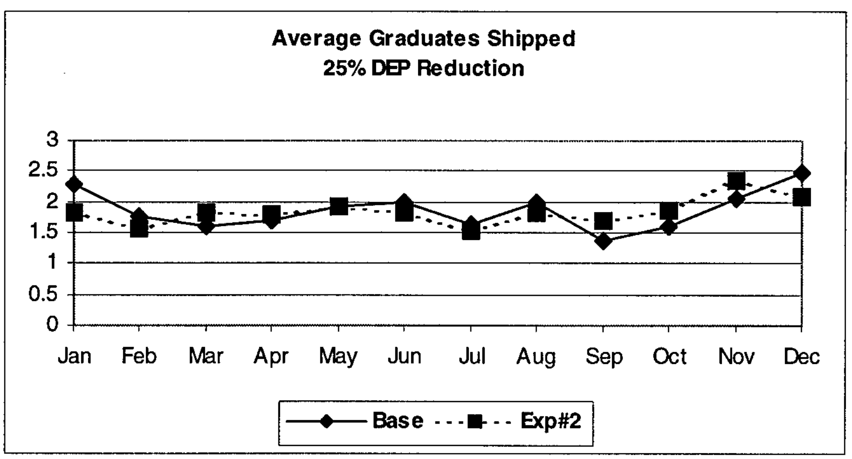
## Experiment #2 Results

### Yearly Averages

| | | Seniors Shipped | Grads Shipped | Total Shipped |
|---|---|---|---|---|
| | Upper | 17.28 | 23.50 | 48.34 |
| Baseline (GAP) | Average | 16.10 | 22.40 | 46.40 |
| | Lower | 14.92 | 21.30 | 44.46 |
| Experiment #2 | Upper | 18.86 | 23.55 | 49.45 |
| 25% DEP | Average | 17.50 | 22.17 | 47.67 |
| Reduction | Lower | 16.14 | 20.78 | 45.88 |

### Experiment #2 Monthly Shipping Patterns



## Experiment #3 Results

| | | Seniors | | Grads | | Total | |
|---|---|---|---|---|---|---|---|
| | | Contracts | Shipped | Contracts | Shipped | Contracts | Shipped |
| | Upper | 19.92 | 17.28 | 24.23 | 23.50 | 50.82 | 48.34 |
| Baseline (GAP) | Average | 18.73 | 16.10 | 23.17 | 22.40 | 49.23 | 46.40 |
| | Lower | 17.55 | 14.92 | 22.11 | 21.30 | 47.64 | 44.46 |
| | | | | | | | |
| | Upper | 24.48 | 22.96 | 28.15 | 27.12 | 62.57 | 59.64 |
| GGG | Average | 23.00 | 21.47 | 26.73 | 25.90 | 60.43 | 57.47 |
| | Lower | 21.52 | 19.97 | 25.32 | 24.68 | 58.30 | 55.29 |
| | | | | | | | |
| | Upper | 13.59 | 11.66 | 18.42 | 18.44 | 38.65 | 35.61 |
| PPP | Average | 12.70 | 10.73 | 17.27 | 17.27 | 36.87 | 33.77 |
| | Lower | 11.81 | 9.80 | 16.12 | 16.09 | 35.08 | 31.92 |
| | | | | | | | |
| | Upper | 20.01 | 18.51 | 25.32 | 24.23 | 52.39 | 49.95 |
| AAA | Average | 18.63 | 17.03 | 23.83 | 22.83 | 50.37 | 47.67 |
| | Lower | 17.25 | 15.56 | 22.35 | 21.44 | 48.34 | 45.38 |
| | | | | | | | |
| | Upper | 18.19 | 15.74 | 23.78 | 22.61 | 49.16 | 44.64 |
| AAP | Average | 16.90 | 14.37 | 22.47 | 21.33 | 47.27 | 42.63 |
| | Lower | 15.61 | 12.99 | 21.15 | 20.06 | 45.37 | 40.62 |
| | | | | | | | |
| | Upper | 16.20 | 15.61 | 20.40 | 18.56 | 42.16 | 39.28 |
| PAP | Average | 15.03 | 14.27 | 19.00 | 17.57 | 40.63 | 37.93 |
| | Lower | 13.87 | 12.92 | 17.60 | 16.58 | 39.10 | 36.58 |
| | | | | | | | |
| | Upper | 20.99 | 19.39 | 27.13 | 26.15 | 56.09 | 53.90 |
| GAA | Average | 19.60 | 18.13 | 25.83 | 24.67 | 54.03 | 51.37 |
| | Lower | 18.21 | 16.88 | 24.53 | 23.18 | 51.97 | 48.83 |
| | | | | | | | |
| | Upper | 21.96 | 19.65 | 28.22 | 27.15 | 58.03 | 55.20 |
| GAG | Average | 20.30 | 18.23 | 26.70 | 25.70 | 55.90 | 53.00 |
| | Lower | 18.64 | 16.81 | 25.18 | 24.25 | 53.77 | 50.80 |
| | | | | | | | |
| | Upper | 20.97 | 17.95 | 25.35 | 24.82 | 52.81 | 49.92 |
| GGP | Average | 19.77 | 16.97 | 23.77 | 23.27 | 50.93 | 47.87 |
| | Lower | 18.57 | 15.98 | 22.18 | 21.71 | 49.06 | 45.81 |
| | | | | | | | |
| | Upper | 16.95 | 15.05 | 22.80 | 22.39 | 46.47 | 43.26 |
| GPP | Average | 15.87 | 13.83 | 21.53 | 21.17 | 44.80 | 41.50 |
| | Lower | 14.78 | 12.61 | 20.26 | 19.94 | 43.13 | 39.74 |

## $2^3$ Factorial Experiment to Identify Key Success Factors

| Design Settings | | | | | | |
|---|---|---|---|---|---|---|
| | | SMB/SFB | GMB/GFB | SMA/SFA | GMA/GFA | OTH |
| *TelePr* | Hi(+1) | 0.39 | 0.39 | 0.39 | 0.39 | 0.39 |
| | Lo(-1) | 0.31 | 0.31 | 0.31 | 0.31 | 0.31 |
| | | | | | | |
| *FacePr* | Hi(+1) | 0.39 | 0.39 | 0.39 | 0.39 | 0.39 |
| | Lo(-1) | 0.31 | 0.31 | 0.31 | 0.31 | 0.31 |
| | | | | | | |
| *SalesPr* | Hi(+1) | 0.87 | 0.8 | 0.87 | 0.8 | 0.835 |
| | Lo(-1) | 0.73 | 0.66 | 0.73 | 0.66 | 0.695 |

| | | | | | | Average Totals | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Design | | TelePr | FacePr | SalesPr | | Contracts | Shipped | | Totals | |
| 1 | | -1 | -1 | -1 | | 21.03 | 20.10 | | 631 | 603 |
| 2 | | -1 | -1 | 1 | | 11.50 | 11.23 | | 345 | 337 |
| 3 | | -1 | 1 | -1 | | 19.87 | 18.57 | | 596 | 557 |
| 4 | | -1 | 1 | 1 | | 12.07 | 11.10 | | 362 | 333 |
| 5 | | 1 | -1 | -1 | | 19.90 | 20.03 | | 597 | 601 |
| 6 | | 1 | -1 | 1 | | 13.07 | 12.53 | | 392 | 376 |
| 7 | | 1 | 1 | -1 | | 19.87 | 19.10 | | 596 | 573 |
| 8 | | 1 | 1 | 1 | | 12.27 | 11.40 | | 368 | 342 |
| | | | | Factor Effects | | Contracts | Shipped | | | |
| | | | | TelePr | | 0.158 | 0.517 | | | |
| | | | | FacePr | | -0.358 | -0.933 | | | |
| | | | | SalesPr | | -7.942 | -7.883 | | | |
| | | | | TelePr*FacePr | | -0.058 | -0.560 | | | |
| | | | | TelePr*SalesPr | | 0.725 | 0.283 | | | |
| | | | | FacePr*SalesPr | | 0.242 | 0.300 | | | |
| | | | | TelePr*FacePr*SalesPr | | -0.625 | -0.400 | | | |

**Rerun of Experiment #3 Design Points – Varying Only *SalesPr***

| | | Seniors | | Grads | | Total | |
|---|---|---|---|---|---|---|---|
| Design Point | | Contracts | Shipped | Contracts | Shipped | Contracts | Shipped |
| | | | | | | | |
| | Upper | 19.65 | 16.46 | 23.74 | 22.76 | 51.12 | 47.33 |
| Baseline (GAP) | Average | 18.23 | 15.30 | 22.47 | 21.27 | 48.93 | 45.17 |
| | Lower | 16.82 | 14.14 | 21.19 | 19.77 | 46.75 | 43.00 |
| | | | | | | | |
| | Upper | 27.16 | 23.42 | 32.01 | 30.23 | 68.85 | 63.27 |
| GGG | Average | 25.43 | 21.80 | 30.50 | 28.63 | 66.83 | 61.10 |
| | Lower | 23.71 | 20.18 | 28.99 | 27.04 | 64.82 | 58.93 |
| | | | | | | | |
| | Upper | 13.39 | 12.30 | 18.85 | 18.50 | 38.92 | 36.69 |
| PPP | Average | 12.37 | 11.13 | 17.47 | 16.97 | 36.73 | 34.53 |
| | Lower | 11.34 | 9.96 | 16.08 | 15.44 | 34.55 | 32.38 |
| | | | | | | | |
| | Upper | 20.01 | 18.51 | 25.32 | 24.23 | 52.39 | 49.95 |
| AAA | Average | 18.63 | 17.03 | 23.83 | 22.83 | 50.37 | 47.67 |
| | Lower | 17.25 | 15.56 | 22.35 | 21.44 | 48.34 | 45.38 |
| | | | | | | | |
| | Upper | 17.80 | 15.69 | 23.46 | 22.26 | 48.25 | 45.45 |
| AAP | Average | 16.10 | 14.47 | 21.93 | 20.77 | 46.13 | 43.10 |
| | Lower | 14.40 | 13.24 | 20.41 | 19.27 | 44.01 | 40.75 |
| | | | | | | | |
| | Upper | 14.49 | 12.28 | 21.60 | 20.56 | 42.12 | 39.18 |
| PAP | Average | 13.63 | 11.47 | 20.07 | 19.07 | 40.47 | 37.40 |
| | Lower | 12.78 | 10.66 | 18.53 | 17.57 | 38.81 | 35.62 |
| | | | | | | | |
| | Upper | 22.02 | 19.13 | 25.34 | 25.23 | 54.92 | 51.58 |
| GAA | Average | 20.77 | 17.77 | 23.83 | 23.37 | 53.20 | 49.40 |
| | Lower | 19.52 | 16.40 | 22.32 | 21.51 | 51.48 | 47.22 |
| | | | | | | | |
| | Upper | 23.21 | 20.83 | 26.06 | 27.48 | 58.62 | 56.65 |
| GAG | Average | 21.90 | 19.83 | 24.63 | 26.07 | 56.47 | 54.87 |
| | Lower | 20.59 | 18.84 | 23.20 | 24.65 | 54.31 | 53.09 |
| | | | | | | | |
| | Upper | 21.18 | 18.23 | 26.47 | 24.28 | 55.46 | 50.09 |
| GGP | Average | 19.97 | 17.23 | 24.83 | 22.97 | 53.63 | 48.43 |
| | Lower | 18.76 | 16.24 | 23.20 | 21.65 | 51.81 | 46.78 |
| | | | | | | | |
| | Upper | 18.01 | 15.07 | 21.64 | 21.34 | 47.07 | 43.55 |
| GPP | Average | 16.57 | 13.80 | 20.47 | 19.73 | 44.97 | 41.43 |
| | Lower | 15.13 | 12.53 | 19.29 | 18.13 | 42.86 | 39.31 |

## Simulation Files

### SIMPROCESS Files

| File | Description |
|---|---|
| "Final.spm" | Enhanced Station Recruiting Model |
| "varvals1.txt" | Input file, model parameters for the OTH prospect type |
| "varvals2.txt" | Input file, model parameters for original eight prospect types |

### AweSim Files

| Network File | Description |
|---|---|
| "RECRGEN" | Alpha Version Model, based on Cordeiro and Friend (1998) model |
| "FINAL" | Beta Version Model, fully enhanced Station Recruiting Model |
| "FINALDEP" | Network used with Experiment #2: Reduced DEP Times |
| "ONERECR" | Network used with Supplemental Experimental Design |

| Control File | Description |
|---|---|
| "BASE" | Baseline control, used with "FINAL" |
| "GRADSEN" | Experiment #1 control, give graduates priority in summer and senior priority in non-summer, used with "FINAL" |
| "DEP-25" | Experiment #1 control, 25% DEP time reduction, used with "FINALDEP" |
| "RECRPPP" | Experiment #3, design PPP, three poor recruiters |
| "RECRPAP" | Experiment #3, design PAP, two poor – one average |
| "RECRAAP" | … |
| "RECRAAA" | … |
| "RECRGPP" | … |
| "RECRGAA" | … |
| "RECRGGP" | … |
| "RECRGAG" | … |
| "RECRGGG" | … |
| "DES1" | Supplemental Experimental Design; *TelePr*, *FacePr*, *SalesPr* all at low settings, used with "ONERECR" |
| "DES2" | … |
| "DES3" | … |
| "DES4" | … |
| "DES5" | … |
| "DES6" | … |
| "DES7" | … |
| "DES8" | … |

## Bibliography


1. Asch, Beth J., Rebecca Kilburn, and Jacob A. Klerman. Attracting College-Bound Youth into the Military: Toward the Development of New Recruiting Policy Options. Santa Monica, CA: Rand, 1999.

2. Banks, Jerry, John S. Carson, II, and Barry L Nelson. Discrete-Event System Simulation. Prentice-Hall, Inc., 1999.

3. Cordeiro, James D., Jr., and Mark A. Friend. Using Simulation to Model Time Utilization of Army Recruiters. Master's Thesis. Air Force Institute of Technology, 1998.

4. Eitelberg, Mark J., and Stephen L. Mehay. Marching Toward the 21st Century: Military Manpower and Recruiting. No 154. Westport, Conn.: Greenwood Press, 1994.

5. Law, Averill M., and W. David Kelton. Simulation Modeling & Analysis. McGraw-Hill, Inc. 1991.

6. McHugh, Jane. "Army rolls out big guns to boost recruiting". *Army Times*, August 30, 1999.

7. McHugh, Jane. "Monthly recruiting sign-ups worst in 26 years". *Army Times*, July 26, 1999.

8. McHugh, Jane. "Would better education benefits make you leave?" *Army Times*, May 3, 1999.

9. McLarney, Edward L. Using Simulation to Model The Army Recruiting Station With Multi-Quality Prospects. Master's Thesis. Air Force Institute of Technology, 1999.

10. Murray, Michael P., and Laurie L. McDonald. Recent Recruiting Trends and Their Implications for Models of Enlistment Supply. Santa Monica, CA: Rand, 1999.

11. Neter, John, Micheal H. Kutner, Christopher J. Nachtsheim, and William Wasserman. Applied Linear Statistical Models. Boston, Mass.: McGraw-Hill, 1996.

12. Oken, Carole. and Beth J. Asch. Encouraging Recruiter Achievement: A Recent History of Military Recruiter Incentive Programs. Santa Monica, CA: Rand, 1997.

13. Orvis, Bruce R. Military Recruiting Outlook: Recent Trends in Enlistment Propensity and Conversion of Potential Enlisted Supply. Santa Monica, CA: Rand, 1996.

14. Orvis, Bruce R. and Martin T. Gahart. Enlistment Among Applicants for Military Service: Determinants and Incentives. Santa Monica, CA: Rand, 1990.

15. Pritsker, A. Alan B. and Jean J. O'Reilly. Simulation with Visual SLAM and AweSim. New York: John Wiley & Sons, 1999.

16. "Recruiters lament: 'It's the economy'". *Army Times*, March 15, 1999.

17. Ross, Sheldon M. Introduction to Probability Models. Academic Press, 1997.

18. User's Manual. SIMPROCESS Release 2. Caci Products Company, May 1996.