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THESIS

SENSITIVITY ANALYSIS FOR AN ASSIGNMENT INCENTIVE PAY IN THE UNITED STATES NAVY ENLISTED PERSONNEL ASSIGNMENT PROCESS IN A SIMULATION ENVIRONMENT

by

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March 2004

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The enlisted personnel assignment process is a major part in the United States Navy's Personnel Distribution system. It ensures warfighters and supporting activities receive the right sailor with the right training to the right billet at the right time (R^4) and is a critical element in meeting the challenges of Seapower 21 and Global CONOPS. In order to attain these optimal goals the ways-to-do-it need to be customer-centered and should optimize both, the Navy's needs and the sailor's interests. Recent studies and a detailing pilot in 2002 used a web-based marketplace with two-sided matching mechanisms to accomplish this vision.

This research examines the introduction of an Assignment Incentive Pay (AIP) as part of the U.S. Navy's enlisted personnel assignment process in a simulation environment. It uses a previously developed simulation tool, including the Deferred Acceptance (DA) and the Linear Programming (LP) matching algorithm to simulate the assignment process.

The results of the sensitivity analysis suggested that the Navy should mainly emphasize sailor quality rather than saving AIP funds in order to maximize utility and the possible matches. When adopting such an introduction policy also the percentage of unstable matches under the LP as the matching algorithm was reduced.

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The enlisted personnel assignment process is a major part in the United States Navy's Personnel Distribution system. It ensures warfighters and supporting activities receive the right sailor with the right training to the right billet at the right time (R^4) and is a critical element in meeting the challenges of Seapower 21 and Global CONOPS. In order to attain these optimal goals the ways-to-do-it need to be customer-centered and should optimize both, the Navy's needs and the sailor's interests. Recent studies and a detailing pilot in 2002 used a web-based marketplace with two-sided matching mechanisms to accomplish this vision.

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I. INTRODUCTION

A. BACKGROUND

"There must be some other stimulus, besides love for their country, to make men fond of service…"

George Washington, 1732-1799

"If love of money were the mainspring of all American action, the officer corps long since would have disintegrated."

The Armed Forces Offices, 1950 (Heinl, 1966)

The two quotations above represent two extreme positions on the same topic. Pay and compensation for serving in the military services is not the only incentive but it is certainly a factor one should not forget to consider thoroughly when talking about soldiers and their motivation for service. This summer the United States Navy is introducing a wage differential for serving in an unpopular location or billet with the Assignment Incentive Pay (AIP).

The principles of an all-volunteer force are to recruit the volunteers with the lowest opportunity costs and those who are most willing to serve. The initial step, recruiting volunteers into military service, is already in place. However, the internal labor market represented by the Navy's enlisted personnel assignment system does not necessarily follow this premise. Sailors are often involuntarily assigned to unpopular duty stations in hard to fill billets. As a logical result, the Sailors' differences in personal preferences are usually not sufficiently included in the assignment decision. The important allocation function of the wage as the price of labor is not implemented to reflect willingness to accept the job, and a legally binding order replaces the market mechanism. Consequentially, this creates negative experiences of involuntary, hardly understandable assignments causing some sailors to decide not to reenlist. The intrinsic motivation potential might also suffer severely. A market-based system that matches sailors' and command's preferences and includes wage differentials with respect to individual preferences could significantly reduce the negative side effects of centralized assignment.

To fulfill this urgent demand for flexibility and to counter the market inefficiencies of hierarchical planning Assignment Incentive Pay (AIP) was proposed to represent the crucial allocation function of prices in an internal labor market (CNA, 2000). Offering additional flexible compensation to volunteers will incorporate individual preferences in the assignment process, which ensures the assignment of those with the lowest opportunity costs and the highest willingness to serve at a particular duty station. Because the size of the incentive is determined by closed bidding procedures, a resulting individual market wage will also provide signals for budget allocation. The question "Is this billet really worth the pay?" is more easily answered and the overall monetary compensation for a billet is more easily compared to civilian market competition.

B. PURPOSE

Can this additional wage premium in the form of AIP improve performance of the Assignment process for the Navy's Enlisted Personnel, and what is the right policy to introduce the new AIP? These are the main questions that led to the research and development of this research. In absence of real world statistical data about the introduction and initial success of the AIP, a simulation analysis is conducted to find appropriate suggestions. To simulate the assignment process, the Navy Enlisted Distribution Simulator (NEDSim) is used and adapted for this research. Necessary amendments included changing the profile generator, the utility functions and the performance measures. Although the NEDSim-provided matching mechanisms are currently not employed by the Navy to match Enlisted Personnel to job openings, they represent a matching process that has proven superior to the currently used purely human decision-making process.

C. RESEARCH QUESTIONS

1. Primary Research Questions

- Does Assignment Incentive Pay increase the performance of the Navy’s enlisted personnel assignment process in a simulation environment?
- What is the most effective implementation strategy?

2. Secondary Research Questions

- How can AIP be included in the Navy Enlisted Distribution Simulator (NEDSim)?
- Using different implementation scenarios, does AIP improve the performance results of the simulation?

D. SCOPE AND LIMITATION

1. Scope

The scope includes:

- An overview of the U.S. Navy enlisted assignment process, including a brief review of advantages of a web-based marketplace for the assignment process
- A brief description of the principles of an Assignment Incentive Pay (AIP) within the compensation system and an introduction into the Navy’s pilot project
- A short review of utility functions in two-sided matching simulations
- A review of the earlier developed Navy Enlisted Distribution Simulator (NEDSim), including the used matching algorithms
- The introduction of amendments and necessary changes to NEDSim

- The simulation design and its results in terms of command utility, percent matches and blocking pairs
- Inferring a practicable introduction policy scenario for the Assignment Incentive Pay (AIP) from the simulation results

2. Limitation

The research is limited to the enlisted personnel assignment process in a simulation environment. The profile generation is based on data from research on the Aviation Support Technician (AS) rating and might not be representative for other communities or officers. Additionally, the distribution of the AIP is assumed to be normal and might not reflect the actual spread of AIP over the existing billets.

E. EXPECTED BENEFITS OF THE STUDY

This thesis will provide further insights into the effects of an Assignment Incentive Pay in the enlisted assignment process of the U.S. Navy. It will also provide suggestions for an implementation policy to maximize the Navy's utility derived from the implementation.

F. ORGANIZATION OF THE THESIS

The thesis research is organized in the following steps:

- Conduct literature research including books, magazines, power-point briefings and library data bases
- Participate in the 3rd Annual Navy Workforce Research and Analysis Conference
- Review the U.S. Navy enlisted personnel assignment process
- Discuss a compensation system for the Navy including an Assignment Incentive Pay

- Review and revise the Navy Enlisted Distribution Simulator (NEDSim)
- Conduct sensitivity analysis with the simulation and obtain detailed results
- Provide conclusion and recommendations from detailed results

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II. OVERVIEW OF THE U.S. NAVY ENLISTED ASSIGNMENT PROCESS

A. THE MANPOWER, PERSONNEL AND TRAINING SYSTEM

The United States Navy Manpower, Personnel and Training System can be generally divided into two major parts. United States Navy missions in support of military strategy define Manpower Requirements, which lead to Manpower Programming, which are referred to as the "spaces" or the Manpower process in the MPT-system. These "spaces" describe the required End Strength and Fiscal constraints for the Navy's Personnel. The second part is referred to as the Personnel or "faces" portion, consisting of Personnel Planning and Personnel Distribution. The final product of this complex cycle is force readiness in support of national security and military strategies. Figure 1 summarizes the overall process.

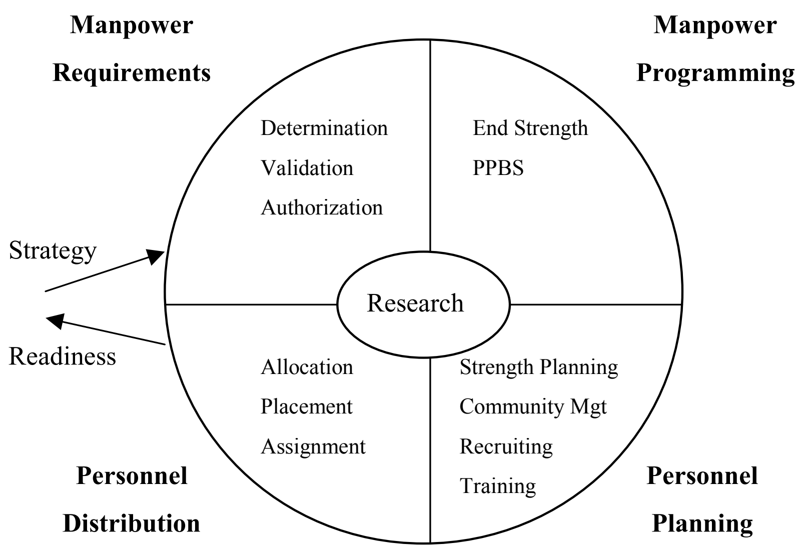

Figure 1. The U.S. Navy Manpower, Personnel and Training System (From: Manpower, Personnel and Training Processes power-point brief by CDR William D. Hatch, June 2002)

Personnel Distribution is the last process of this complex system before it begins its cycle again. The enlisted personnel assignment sub-process plays a major role in the United States Navy's Personnel Distribution system. Its measure of success, providing the right sailor with the right training to the right billet at the right time (R^4), is crucial to supporting Naval Force readiness and meeting the challenging future. This research will therefore focus on this sub-process of the MPT-Cycle.

The personnel distribution process basically consists of three sub-processes forming the "Distribution Triad" (Hatch, 2002). These three sub-processes are Allocation, Placement and Assignment, each having their own responsible "players" and information-systems.

1. The Allocation Sub-Process

The Navy Personnel Command (NPC) is the responsible authority for allocation management within the personnel Distribution process. It first identifies sailors projected to rotate to a new assignment within the next nine months, excludes non-distributable inventory from the process, and allocates the distributable inventory to the four Manning Control Authorities (CINCLANT, CINCPAC, BUPERS, Reserve). Non-distributable inventory includes transients, prisoners, patients and holdees, sailors in training and other personnel not assignable. To ensure a prioritized balance of the distributable inventory, NPC uses billet information from the Total Force Manpower Management System (TFMMS) and the Enlisted Master File (EMF), which already includes manning policy, to determine requisition priority. The Chief of Naval Operations (CNO) determines manning priorities 1 and 2 while priority 3 reflects the MCA's interests. That way, the resulting Navy Manning Plan (NMP) reflects a "Fair Share" of the prioritized distributable inventory among activities by rate, rating and Navy Enlisted Code (NEC).

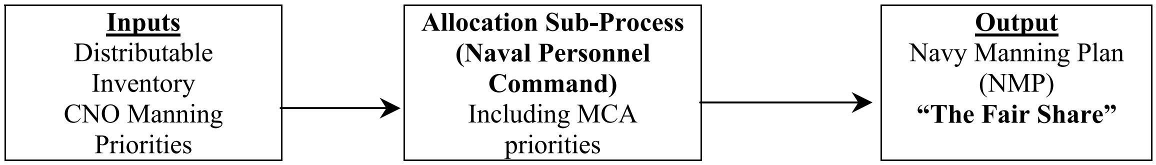

Figure 2. The Allocation Sub-Process (After: Ho, 2002)

2. The Placement Sub-Process

As the second part in the distribution triad, the placement sub-process follows allocation management. The major player here is the Enlisted Placement Management Center (EPMAC), which acts as a principal agent for the commands using the Navy Manning Plan to provide the detailers in the assignment sub-process with requisitions in the Enlisted Personnel Requisition System (EPRES). In doing so, EPMAC negotiates the equitably spread over activities with the ultimate goal of having the right sailor at the right time in the right place with the right skills (R^4). Also included in the placement sub-process is a projection of command losses and activity determined requirements above the NMP.

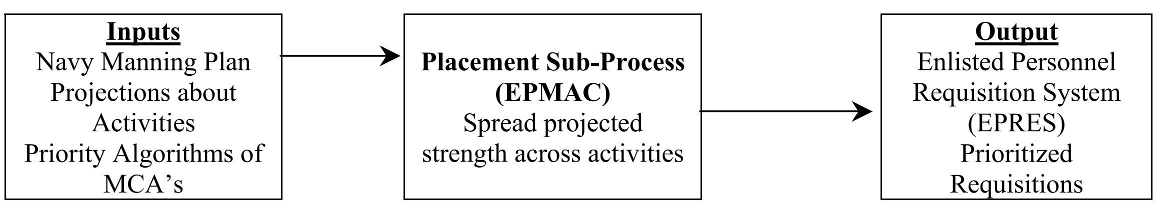

Figure 3. The Placement Sub-Process (After: Ho, 2002)

3. The Assignment Sub-Process

In the final step of the triad, the prioritized requisitions are filled with sailors meeting the specifications. The assignment officers, commonly known as "detailers", match people and billets with regard to the Sailor's needs as well as the Navy's needs.

In doing so, the detailers try to optimize readiness and stability for the Navy's activities and provide equal opportunity for the sailors getting their desired assignment. The detailers use the prioritized requisition information provided by EPRES, which is further passed on to the Enlisted Assignment Info System (EAIS), to determine the demand side of this process; the sailors, as the supply side, provide their preferences in the Job Advertising and Selection System (JASS). JASS was introduced in 1995 and is an online information and decision support system that helps the US-Navy Sailors, wherever they are, get information about current job offers and apply for jobs in a prioritized list. This information system avoids long negotiations over the telephone and helps to decrease disadvantages for sailors assigned to ships or remote locations who have limited opportunities to contact their detailer about available billets (Short, 2000). Every Sailor is permitted to view JASS via the BUPERS Homepage and to update their knowledge about job availabilities from any Internet connection around the world. Job applications, however, can only be made by Command Career Counselors for the individual sailor. Command Career Counselors (CCCs) serve a two sided quality control function. On one side they're ensuring the eligibility of the applying sailor for the desired job and on the other side they're advising the sailor about career and job application decisions. Figure 4 summarizes the assignment sub-process within the Personnel Distribution Triad.

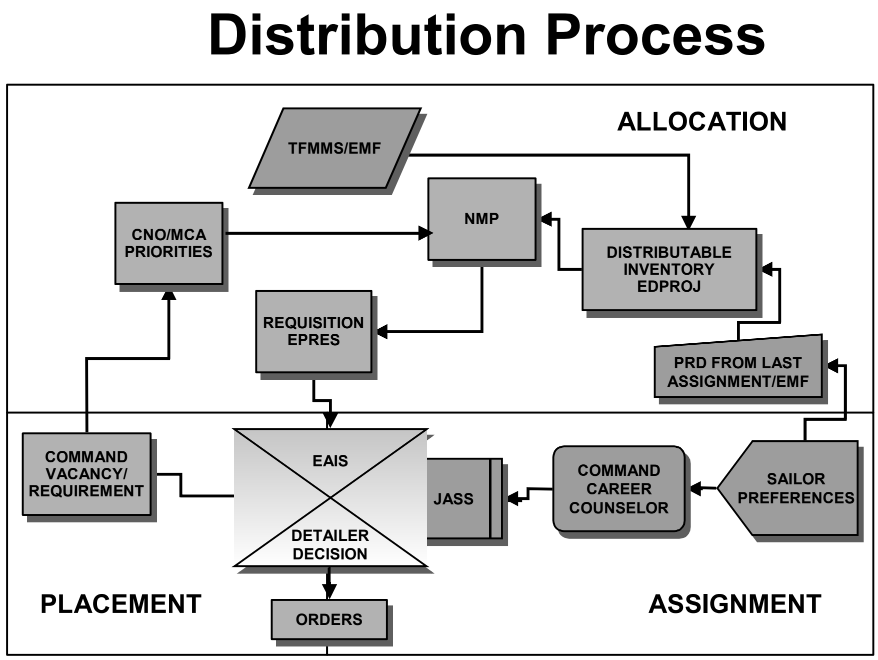

Figure 4. The Personnel Distribution Process (From: Hatch, 2002)

As described above, the detailer is the principal agent (Ho, 2002) and the sailor's advocate in the assignment sub-process. With a cycle-time of two weeks, detailers eventually assign about 45 sailors to 60 billets during this period. Besides considering mandatory attributes of the sailor, such as rate, rating, Navy Enlisted Classification (NEC), gender, Projection Rotation Date (PRD), sea-shore rotation cycles and security classification, the detailer should also minimize monetary expenditures, such as permanent Change of Station costs (PCS), while on the other hand maximizing the sailors' satisfaction for their next assignment. This process is additionally complicated with numerous and changing policies by the DOD, CNO, MCA and CNPC.

Once the assignment decision is made, orders are issued electronically through the Enlisted Assignment Information System (EAIS). Billet/sailor matches for rate E-5 and above are additionally scanned by EPMAC for fit and policy performance. Sailors or billets not successfully matched reenter the assignment sub-process for the next two-week cycle.

B. ADVANTAGES OF A WEB-BASED MARKETPLACE TO ASSIGN ENLISTED PERSONNEL

Although the detailers are doing their best to fulfill multiple stakeholder requirements, there still remain some areas for improvement in the process. Top-priority billets might not be on the top of the sailor's preference list and undesirable jobs might have to be filled. If this is the case, the transparency and logic of the assignment process gains incredible advantages by improving the sailor's acceptance of an unwanted job and location. With only the detailer finally deciding on how to balance all interests, both sailors and commands perceive the assignment process to be subjective and often distrust the detailers. Sailors also value the detailing process itself as more important than the actual outcome. Especially because they understand that their primary job or location of choice might not be the Navy's first priority, they expect honesty, timeliness and reasonable explanations with their new orders (Short, 2000).

1. Disadvantages And Inefficiencies In The Current Assignment Sub-Process

The current assignment process is highly labor intensive with about 294 enlisted detailers responsible for about 330,000 enlisted personnel (Ho, 2002). The detailers are trying to spread the scarce commodity "Sailor" evenly across the four Manning Control Authorities. A possible intervention in the process for ratings E-5 and above by EPMAC, which actually happens in about 3% of these assignments, makes the process even more burdensome. As a human being facing all these numerous and in part volatile requirements, the detailer naturally is subject to human error and might make out-of-the-moment sub-optimal decisions. Additionally, command career counselors are sometimes unfamiliar with all ratings (approximately 90), and there is rarely an alternate counselor present in their absence, so detailers have to spend significant time counseling via phone instead of career planning. On the demand side, a certain amount of mistrust arises from perceived subjectivity in the process, generating numerous phone calls from commands to detailers emphasizing the importance of filling a certain billet.

In addition to the psychological disadvantages of a centrally planned internal labor market, such as the Navy's enlisted assignment process, Market inefficiencies from textbook economics are obvious. Hierarchical planning and assigning jobs to people always incorporates the risk of sub-optimal solutions.

In a market-based labor market, demand and supply of labor are balanced by the important function of the wage as the price of labor. The employee, being the supplier of labor, and the employer, as the demanding side, agree on a certain wage. For this "price" the job seeker is willing to provide work and the company with the job offer is willing to employ it.

This commonly known simple model of a labor-market mechanism leads to an equilibrium quantity of labor employed at an equilibrium wage. The general properties are displayed in Figure 5:

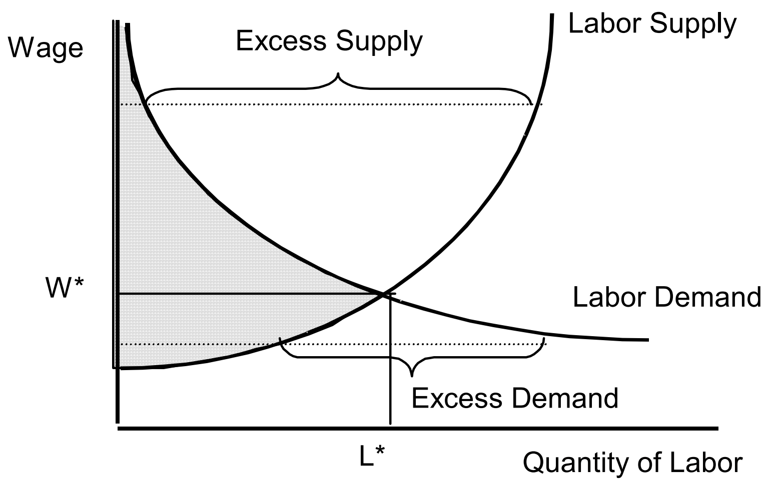

Figure 5. Market-Based Labor Markets (From: Gates, 2001)

Although this model represents the basic principles of the external labor market, not many private firms use it to assign their employees to new jobs. The matching of potential candidates to available jobs often follows the need of the moment or hierarchical planning, like the Navy's enlisted assignment process.

As a logical result, the Sailors' differences in personal preferences are usually not sufficiently included in the assignment decision. The important allocation function of wages as the price of labor is not implemented to reflect willingness to accept the job, and a legally binding order replaces the market mechanism. Consequentially, this creates negative experiences of involuntary, hardly understandable assignments and some sailors might decide not to reenlist. The intrinsic motivation potential might also suffer severely.

A market-based system that matches sailors' and command's preferences and includes wage differentials with respect to individual preferences could significantly reduce the negative side effects of centralized assignment.

2. Possible Improvements By A Market-Based Matching System

Mechanisms to reduce the above described negative impacts, which have been used in the past and reflect both sides of interest in a labor market, are two-sided matching agents. Three different approaches have been in use to assign several job seekers to several jobs. These approaches are Deferred Acceptance (DA), Linear Programming (LP) and the Priority approach. The most important algorithms still employed are the former two. The DA mechanism generally guarantees stable matches of jobs and job seekers and is currently used in the U.S. to assign medical students to residency programs (Gates, 2001); the LP-model is used in British hospitals and incorporates the risk of unstable matches (Ho, 2002). An unstable match describes the specific situation where an algorithm produced match leaves room for a mutually preferable choice for both parties. However, LP does not merely create matches from priority lists of employers and job seekers, but can maximize overall utility of both. Details for the mechanisms of both algorithms will be given in chapter five. The use of an agent-based system as a tool to provide the detailer with objective information about optimal matching solutions will improve the process in two ways: It provides transparency for sailor and commands, and it decreases the possibility of inefficiencies through out-of-the-moment solutions.

In addition to a computer-based matching system as a tool for the detailer to find an overall optimal solution, introducing wage differentials in the Navy's Enlisted Personnel internal job market will incorporate the individual sailor's preferences in the assignment process. The Navy usually accomplishes this with bonuses in addition to the rank-related salaries.

3. Current Incentive Pay Models

Most commonly used bonus systems in the Navy's Enlisted Personnel community are Enlistment Bonuses (EB) and Selective Reenlistment Bonuses (SRB). While Enlistment Bonus Strategies usually offer advantageous loans for college education or lump sum up front monetary incentives, SRB's are financial incentives to stay in the Navy. Both incentive systems encourage Sailors to make an enlistment or reenlistment decision to fulfill recruiting requirements or to maintain sufficiently high retention.

These strategies attempt to influence the external labor market supply curve, but up to 2003 no incentive pay existed to reflect personal preferences in internal labor market decisions. Beginning in April 2003, the Navy is filling this gap with an Assignment Incentive Pay (AIP), which will be described in depth in the following chapter.

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III. FUTURE FORCE COMPENSATION STARTEGY

A. THE RIGHT COMPENSATION SYSTEM

The assistant Secretary of the Navy for Manpower and Reserve Affairs, the honorable William A. Navas Jr., in his opening comments at the Third Annual Navy Workforce Research and Analysis Conference (2003), emphasized that the future vision for a Naval Warrior includes cost-effective use of all human resources and the employment of a qualified and motivated work force. This also means efficient compensation as a motivator and management tool.

Following this guideline, the Center For Naval Analyses examined the present compensation system for the Navy's enlisted personnel and identified four major purposes for an effective compensation system (CNA, 2000):

- Attract and retain workers
  - Overall
  - Critical skills
  - High Quality
- Motivate effective work
- Allocate workers among jobs
- Organization-specific goals
  - Maintain pay equity
  - Provide subsistence

And do all this at the lowest Possible cost!

Figure 6. What should a compensation system do? (From: CNA, 2000)

They concluded that three of these goals, namely "attracting and retaining enough people", "promoting equity" and "providing subsistence", are very well met by the

Navy's current compensation system. However, the allocation of people across jobs and the purpose of attracting and retaining people in some critical skill areas aren't very well met. The same study also counters the common equity argument against assignment and occupational differential with the fact that pay differentials already exist and do create differences. Special pays, like sea, submarine, nuclear pay or pay variations for doctors, as well as housing and subsistence allowances pay differentials by marital status, introduce significant differences. These already existing differentials target certain groups and not general problems of filling certain billets in unpopular locations. Instead, non-monetary incentives are in place that put additional constraints on the distribution system and lower overall fleet readiness. The use of sea duty credits as an incentive for overseas shore billets is an example.

Additionally, in times of a flourishing economy, a low retention and high Sailor dissatisfaction represent serious challenges to the Navy's personnel system. Other challenges involve future forecasts, as the requirements for enlisted personnel change. With new platforms and civilian educational trends, the skill requirements for the workforce will also change. Although some uncertainty exists as to what technical skills will be required, it is generally agreed that the future sailor will have to apply general principles in technical fields, define problems, establish facts, draw conclusions and communicate technical problems and solutions (CNA, 2000). These changes in technology and skill requirements, together with changes in the population's educational structure, like a greater portion of the population attending college, will lead to an incompatibility with the current pyramidal form of Navy manpower requirements and grade structure. Some junior-grades will have to complete less skilled tasks, but the vast majority of enlisted personnel will be skilled technical decision-makers. As a result, differentiating through fast promotion may no longer be an opportunity and lateral entries may create additional frictions to career expectations. The rather inflexible current compensation system might not be able to reward the needed increased technical skills and retention, and motivation could suffer severely. A more flexible compensation and career structure is unavoidable to successfully meet these future challenges.

B. AN ASSIGNMENT INCENTIVE PAY

1. General Principles and Sailor Responsiveness

The principles of an all-volunteer force is to recruit the volunteers with the lowest opportunity costs and those who are most willing to serve. In the initial step, getting volunteers into military service, these principles are indeed in place and working. However, the internal labor market represented by the Navy's Enlisted Personnel Assignment system does not necessarily follow this premise. Sailors are often being assigned to duty stations involuntarily in unpopular hard to fill billets.

To fulfill the earlier described urgent demand for flexibility and to counter the market inefficiencies of hierarchical planning, an Assignment Incentive Pay (AIP) was proposed to represent the crucial allocation function of prices in an internal labor market (CNA, 2002). Offering additional flexible compensation to volunteers will incorporate individual preferences in the assignment process and ensure the assignment of those with the lowest opportunity costs and the highest willingness to serve at a particular duty station. Because the height of the incentive will be determined by closed bidding procedures, the resulting individual market wage will also provide signals for budget allocation. The question "Is this billet really worth the pay?" is more easily answered and the overall monetary compensation for a billet is more easily compared to civilian market competition.

The overall sailor responsiveness to an assignment incentive pay can only be estimated at this point, but actual data will be available by the beginning of 2004, along with the experience of the first AIP pilot program with oversea billets in Europe. However, surveys and studies by the CNA (2002) used historical data to infer that sailors will volunteer for less preferred duty given a pay incentive. Estimated results based on experiences with sea pay indicate incentives are required in the area of $ 50,000 per additional work year.

2. The Assignment Incentive Pay Pilot

After over two years of studies and cost benefit analyses, the first AIP pilot started in mid-2003, offering Assignment Incentive Pay for overseas billets in Naples, Sigonella and Misawa. An Implementation Planning Team oversees the detailed rules and policies. Members are the MCAs, COMMANDER IN CHIEF U.S. Naval Forces Europe (CINCUSNAVEUR), NPC (PERS-4), EPMAC, OPNAV (N13), CNA, NPRST and contractors.

The pilot will include enlisted sea-shore rotation ratings only. Sea credit will no longer be given for these oversea billets to gain significant pay back for the AIP expenses. After completing these assignments, the sailors will be available for sea duty again.

The stated objective is to attract volunteers to difficult-to-fill jobs in the described locations (Cunningham, 2002). Although significant headroom is given with up to a \$1500 per month incentive pay ceiling, the initial maxima are differentiated by location and pay grade:

Table 1. AIP Maximum Rates by Pay grade and Location (From: Cunningham 2003)

Location	E7-9	E5-6	E4
Sigonella	\$450	\$400	\$350
Naples	\$450	\$400	\$350
Misawa	\$200	\$150	\$100

.

These maxima reflect both the urgency that exists to fill the billet and the difficulty with filling the billet.

To match sailors and jobs with the appropriate AIP, the sailors submit their bids through JASS in the Distributive Incentive Management System (DIMS). The bids are non-disclosed, so called sealed bids, in \$50 increments. DIMS tracks and manages the allocation of monetary and non-monetary distribution incentives as well as activity manning and JASS vacancy. Forecasting modules allow expenditure and obligation planning. Additionally, customized report tools enable data analysis at all desired reporting levels (Rouse, 2002). The following screenshot provides an impression of the planned software design:

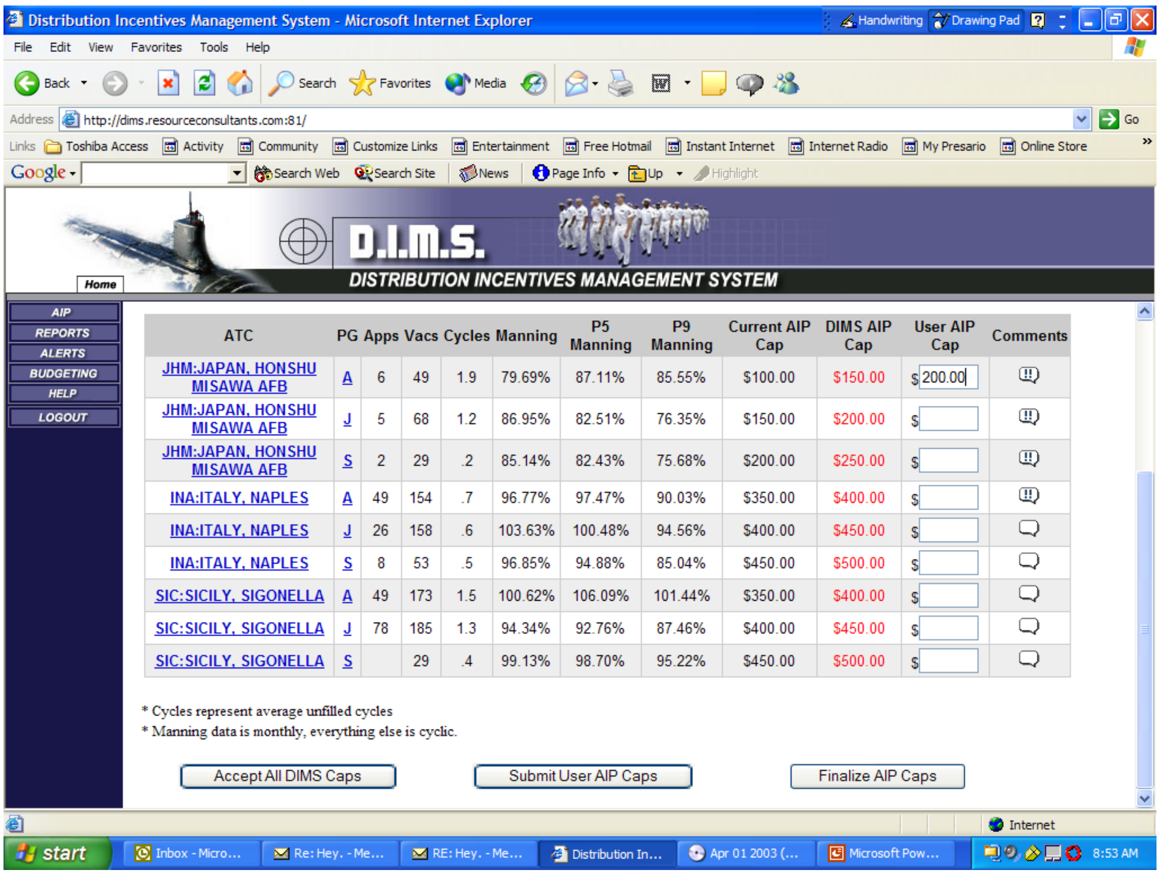

Figure 7. Screenshot: Distributive Incentive Management System (DIMS), (From: Rouse, 2003)

The bidding cycles are synchronized with the detailer's current two-week requisition cycles. Although the detailers still make the final decision, they do not see any bids until all qualified bids are submitted ; they then add PCS and retraining costs to the equation. The decision rationale must follow the decision matrix and has to be documented if deviation from the lowest bid is unavoidable. If no qualified bid is received within the two-week's cycle, the bidding will continue for another cycle, eventually with an increased maximum bid. Although, the decision matrix and the business rules for an eventually unavoidable involuntarily assignment are still under development, the small start with Naples, Sigonella and Misawa is expected to be expanded after two to four requisition cycles. Figure 8 shows the estimated growth plan as of April 2003:

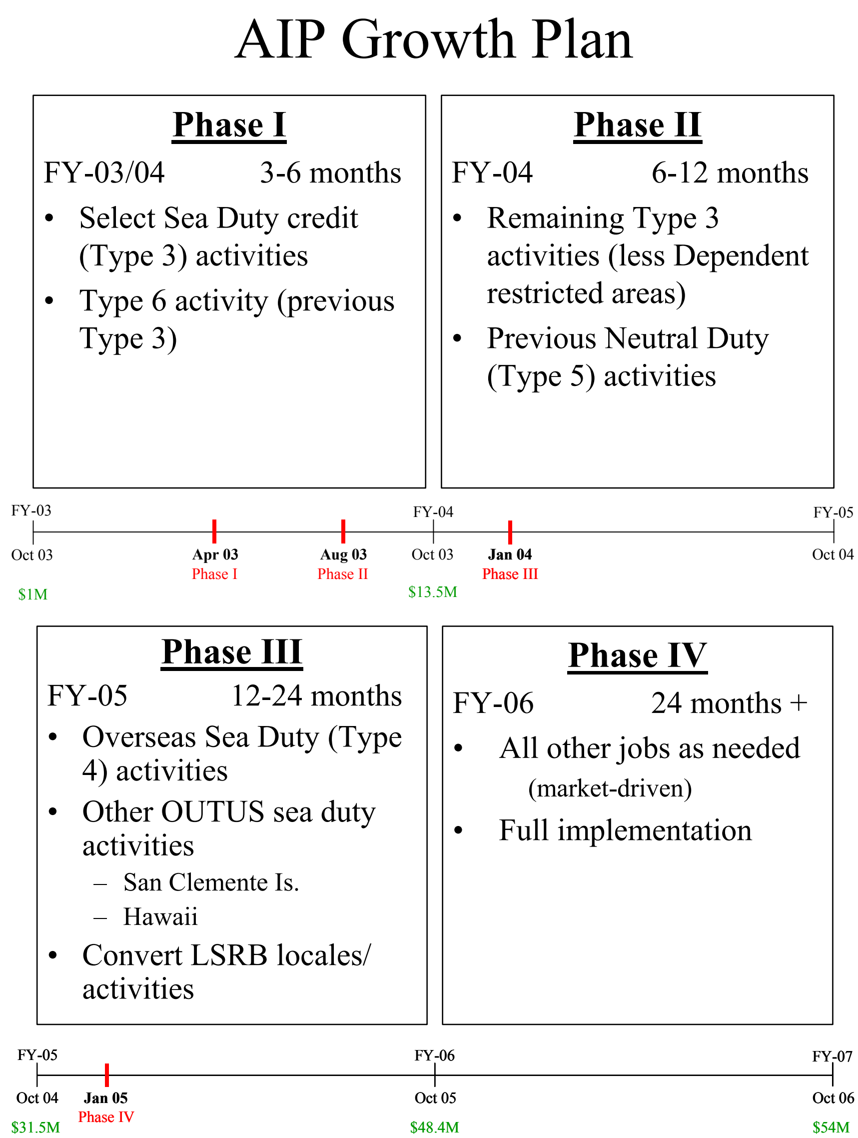

Figure 8. AIP Growth Plan (From: Cunningham, 2003)

The Navy's budget reflects the pilot as well as the further growth with installments of one million dollars in fiscal year (FY) 2003 up to 54 million dollars in

FY07. Program and IT layout will be evaluated before each step and adjustments will be made as necessary.

Despite all the design efforts, sailor acceptance and responsiveness to this new incentive is crucial for its success. Although this incentive creates additional expenses at first, and will be added to PCS and training costs, the overall gain in sailor satisfaction and higher retention, particularly in times of economic booms, should yield sufficient return on investment. Due to the lack of survey data about the success of the brand new AIP, this paper will analyze the impact of AIP and its importance for the U.S. Navy in a simulation environment, using stylized utility functions for sailors and commands. The utility functions include AIP and weights that an individual sailor or the Navy might put on AIP as part of overall utility.

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IV. UTILITY FUNCTIONS IN AGENT BASED TWO-SIDED MATCHING SIMULATIONS

A. PREVIOUS SIMULATION DESIGN AND POSSIBLE CHANGES

In the absence of real life data from the implemented pilot study, a simulation-based sensitivity analysis is usually the only way to estimate success and give reasonable advice for an implementing strategy. In previous research, Low and Ho (2002) developed a powerful tool to compare the possible matching mechanisms. Their Navy Enlisted Distribution Simulator (NEDSIM) was implemented in Microsoft Excel with an advanced solver platform to facilitate the needs for several variables in the linear program (LP) as a matching mechanism. Both mechanisms, the deferred acceptance (DA) algorithm as well as the LP, were used and compared across a variety of performance measures. Although the focus of this thesis is not to compare the two mechanisms, they both had advantages and disadvantages over each other. To cover all aspects of the assignment process replacing the human detailer in the simulation it seems adequate to keep both mechanisms and not to discard one or the other result. On the other hand, the focus of this thesis is different from Lo and How's approach. While they investigated the strengths of the two matching mechanisms to ultimately decide on the most appropriate mechanism for a revised Navy Enlisted Distribution Assignment system, this research only uses simulation as a tool to replace the existing assignment system and examine the introduction of assignment incentive pay.

As mentioned earlier, keeping both original matching mechanisms is an adequate choice to include all their individual advantages. While the LP has proven to perform better in the area of percent matches than the DA, the DA was significantly better in producing stable matches. Unstable matches are generally referred to as matches where both the matched sailor and the matched command would have preferred another matching partner over the assigned one. This situation would create a situation of instability with both matched partners trying to change the assignment.

Other parts of the simulation however needed revision to adapt to this research. Along with these changes a central question occurs like in all simulations involving utilities: What is the appropriate form of the utility function?

B. CONCEPT OF THE NEW UTILITY FUNCTION DESIGN

In all previous simulations of the assignment process, utility functions of the commands and the sailors were used to generate preference lists and to apply the appropriate matching algorithms. The general choice between a multiplicative and an additive form has to be made to continue with the simulator design. The multiplicative form, also known as the Cobb Douglas utility function, implies interdependencies between the individual factors within the utility function. Changing the value of one part in the function changes the incremental value in another part. The individual elements in the utility function affect the incremental values of the other elements. Ng and Soh (2001) used this kind of utility function in their simulation. It followed the general form:

$$U = A^{\alpha_1} * B^{\alpha_2} * C^{\alpha_3}$$

where:

U = Total utility of the sailor or command

A, B, C = Utility derived from factors A,B,C

Weights $\alpha_1 + \alpha_2 + \alpha_3 = 1$

However, Low and Ho (2002) argued that this might not be a realistic relationship between the individual parts in the function. An increase of value from one part might not necessarily increase the incremental value of another one. They used an additive form instead, that can be generally described as follows:

$$U = \alpha_1 A + \alpha_2 B + \alpha_3 C$$

where:

U	=	Total utility of the sailor or command
A, B, C	=	Utility derived from factor A, B or C.

$\alpha_1 + \alpha_2 + \alpha_3 = 1$

This research will follow the latter approach because of the lack of evidence for the interrelationship amongst the utility function elements. In a realistic scenario of the assignment process, a sailor might have independent preferences for pecuniary or non-pecuniary aspects of his future job. Then again, he might very well value the monetary aspect of his work more highly than all the other preference factors. The additive utility function seems to incorporate the most realistic scenario.

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V. IMPLEMENTATION OF THE NEW SIMULATION DESIGN IN THE NAVY ENLISTED DISTRIBUTION SIMULATOR (NEDSIM)

A. THE ORIGINAL NEDSIM

The original NEDSim included four components. It created a random list of both sailor and command preference factors using a profile generator. Using these lists and computing the resulting utility levels, it then assembled a sailor and a command preference list. Based on the two matching mechanisms it subsequently matched sailors to billets and finally provided summary reports of the simulation.

The following figure illustrates the links between components:

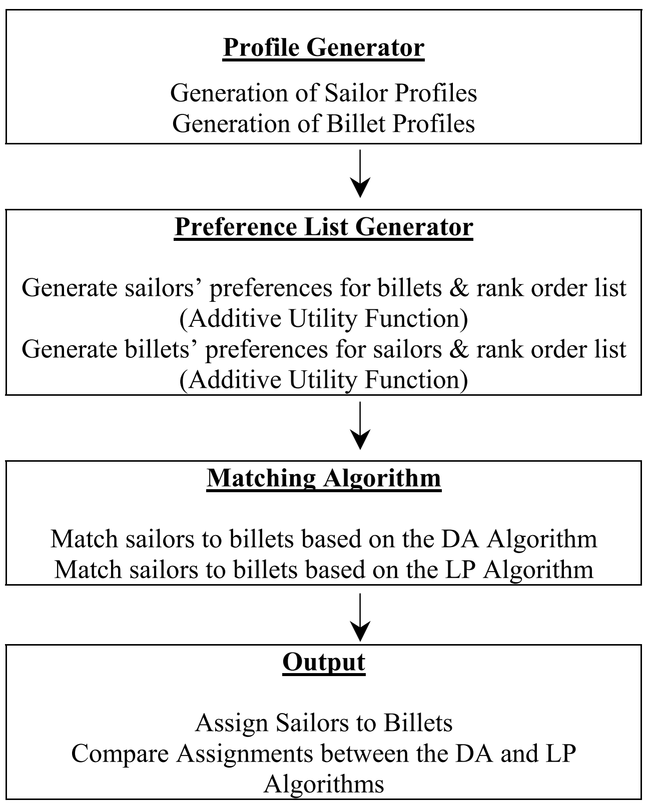

Figure 9. Components of the Navy Enlisted Distribution Simulator (NEDSim) (From: Ho, 2002)

The typical two weeks assignment requisition cycle tries to match about 45 sailors to 60 billets. About 15 percent of these billets are priority 1 coded and have to be filled first. The remaining billets have priority 2 or 3 and are considered thereafter. Sailors are permitted to submit five choices for their next command in a prioritized list in JASS as described in Chapter II. Following the reality NEDSim used preference lists with a length of five for sailors and commands. To gain statistically significant results, Low and Ho (2002) simulated 100 two-week requisition cycles.

1. The Profile Generator

Within the profile generator, NEDSim generates billet and sailor characteristics based on discrete probability distributions derived from the profile of the aviation community used for the simulation. Data from the Enlisted and Billet Master File was used to shape sailor and billet profiles and to determine the underlying probability distributions.

a Sailor Profile

Simulated sailor characteristics were grade, NEC, experience and performance. While the distribution of ranks was easily derived from the Enlisted Master File (EMF), NEC's had to be grouped into five NEDSim categories to facilitate the simulation. The sailor from the aviation community could come from a variety of previous billets, resulting in a broad spectrum of possible experience. Shore assignments include AIMD detachments, recruiting commands, training commands and air wings, while sea billets exist on Aircraft Carriers (CV's), amphibious ships (LHD's, LHA's) and mine command ships (MCS). Sailor characteristics and underlying probability distributions used by NEDSim are listed in Table 2:

Table 2. Probability Distribution of Sailor Characteristics (From: Ho, 2002)

Characteristic	Probability Distribution				
Rate (Paygrade)	E3 10%	E4 30%	E5 31%	E6 21%	≥E7 8%
NEC	7600 32%	7607 24%	7612 11%	7614 18%	7699 15%
Experience	CV 30%	LPD / LHA / LHD / MCS 14%	Other Sea 12%	AIMD 29%	Other Shore 15%
Performance	Not promote 10%	Progressing 30%	Promotable 30%	Must promote 20%	Early promote 10%

b Billet Profile

Billet characteristics included rate, location, NEC, promotional prospects of the assignment and whether it is ashore or at sea. Rate, provided by the Billet Master File (BMF) and locations were grouped into five main regional areas. NEC also was obtained from the BMF for the AS rated sailors. Promotional prospects or visibility, on the other hand, had to be estimated by the deviation of the billet rate from the sailor's rate. A billet rate that is indeed much higher than the sailor's rate represents high visibility and high promotion prospects. The existing number of billets was broken down into shore and sea characteristics according to their platform profile. Billet characteristics and probability distributions are given in Table 3:

Table 3. Probability Distribution of Billet Characteristics (From: Ho, 2002)

Characteristic	Probability Distribution				
Rate (Paygrade)	E3 14%	E4 28%	E5 32%	E6 18%	≥E7 8%
Location	East Coast (CEC) 33%	Gulf Coast (CGC) 13%	South West (CSW) 25%	North West (CNW) 10%	OCONUS (OPL) 19%
NEC	7600 24%	7607 22%	7612 16%	7614 26%	7699 12%
Visibility	Low 16%	Moderate 20%	Average 24%	High 21%	Excellent 19%
Platform Profile	CV 28%	LPD / LHA / LHD / MCS 13%	Other Sea 8%	AIMD 40%	Other Shore 9%
Shore	Sea 51%			Shore 49%	

2. The Preference List Generator

For every sailor, the simulation models a preference list of billets, and for every billet a preference list of sailors, using additive utility functions and the random number generator in MS Excel with the above mentioned discrete probability functions. Following Buttler and Molina's (2002) research on preferences, the sailor's utility function consisted of four preference factors, including family life, location, and job factors. Modeled in an additive utility function, NEDSim used the following equation:

$$\text{Sailor Utility} = \alpha_{FL}\,(\text{Family Life}) + \alpha_{L}\,(\text{Location}) + \alpha_{J1}\,(\text{Promotion}) + \alpha_{J2}\,(\text{Shore})$$

where : $\alpha_{FL} + \alpha_{L} + \alpha_{J1} + \alpha_{J2} = 1$

(each α is generated randomly)

Family life was believed to be mainly determined by the spouse's employment opportunities. Therefore, job growth rates were used to rank the five locations above in a general pay-off matrix. With a similar technique, costs of living in the different locations lead to a pay-off matrix for the location preference factor. Job factors, on the other hand, had to be split across two parts of the utility function: visibility and shore. While visibility was directly derived by comparing sailor and billet rank, shore was set to maximum utility for shore and minimum utility for sea. A summary of all four sailor pay-off matrices is given in Table 4:

Table 4. Pay-off for Sailor Preference Factors in the Sailor Utility Function (After: Ho, 2002)

	Score	Family Life Billet Location (Job Growth Rates in repr. Cities)	Location Factor Billet Location (Cost of Living Index in repr. Cities)	Promotion Factor Billet Visibility	Shore Factor
Excellent	5	Gulf Coast (CGC) Pensacola (3.94%)	Gulf Coast (CGC) Pensacola (94.9%)	(Billet rate ≥ 2 rates above Sailor rate)	yes
High	4	East Coast (CEC) Norfolk (2.14%)	East Coast (CEC) Norfolk (96.6%)	(Billet rate = 1 rate above Sailor rate)	
Average	3	Southwest (CSW) San Diego (2.10%)	OCONUS (OPL)	(Billet rate = Sailor rate)	
Moderate	2	Northwest (CNW) Bremerton (0.91%)	Northwest (CNW) Bremerton (100%)	(Billet rate = 1 rate below Sailor rate)	
Low	1	OCONUS (OPL)	Southwest (CSW) San Diego (136.4%)	(Billet rate ≤ 2 rates below Sailor rate)	no

While the out of continental U.S. (OCONUS) location was perceived to have the lowest job growth rate compared with the United States, it was assigned an average utility score for the cost of living. Although applying for a job with a rate more than one pay grade lower or higher than the sailor's is not realistic, NEDSim covered the whole spectrum and assigned low command utility to the big rate differences to reflect reality.

Not knowing how the individual sailor perceives the importance of the different preference factors, the weights α were determined randomly in excel.

Butler and Molina (2002) not only surveyed the preferences of the sailor in the matching process but also asked the other side of the process – the commands- about their preferences. As a result, the most important preference factors for the commands were found to be the sailor's NEC, pay grade, experience and past performance, resulting in the following utility function:

$$\text{Command Utility} = \beta_{NEC}(\text{NEC}) + \beta_{pay}(\text{Paygrade}) + \beta_{exp}(\text{Experience}) + \beta_{perf}(\text{Performance})$$

where : $\beta_{NEC} + \beta_{pay} + \beta_{exp} + \beta_{perf} = 1$

(each β is generated randomly)

The correct NEC was perceived to be very important and is determined to be a binary attribute leaving no room for more than two levels. Consequently the correct NEC was assigned maximum score and any deviation was assigned a minimum score. As mentioned earlier, sailors actually cannot apply for jobs with a pay grade more than one level different from their current grade. Also a higher pay grade of the sailor includes less promotional obligation on the Navy's side. NEDSim therefore assigned the highest score to a correct pay grade and the lowest score to a pay grade one below. A pay grade one above received an average score. For the experience factor, the present and future platforms were compared. A sailor who came from the same platform to which he was supposed to go scored a 5. A sailor who stayed on sea or shore duty received a 3 and a sailor who had to change platform and duty type received a 1. The performance factor was generated in five categories with a normal distribution. Table 5 summarizes the pay-off for command preference factors:

Table 5. Pay-off for Sailor Preference Factors in the Command Utility Function (After: Ho, 2002)

Score	NEC	Paygrade	Experience	Performance
5	Correct (Sailor NEC = Billet NEC)	Correct	Highly relevant (Sailor Unit = Billet Unit)	Early Promote
4	--	--	--	Must Promote
3	--	One above	Somewhat relevant (Sailor Sea/Shore = Billet Sea/Shore)	Promotable
2	--	--	--	Progressing
1	Incorrect (Sailor NEC ≠ Billet NEC)	One below	Not relevant (Sailor Sea/Shore ≠ Billet Sea/Shore)	Not Promote

3. Matching Algorithm

NEDSim employed two matching mechanisms to compare their performance in the simulated assignment process. The deferred acceptance algorithm (DA) is widely used to match medical interns and hospitals in the United Sates and Great Britain, and the linear program algorithm (LP) is used in Newcastle and Birmingham hospitals (Ho, 2002). Both algorithms will be described briefly with an emphasis on the Navy assignment process application.

a The Deferred Acceptance Algorithm

As a prerequisite for applying the deferred acceptance algorithm, both types of potential matching partners have to have a rank-order profile. The preference lists of sailors and commands serving that purpose. In the next step, the bias-determining side "proposes" to her most preferred partner. The mechanism was first introduced by Gale and Shapely (1962) who used marriage partners as an example. Some terminology to describe the algorithm from this original example is still widely used. Also the immanent mechanism bias needs to be pre-defined. In our case, a sailor bias would give the sailor side the first priority to choose its most preferred partner. Each command that has the proposing sailor in its preference list accepts the proposal temporarily. In the case that two sailors have chosen the same command in the iteration step, the sailor who is most preferred by that command will be temporarily accepted. All other proposals are rejected. The remaining sailors are then moved down their preference list to repeat the process. Each command holds only the best sailor's proposal with respect to its preference list. When none of the proposals are rejected any more, the algorithm stops and the deferred accepted matches become realized matches. The following example illustrates the mechanism:

Suppose five Sailors, S_n with n= 1,2,3,4,5, have issued preference Lists with the length of 6 and eight commands, C_m with m=1,2…8, have preference lists containing 5 sailors each. The deferred acceptance algorithm would run through the following steps in a sailor-biased mode:

Step 1: The sailors' first choices are proposed. Sailor 3 and sailor 4's proposals are temporarily accepted. Sailors 1, 2 and 5 have proposed to the same command as sailor 4, but they are lower on the command's preference list and therefore were refused.

Sailor #1	Sailor #2	Sailor #3	Sailor #4	Sailor #5
6	6	2	6	6
3	3	5	8	8
4	4	7	3	3
8	8	3	4	4
2	2	4	1	2
5	5	6	2	5

Comd #1	Comd #2	Comd #3	Comd #4	Comd #5	Comd #6	Comd #7	Comd #8
2	2	2	2	2	4	2	2
5	5	5	5	5	2	4	1
1	1	1	1	4	3	1	4
4	4	4	4	1	1	3	3
3	3	3	3	3	5	5	5

Sailor 1	Sailor 2	Sailor 3	Sailor 4	Sailor 5
~~6~~	~~6~~	2	6	~~6~~

Step 2: The sailors' second choices are proposed. Sailor 2 and sailor 5's proposals are temporarily accepted. Sailor 1 has proposed to the same command as sailor 2, but he is lower on the command's preference list and therefore refused.

Sailor #1	Sailor #2	Sailor #3	Sailor #4	Sailor #5
6	6	2	6	6
3	3	5	8	8
4	4	7	3	3
8	8	3	4	4
2	2	4	1	2
5	5	6	2	5

Comd #1	Comd #2	Comd #3	Comd #4	Comd #5	Comd #6	Comd #7	Comd #8
2	2	2	2	2	4	2	2
5	5	5	5	5	2	4	1
1	1	1	1	4	3	1	4
4	4	4	4	1	1	3	3
3	3	3	3	3	5	5	5

Sailor 1	Sailor 2	Sailor 3	Sailor 4	Sailor 5
~~6~~	~~6~~	2	6	~~6~~
~~3~~	3			8

Step 3: The remaining sailor 1's third choice is proposed. He is not rejected because he is on his third choice command's preference list. No offers are rejected at this step and the temporary acceptances become permanent matches.

Sailor #1	Sailor #2	Sailor #3	Sailor #4	Sailor #5
6	6	2	6	6
3	3	5	8	8
4	4	7	3	3
8	8	3	4	4
2	2	4	1	2
5	5	6	2	5

Comd #1	Comd #2	Comd #3	Comd #4	Comd #5	Comd #6	Comd #7	Comd #8
2	2	2	2	2	4	2	2
5	5	5	5	5	2	4	1
1	1	1	1	4	3	1	4
4	4	4	4	1	1	3	3
3	3	3	3	3	5	5	5

Sailor 1	Sailor 2	Sailor 3	Sailor 4	Sailor 5
~~6~~	~~6~~	2	6	~~6~~
~~3~~	3			8
4				

Figure 10. Preference lists and iterative steps under the DA (After: Gates, 2002)

The DA algorithm produces the stable pairs (S_1,C_4), (S_2,C_3), (S_3,C_2), (S_4,C_6) and (S_5,C_8) in a sailor-biased run. A command-biased run would have yielded minor differences with sailor 1 being assigned to command 8 rather than 4 and sailor 5 assigned to command 4 rather than command 8. As described earlier, the DA does not allow for unstable matches. No matched pair will mutually try to change the assignment.

b The Linear Programming

The LP also uses the preference lists for its mechanism. While original versions of the algorithm have assigned weights to priority ranks and tried to maximize the combined weights of the matched pairs, Ho and Low (2002) used the utility values for sailors and commands directly. Any possible match between commands on the sailor's preference list and sailors on the command's preference list have an assigned combined utility value for this match. Using the denotation of the example above, the problem can be expressed as follows:

$$\text{Max } \sum U_{SC}\Xi_{SC}$$

Subject to: $U_{SC} = 0.5\ U_S + 0.5\ U_C$ (Combined sailor and command utility)

$\Xi_{SC} \in [0,1]$ for all S_n, C_m

with Ξ_{SC} being a binary variable indicating if a match occurs.

Unlike the DA algorithm, the LP will not generally avoid unstable matches because the sum of the combined utilities of all possible matches might be higher including these constellations. The number of unstable matches for this mechanism was therefore tracked as an additional performance measurement.

4. Output And Performance Measures

NEDSim provides a wide variety of performance measures. They can generally categorized as quantity and quality measures. The quantity of matches was measured as the number of matches over total number of sailors available (percent sailor match), as well as the percent billet match describing the number of matches over the total number of billets available. On the other hand, the quality performance indicators are average total utility, sailor utility, command utility and, as mentioned above, the percent unstable matches for the LP. Ho and Low (2002) also used composite performance measures combining total average utility, percent stable matches and percent matched in a product function.

All results were recorded in one result worksheet for further evaluation. Figure 11 illustrates the excel output page for the original NEDSim design:

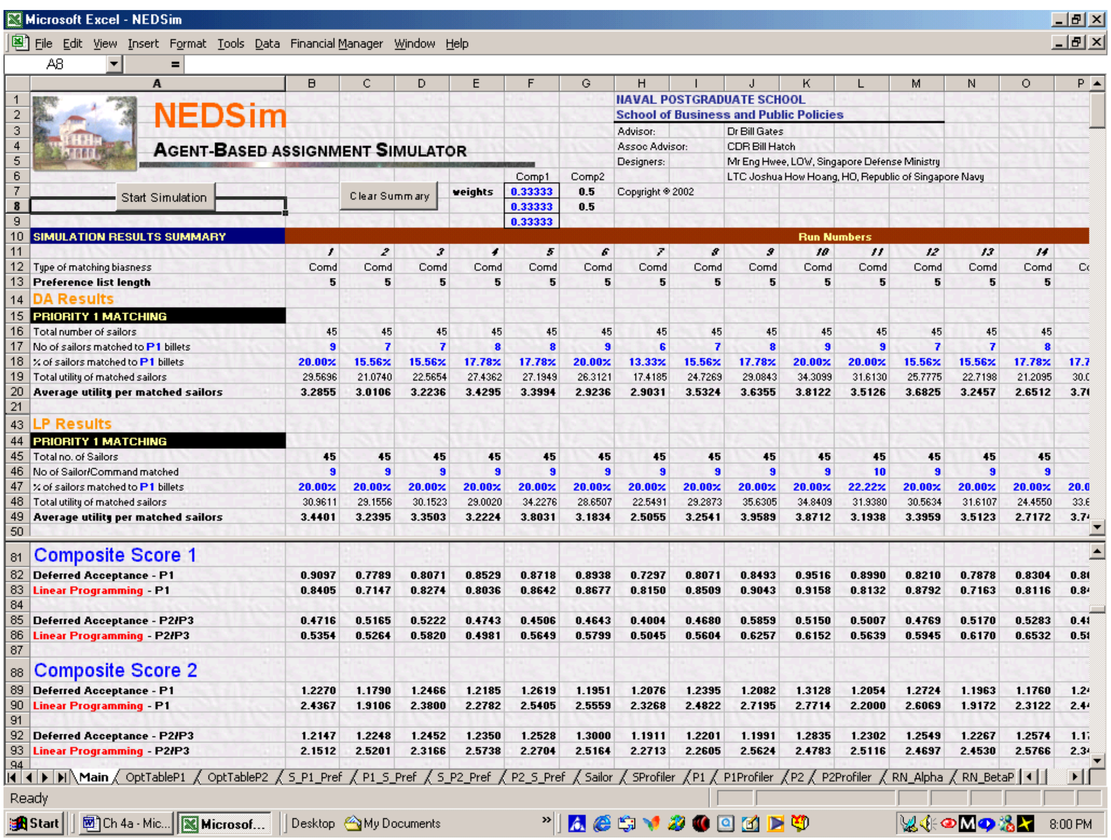

Figure 11. Output page of NEDSim (From: Ho, 2002)

B. CHANGES IN THE SIMULATION – THE NEW PROFILE GENERATOR

While keeping the matching mechanisms made intuitive sense, the profile generators leading to the preference lists produced by utility functions did not reflect any bonus or financial incentive. Therefore some amendments were necessary, to introduce the assignment incentive pay in the simulation.

Assignment Incentive Pay basically represents another element in both profile generators and utility functions. An additional pay portion obviously has the opposite effect on the utility of sailors and the Navy. While the Navy has to cover an expense, the sailor gains additional earnings. The additional preference factor on the sailor side can be modeled as an additional element in his utility function, depending on the size of the AIP for the billet. An individual billet with a comparably high AIP assigned to it will represent a higher AIP utility value to the sailor than a billet with low AIP. To be consistent with the original NEDSIM design, the scale for the AIP utility portion was chosen to range from 1 to 5 with the following amended Pay-off Matrix for billet characteristics:

Table 6. Pay-off Matrix for Billet Characteristics (After: Ho, 2002)

Family Life Factor	**Location Factor**	**Billet Visibility**	**Billet Sea or Shore**	**AIP**	**Score**
Excellent	Excellent	Excellent (Billet rate ≥ 2 rates above Sailor rate)	Shore	Excellent	5
High	High	High (Billet rate = 1 rate above Sailor rate)		High	4
Average	Average	Average (Billet rate = Sailor rate)		Average	3
Moderate	Moderate	Low (Billet rate = 1 rate below Sailor rate)		Moderate	2
Low	Low	Extremely Low (Billet rate ≤ 2 rates below Sailor rate)	Sea	Low	1

The profile generator was extended to generate the fifth preference factor with a symmetric, centered, discrete probability function. The distribution was assumed to be normal. The extended profile was then modeled in a new utility function for the sailor.

$$\text{Sailor Utility} = \alpha_{FL}\,(\text{Family Life}) + \alpha_{L}\,(\text{Location}) + \alpha_{J1}\,(\text{Promotion}) + \alpha_{J2}\,(\text{Shore}) + \alpha_{AIP}\,(\text{AIP})$$

$$\text{where}: \alpha_{FL} + \alpha_{L} + \alpha_{J1} + \alpha_{J2} + \alpha_{AIP} = 1$$

Due to the high uncertainty about how valuable the additional pay is for the individual sailor, the weights of the utility portions of the sailor were still generated randomly.

The appropriate AIP element also extended the command utility function.

$$\text{Command Utility} = \beta_{NEC}(\text{NEC}) + \beta_{pay}(\text{Paygrade}) + \beta_{exp}\,(\text{Experience}) + \beta_{perf}\,(\text{Performance}) + \beta_{AIP}\,(\text{AIP})$$

$$\text{where}: \beta_{NEC} + \beta_{pay} + \beta_{exp} + \beta_{perf} + \beta_{AIP} = 1$$

However, the command's weights weren't generated randomly but set by Navy Policy (allowing the Navy to vary the emphasis on minimizing AIP costs), and varied by sensitivity analysis. Moreover, the AIP preference factor in the command utility function had to be linked to the sailor's AIP preference factor because of the earlier mentioned inverse utility relationship for a specific sailor-billet match.

To ensure this relationship, the command AIP value was set to be the maximum score (5) plus one, reduced by the sailor's AIP value (6 – Sailor AIP). This way, every match incorporated an inverse utility drawn from AIP for sailors and commands. For example, a high AIP attached to the voluntarily acceptance of a potential assignment would give the sailor a high utility score from the potential match. If this value is 5, the AIP value for the command for that particular match would be automatically set to the 1, which is the lowest possible score in that part of the utility function. While this inverse relationship for the AIP portion of both utility functions is established, the weight the individual places on AIP is randomized for the sailor and preset according to the sensitivity analysis scenario for the command.

C. PERFORMANCE MEASUREMENT

The wide variety of available performance measures offered by the original NEDSim clearly exceeded the needs for this simulation. Because the main focus of interest was on the success of the simulated Navy assignment process and the effect of different AIP policies, only three measures were chosen to provide further insight.

The most important measure is command utility. The Navy is facing the challenge of deciding how to implement the new incentive pay and is interested in determining what policy provides the highest payback to the Navy.

On the other hand, the matching process can also be viewed as successful if the percentage of sailors matched is high. As mentioned earlier one priority is voluntary assignments, and a high percentage of voluntarily matched sailors represents a high percentage of satisfied and productive sailors.

Finally, a system-immanent performance measure comes automatically using linear programming in the matching process. The number of unstable matches needs to be minimized to reduce interference with detailers' assignment decisions. If both the sailor and the matched command prefer a different partner to the matched one, they would both be likely to interfere and search for another assignment solution.

The three chosen performance measures are readily provided by the original NEDSim layout and can be analyzed for the different scenarios. Excel provides the appropriate statistics analysis tools.

D. SENSITIVITY ANALYSIS DESIGN

Sensitivity analysis generally compares two extreme scenarios to each other and to a base case. The results, in terms of command utility, average percent matches and average percent of unstable matches, will be reported in part VI of this paper.

The base case, called “equal”, is a command utility function with equal weights on all preference factors. This scenario represents a Navy that draws equally weighted utility from quality, performance measures and the AIP expense. Not spending money on AIP is as important as the quality of the sailor. The first extreme case, called “money”, incorporates a command utility function with a disproportionally high weight on the AIP portion. The Navy tries to save money and is less interested in quality and performance factors. The other extreme case, “quality”, on the other hand has a disproportionally low weight on the AIP portion and represents the Navy’s interest in quality and performance rather than saving AIP expenses. Table 7 summarizes the weights for the different scenarios:

Table 7. The Command Utility Function Weights in the three scenarios

Scenario	β_{NEC}	β_{pay}	β_{exp}	β_{perf}	β_{AIP}
Equal	0.2	0.2	0.2	0.2	0.2
Money	0.1	0.1	0.1	0.1	0.6
Quality	0.22	0.22	0.22	0.22	0.12

Following the current US Navy detailing process for Enlisted Personnel, a typical two weeks requisition cycle was simulated with 60 billets available for 45 sailors. About 15% of the billets are priority 1 coded. The simulation followed this approach, with 9 out of the 60 billets being P 1 billets. These assumptions are consistent with Ho and Low’s approach and follow earlier runs conducted by Ng and Soh (2001) and study results by Short (2000). Also following the original NEDSIM settings, the preference list length was kept at five potential choices. To obtain sufficient data for a statistically significant analysis, 100 requisition cycles were simulated and reported.

In a second step, the preference list lengths were doubled to ten potential choices to possibly improve the original results. Earlier simulations found a fundamental pay-off relationship, illustrated by Figure 12, that suggest this change is promising.

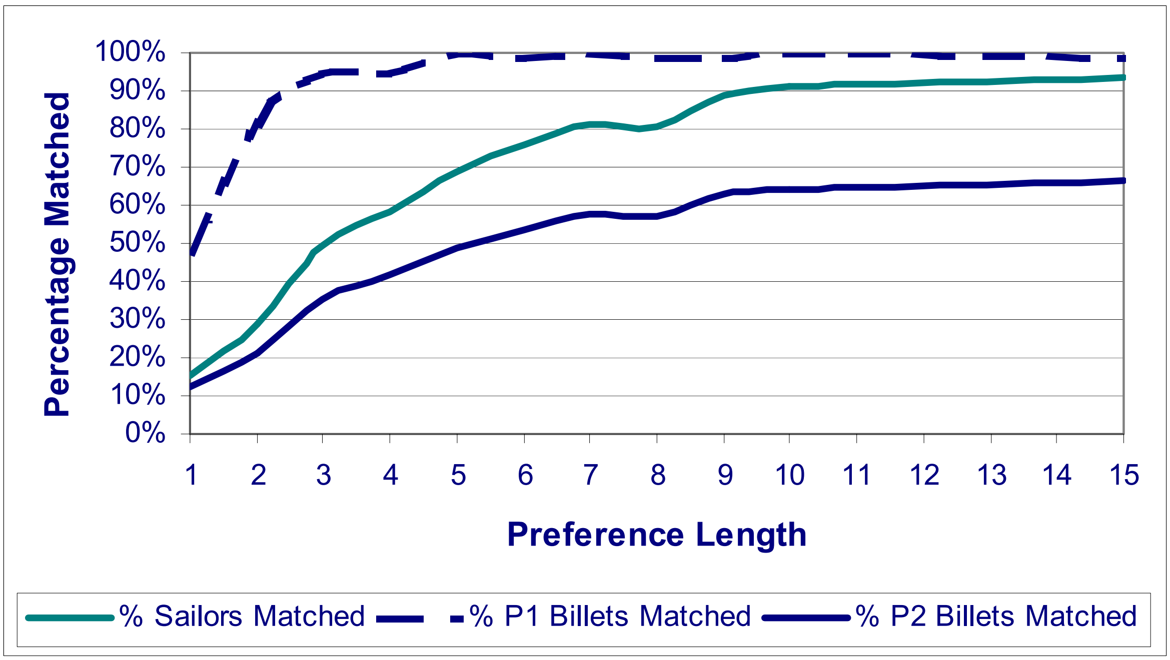

Figure 12. Pay-off between percentage matched and preference list length (After: Gates, 2002)

VI. RESULTS AND OUTCOMES OF THE SENSITIVITY ANALYSIS

A. OVERALL FINDINGS

The simulation results and findings proved to be consistent with previous research and anecdotal evidence. The “quality“ scenario always showed higher average command utility, generally the highest percentage of matches and the lowest percentage of unstable matches when the LP is used. “Quality” provides up to 66.6% higher average command utility and cuts the unstable matches for the P2/P3 billets in half (significant at 10%-level). A doubled preference list length furthermore lowers unstable matches significantly for P1 billets under “quality”. It also increases the average percentage of matches significantly (almost tripled for “Quality” P2/3 billets). The following two tables summarize these results:

Table 8. Simulation results for P1 billets in the three different scenarios (if not stated otherwise, all differences are significant at the 1%-level)

P1 Billets	Average Percentage Matches		Average Command Utility		Percent Unstable Average
	DA	LP	DA	LP	LP
Equal (A)	82.1	98.2	24.07	26.6	31.57
Money (B)	82.55	98.65	15.26	16.72	31.92
Quality (C)	82.45	97.8	25.42	27.68	31.98
Significant differences	None	None	Yes, all	Yes, all	None
Double Preference List:					
Money (D)	100	99.45	18.58	18.0	28.53
Quality (E)	100	100	30.38	29.93	24.64
Significant differences	B-D C-E	C-E	B-D C-E D-E	B-D C-E D-E	B-D(10%) C-E D-E(10%)

Table 9. Simulation results for P2/3 billets in the three different scenarios (if not stated otherwise, all differences are significant at the 1%-level)

P2 Billets	Average Percentage Matches		Average Command Utility		Percent Unstable Average
	DA	LP	DA	LP	LP
Equal (A) Money (B) Quality (C) Significant differences	17.45 17.59 17.68 None	41.8 41.58 41.84 None	18.62 13.34 19.11 A-B B-C	16.86 14.99 17.34 A-B B-C	1.13 1.18 0.53 C-A C-B at 10%level
Double Preference List:					
Money (D) Quality (E) Significant differences	34.1 55.1 B-D C-E D-E	53.99 55.11 B-D C-E	25.82 32.54 Yes, all	29.0 30.24 B-D C-E D-E (5%)	1.99 1.19 B-D(10%) C-E(10%) D-E(10%)

B. RESULTS IN DETAIL

Because of the possibly different results from the two matching mechanisms the results for command utility and average percent matches will be reported separately and summarized in closing. Unstable matches are a linear program symptom only. Section B 3 of this chapter will consequently report just LP results.

1. Comparison Of Command Utility

a Results from the Deferred Acceptance Algorithm

Figure 13 shows the command utility derived from all successfully matched sailors to P1 billets in the three scenarios. Although the difference between scenarios “equal” and “quality” is hard to identify visually, the lower command utility from scenario “money” is more than obvious and follows the initial expectations.

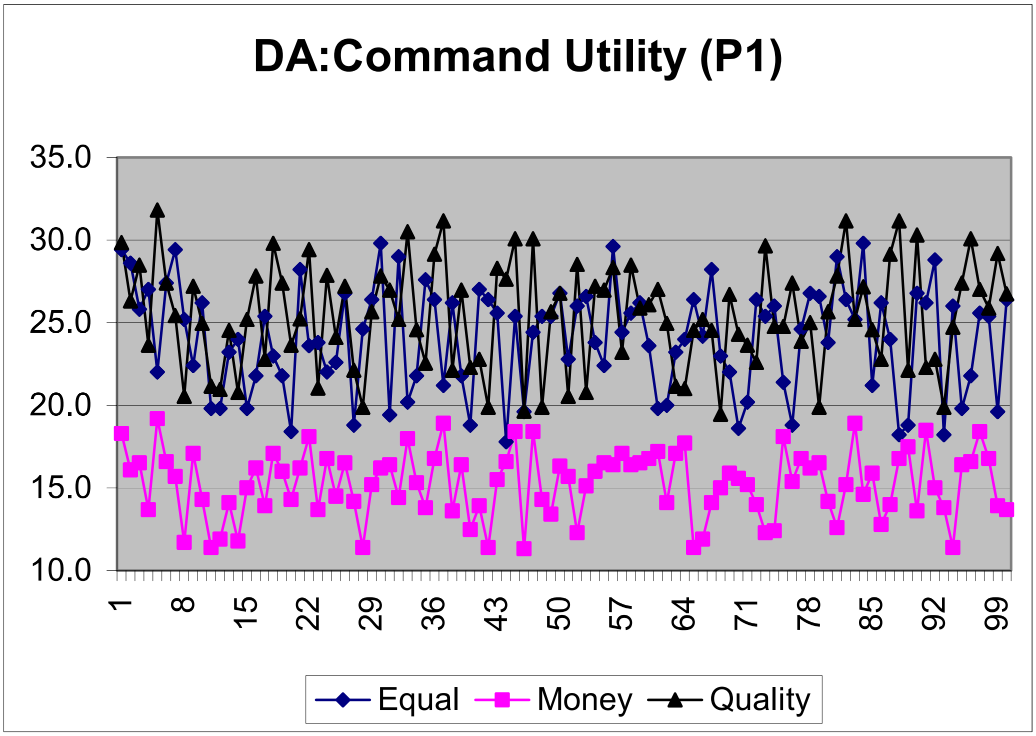

Figure 13. DA: Command Utility from Sailors matched to P1 Billets

However, the mean of the command utility in the "quality" scenario is indeed about 5.6% higher than in the "equal" scenario. This difference of the means proves to be statistically significant even at the 1% level.

Table 10. Two-Sample t-test on Means Assuming Unequal Variances for Command Utility of matched P1 Billets using the Deferred Acceptance Algorithm

	Equal	*Quality*
Mean	24.07	25.4216
Variance	10.25	10.32032
Observations	100	100
Hypothesized Mean Difference	0	
df	198	
t Stat	-2.98008	
P(T<=t) one-tail	0.001621	
t Critical one-tail	2.345332	
P(T<=t) two-tail	0.003243	
t Critical two-tail	2.600882	

All other mean differences are statistically significant at the 1% level as visually indicated by Figure 5. The command utility for “money” is 36.6% lower than for “equal”; “quality” shows 66.6% higher command utility than “money”. Table 11 shows the corresponding t-tests.

Table 11. Two-Sample t-test on Means Assuming Unequal Variances for Command Utility of matched P1 Billets using the Deferred Acceptance Algorithm

Compare Means of	Equal and Money		Money and Quality	
Mean	24.07	15.256	15.256	25.4216
Variance	10.25	4.13158	4.13158	10.32032
Observations	100	100	100	100
Hypothesized Mean Difference	0		0	
df	168		167	
t Stat	23.2418		-26.7406	
P(T<=t) one-tail	1.15E-54		1.52E-62	
t Critical one-tail	2.348752		2.348879	
P(T<=t) two-tail	2.29E-54		3.04E-62	
t Critical two-tail	2.605411		2.605593	

When looking at the results for matching the remaining sailors to P2/P3 billets, the graph shows somewhat different results.

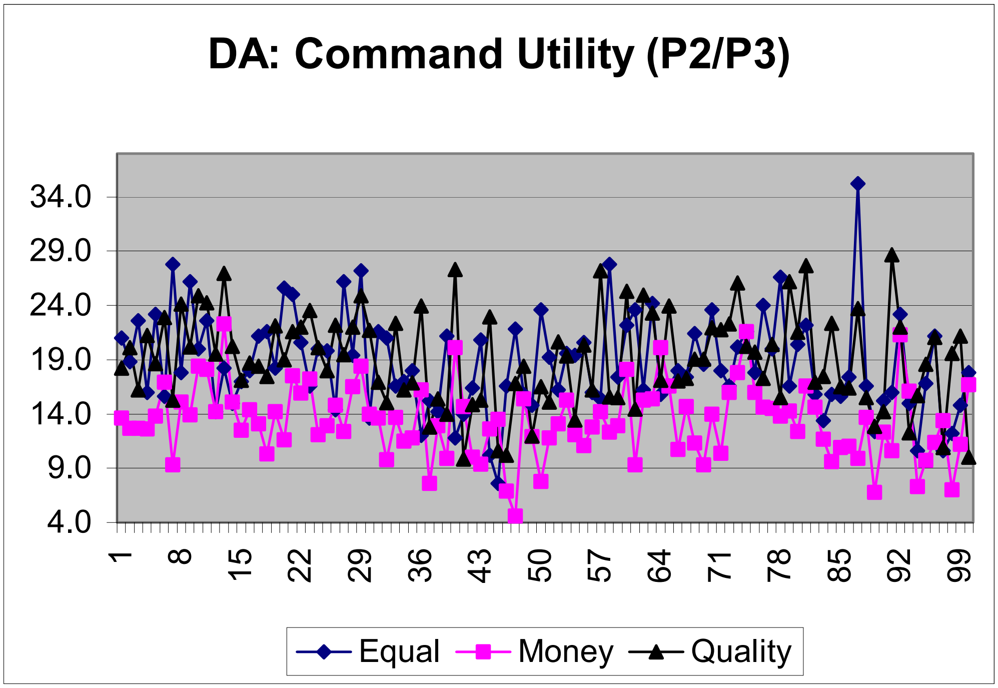

Figure 14. DA: Command Utility from Sailors matched to P2/P3 Billets

Although scenario "money" still shows the lowest values of the three, the difference between the other two scenarios is not as big as with the P1 billets. This time "quality" shows only 2.5% higher results on average than "equal" and the difference isn't statistically significant. However, the differences from "equal" to "money" (28.4%) and "money" to "quality" (43.2%) have p-values very close to zero.

Table 12. Two-Sample t-test on Means Assuming Unequal Variances for Command Utility of matched P2/P3 Billets using the Deferred Acceptance Algorithm

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	18.624	19.1056	18.624	13.34	13.34	19.1056
Variance	19.86204	18.56293	19.86204	11.21697	11.21697	18.56293
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	198		184		187	
t Stat	-0.77693		9.478273		-10.5653	
P(T<=t) one-tail	0.219065		6.59E-18		4.65E-21	
t Critical one-tail	2.345332		2.346787		2.346451	
P(T<=t) two-tail	0.43813		1.32E-17		9.29E-21	
t Critical two-tail	2.600882		2.60281		2.602374	

b Results from the Linear Programming

When using Linear Programming as the matching procedure for the P1 billets the results in terms of command utility are similar.

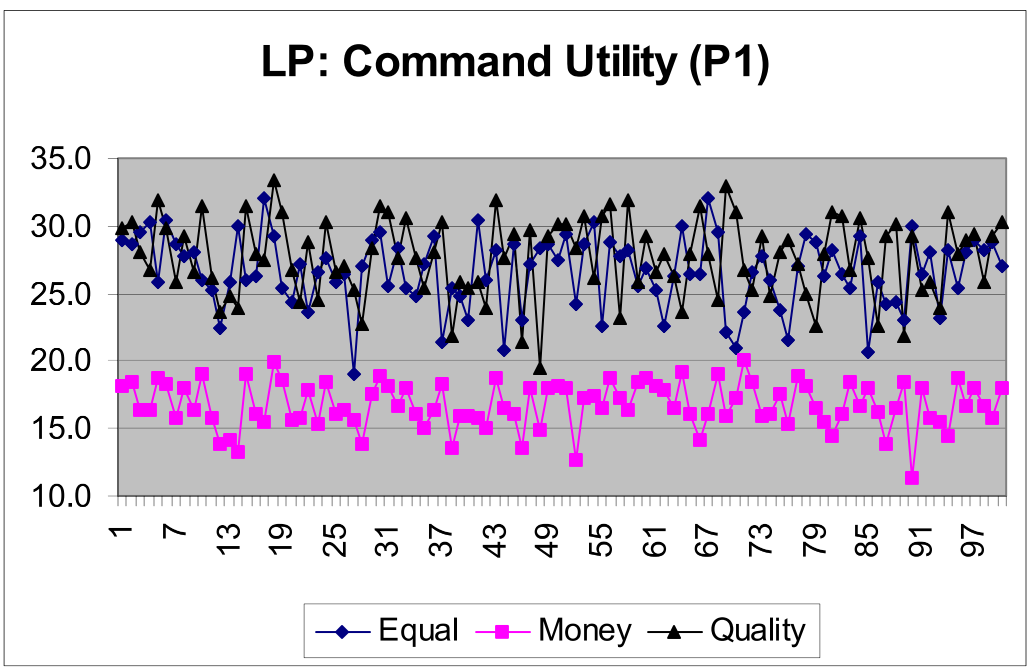

Figure 15. LP: Command Utility from Sailors matched to P1 Billets

"Quality" shows 4 % higher results on average than "equal" and the difference is statistically significant. The differences from "equal" to "money" (37.1 %) and "money" to "quality" (65.4 %) again have p-values close to zero.

Table 13. Two-Sample t-test on Means Assuming Unequal Variances for Command Utility of matched P1 Billets using Linear Programming

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	26.602	27.6768	26.602	16.728	16.728	27.6768
Variance	7.038784	8.381533	7.038784	2.918804	2.918804	8.381533
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	197		169		160	
t Stat	-2.73704		31.29076		-32.5702	
P(T<=t) one-tail	0.003383		1.62E-72		8.43E-73	
t Critical one-tail	2.345423		2.348615		2.34988	
P(T<=t) two-tail	0.006767		3.23E-72		1.69E-72	
t Critical two-tail	2.601009		2.605229		2.606903	

When using Linear Programming to match the remaining sailors to P2 and P3 billets, the differences between the scenarios appeared to be significantly smaller than the results from the Deferred Acceptance Algorithm, but the statistical significance of the differences of the means proved to be similar.

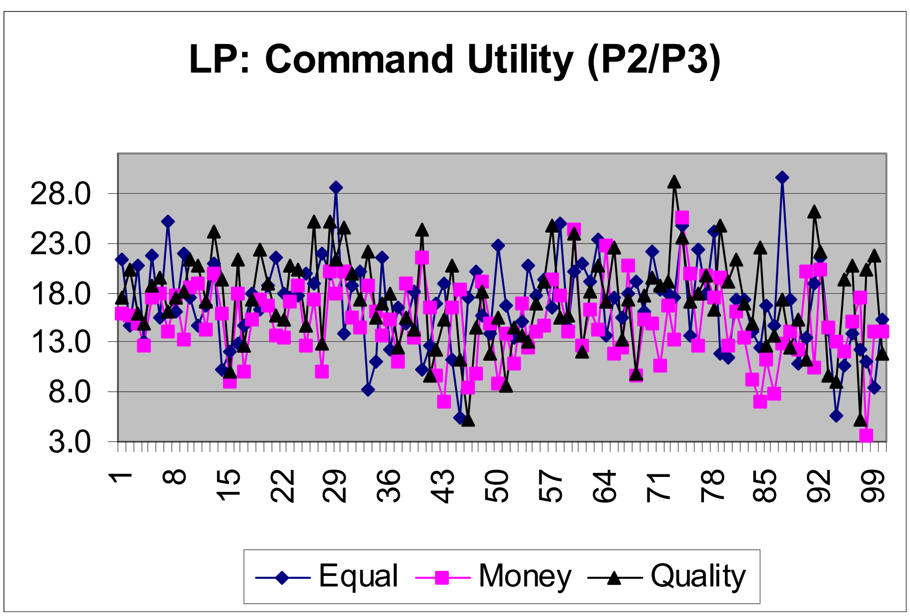

Figure 16. LP: Command Utility from Sailors matched to P2/P3 Billets

This time “quality” shows 2.9% higher results on average than “equal” and the difference is again not statistically significant. The differences from “equal” to “money” (11.1%) and “money” to “quality” (15.7%) have again p-values very close to zero but are less than half as big as with the Deferred Acceptance Algorithm.

Table 14. Two-Sample t-test on Means Assuming Unequal Variances for Command Utility of matched P2/P3 Billets using Linear Programming

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	16.862	17.3436	16.862	14.989	14.989	17.3436
Variance	20.43288	21.4728	20.43288	15.40402	15.40402	21.4728
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	198		194		193	
t Stat	-0.74396		3.128762		-3.8774	
P(T<=t) one-tail	0.228891		0.001013		7.23E-05	
t Critical one-tail	2.345332		2.345723		2.345823	
P(T<=t) two-tail	0.457782		0.002026		0.000145	
t Critical two-tail	2.600882		2.60141		2.601537	

2. Comparison of Average Percent Matches

In general, neither the deferred acceptance algorithm nor the linear program produced statistically significant different solutions in the three scenarios for preference list lengths of five. However, for the sake of completeness, the t-tests for the differences of the mean values with assumed unequal variances are given below.

a Results from the Deferred Acceptance Algorithm

The average percentage matches for the three scenarios “equal”, “money” and “quality” did not differ at any meaningful, significant level, as shown in Tables 15 and 16. This is true not only for the P1 but also for the P2/P3 billets.

Table 15. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P1 Billets using the Deferred Acceptance Algorithm

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	0.164238	0.164906	0.164238	0.165129	0.165129	0.164906
Variance	0.000408	0.000421	0.000408	0.000392	0.000392	0.000421
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	198		198		198	
t Stat	-0.23193		-0.31495		0.078208	
P(T<=t) one-tail	0.408415		0.376566		0.468871	
t Critical one-tail	2.345332		2.345332		2.345332	
P(T<=t) two-tail	0.81683		0.753132		0.937742	
t Critical two-tail	2.600882		2.600882		2.600882	

Table 16. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P2/P3 Billets using the Deferred Acceptance Algorithm

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	0.174472	0.176753	0.174472	0.175884	0.175884	0.176753
Variance	0.001817	0.00163	0.001817	0.001633	0.001633	0.00163
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	197		197		198	
t Stat	-0.38854		-0.24041		-0.15213	
P(T<=t) one-tail	0.34902		0.40513		0.439619	
t Critical one-tail	2.345423		2.345423		2.345332	
P(T<=t) two-tail	0.698039		0.810261		0.879238	
t Critical two-tail	2.601009		2.601009		2.600882	

b Results from the Linear Programming

The matching results using the linear program showed remarkably higher results, but did not differ significantly between the different scenarios as mentioned above. However, the differences did not yield as high p-values as did the DA results. The difference of the means between "money" and "quality" for the P1 billets showed significance almost at the 10%-level. The appropriate t-test results are given in Tables 17 and 18:

Table 17. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P1 Billets using Linear Programming

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	0.196448	0.19556	0.196448	0.197336	0.197336	0.19556
Variance	6.69E-05	0.000119	6.69E-05	0.000102	0.000102	0.000119
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	183		190		197	
t Stat	0.650444		-0.68256		1.192436	
P(T<=t) one-tail	0.258111		0.247859		0.117262	
t Critical one-tail	2.346897		2.346133		2.345423	
P(T<=t) two-tail	0.516221		0.495719		0.234525	
t Critical two-tail	2.602956		2.601955		2.601009	

Table 18. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P2/3 Billets using Linear Programming

Compare Means of	Equal and Quality		Equal and Money		Money and Quality	
Mean	0.418015	0.418437	0.418015	0.415763	0.415763	0.418437
Variance	0.005102	0.005338	0.005102	0.00502	0.00502	0.005338
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	198		198		198	
t Stat	-0.0413		0.22383		-0.26273	
P(T<=t) one-tail	0.483549		0.41156		0.396516	
t Critical one-tail	2.345332		2.345332		2.345332	
P(T<=t) two-tail	0.967099		0.823121		0.793032	
t Critical two-tail	2.600882		2.600882		2.600882	

3. Comparison of Unstable Matches

In the third performance measurement area, the behavior of the linear program with respect to the unstable matches or blocking pairs was of interest under the different scenarios. If the Navy uses this matching algorithm in the assignment process, this would be an important indicator for sailor and command satisfaction.

With a preference list length of five, the P1 billet simulation did not return a statistically significant difference between the three scenarios.

Table 19. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent of Unstable Matches of matched P1 Billets using Linear Programming

	Equal and Quality		Equal and Money		Quality and Money	
Mean	0.315694	0.319806	0.315694	0.319167	0.319167	0.319806
Variance	0.035396	0.040767	0.035396	0.031924	0.031924	0.040767
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	197		197		195	
t Stat	-0.14897		-0.13382		-0.0237	
P(T<=t) one-tail	0.440866		0.446839		0.490559	
t Critical one-tail	1.652625		1.652625		1.652706	
P(T<=t) two-tail	0.881733		0.893678		0.981119	
t Critical two-tail	1.97208		1.97208		1.972203	

On the other hand the P2/P3 billet simulation showed significant results at the 10%-level, indicating that the "quality" scenario will produce a 0.65 percentage points, or 44.5%, lower proportion of unstable matches compared with the "money" scenario. Figure 17 compares unstable matches for the P2/P3 billets.

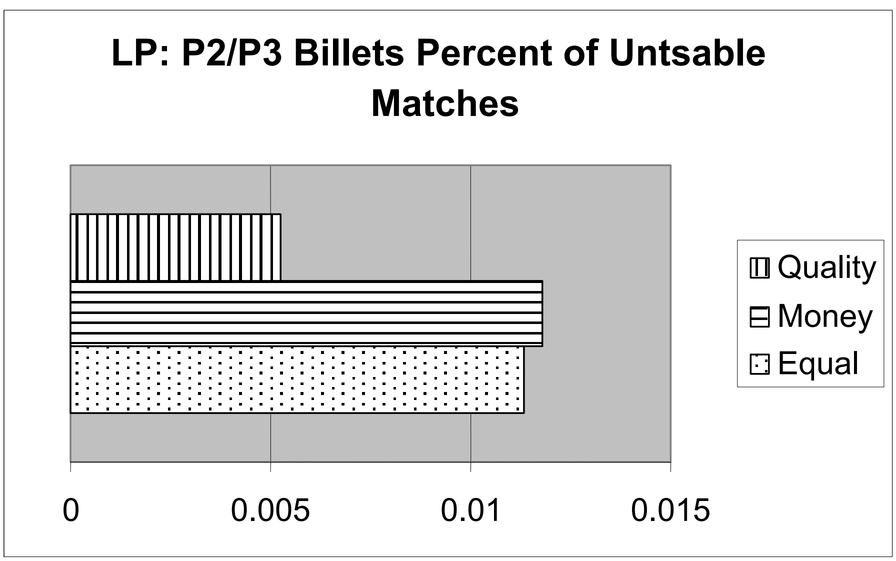

Figure 17. LP: Percent of unstable matches with P2/P3 Billets

The following section will provide evidence that this positive effect of the "quality" scenario is even bigger with doubled preference lists.

4. Results With Doubled Preference Lists

a Command Utility

Average command utility generally increased with the doubled preference list length. For P1 billets it accounted for a 20% improvement for the already best performing scenario, "quality"; with the P2/P3 billets using the linear program the average utility increased by 74.39% in the same scenario. All positive effects on the average command utility of using the double preference list length were significant at all levels.

Table 20. Two-Sample t-test on Means Assuming Unequal Variances for Average Command Utility of matched P1 Billets using the Deferred Acceptance Algorithm and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	15.256	18.575	25.4216	30.3836	18.575	30.3836
Variance	4.13158	0.39947	10.32032	2.008141	0.39947	2.008141
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	118		136		137	
t Stat	-15.5922		-14.132		-76.1036	
P(T<=t) one-tail	9.73E-31		9.1E-29		2.8E-114	
t Critical one-tail	2.358365		2.354082		2.353872	
P(T<=t) two-tail	1.95E-30		1.82E-28		5.7E-114	
t Critical two-tail	2.618144		2.612469		2.612196	

Table 21. Two-Sample t-test on Means Assuming Unequal Variances for Average Command Utility of matched P2/3 Billets using the Deferred Acceptance Algorithm and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	13.34	25.822	19.1056	32.5364	25.822	32.5364
Variance	11.21697	16.69729	18.56293	20.54358	16.69729	20.54358
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	191		197		196	
t Stat	-23.625		-21.4772		-11.0027	
P(T<=t) one-tail	6.93E-59		8.35E-54		1.55E-22	
t Critical one-tail	2.346032		2.345423		2.345523	
P(T<=t) two-tail	1.39E-58		1.67E-53		3.09E-22	
t Critical two-tail	2.60181		2.601009		2.601155	

Table 22. Two-Sample t-test on Means Assuming Unequal Variances for Average Command Utility of matched P1 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	16.728	18.005	27.6768	29.9348	18.005	29.9348
Variance	2.918804	0.483712	8.381533	2.112215	0.483712	2.112215
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	131		146		142	
t Stat	-6.92294		-6.97041		-74.0435	
P(T<=t) one-tail	8.91E-11		5.05E-11		1.2E-115	
t Critical one-tail	2.355155		2.352162		2.352899	
P(T<=t) two-tail	1.78E-10		1.01E-10		2.4E-115	
t Critical two-tail	2.613888		2.609922		2.610905	

Table 23. Two-Sample t-test on Means Assuming Unequal Variances for Average Command Utility of matched P2/3 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	14.989	29.003	17.3436	30.2444	29.003	30.2444
Variance	15.40402	19.80272	21.4728	20.74139	19.80272	20.74139
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	195		198		198	
t Stat	-23.6183		-19.8558		-1.94961	
P(T<=t) one-tail	2.09E-59		2.7E-49		0.026317	
t Critical one-tail	2.345623		2.345332		2.345332	
P(T<=t) two-tail	4.18E-59		5.39E-49		0.052635	
t Critical two-tail	2.601282		2.600882		2.600882	

b Average Percent Matches

The effect of the doubled preference list length is even stronger with respect to the average percent matches. For the P1 billets under the deferred acceptance algorithm, all scenarios are raised to a 100% match (20% of the sailors means 100% of the billets are filled) and with the linear program "quality" yields the same effect. The scenario "money" is very close with 99.45% matched.

Table 24. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P1 Billets using the Deferred Acceptance Algorithm and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10
Mean	0.165129	0.2	0.164906	0.2	
Variance	0.000392	1.84E-16	0.000421	1.84E-16	
Observations	100	100	100	100	No differences
Hypothesized Mean Difference	0		0		
df	99		99		
t Stat	-17.6141		-17.1016		
P(T<=t) one-tail	1.42E-32		1.29E-31		
t Critical one-tail	2.364604		2.364604		
P(T<=t) two-tail	2.83E-32		2.57E-31		
t Critical two-tail	2.626402		2.626402		

Table 25. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P1 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	0.197336	0.198888	0.19556	0.20111	0.198888	0.20111
Variance	0.000102	0.000423	0.000119	2.36E-05	0.000423	2.36E-05
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	144		137		110	
t Stat	-0.67731		-4.63915		-1.05173	
P(T<=t) one-tail	0.249647		4.04E-06		0.147613	
t Critical one-tail	2.352517		2.353872		2.360721	
P(T<=t) two-tail	0.499294		8.08E-06		0.295226	
t Critical two-tail	2.610395		2.612196		2.621273	

The average percent matched for the P2/P3 billets with the doubled preference list length also improves the most when using the deferred acceptance algorithm under the “quality“ scenario. The value increases by 37.42 percentage points (211%) and is then very close to the results provided by the linear program.

Table 26. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P2/3 Billets using the Deferred Acceptance Algorithm and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	0.175884	0.341043	0.176753	0.551109	0.341043	0.551109
Variance	0.001633	0.001775	0.00163	0.005468	0.001775	0.005468
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	198		153		157	
t Stat	-28.2913		-44.4348		-24.6831	
P(T<=t) one-tail	8.67E-72		1.18E-89		3.21E-56	
t Critical one-tail	2.345332		2.350971		2.350334	
P(T<=t) two-tail	1.73E-71		2.36E-89		6.41E-56	
t Critical two-tail	2.600882		2.60834		2.607503	

Table 27. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent Matches of matched P2/3 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
	B	*D*	*C*	*E*	*D*	*E*
Mean	0.415763	0.539895	0.418437	0.551109	0.539895	0.551109
Variance	0.00502	0.005993	0.005338	0.005468	0.005993	0.005468
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	196		198		198	
t Stat	-11.8281		-12.7627		-1.04748	
P(T<=t) one-tail	5.17E-25		6.49E-28		0.148077	
t Critical one-tail	2.345523		2.345332		2.345332	
P(T<=t) two-tail	1.03E-24		1.3E-27		0.296155	
t Critical two-tail	2.601155		2.600882		2.600882	

c Percent Unstable Matches

As previously mentioned the increase in preference list length increases the difference between the scenarios “money” and “quality” in terms of unstable matches for the P2/3 billets. In fact, the “quality“ scenario yields 0.8 percentage points fewer blocking pairs than the “money“ scenario. Additionally, for the P1 billets a statistically significantly lower number of blocking pairs occur with “quality”, a distinction that wasn’t observable earlier with the shorter preference list length.

Table 28. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent of Unstable Matches of matched P1 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	0.319167	0.285297	0.319806	0.246444	0.285297	0.246444
Variance	0.031924	0.03524	0.040767	0.033115	0.03524	0.033115
Observations	100	99	100	100	99	100
Hypothesized Mean Difference	0		0		0	
df	196		196		197	
t Stat	1.303436		2.698967		1.482215	
P(T<=t) one-tail	0.096978		0.003781		0.06994	
t Critical one-tail	1.652666		1.652666		1.652625	
P(T<=t) two-tail	0.193955		0.007563		0.139881	
t Critical two-tail	1.972139		1.972139		1.97208	

Table 29. Two-Sample t-test on Means Assuming Unequal Variances for Average Percent of Unstable Matches of matched P2/3 Billets using the Linear Program and doubled Preference List Lengths (PLL)

Compare Means of	Money PLL 5 and 10		Quality PLL 5 and 10		Money and Quality PLL 10	
Mean	0.011795	0.019926	0.005249	0.011901	0.019926	0.011901
Variance	0.001257	0.001892	0.000741	0.000963	0.001892	0.000963
Observations	100	100	100	100	100	100
Hypothesized Mean Difference	0		0		0	
df	190		195		179	
t Stat	-1.44894		-1.61144		1.502058	
P(T<=t) one-tail	0.074502		0.054351		0.067422	
t Critical one-tail	1.652913		1.652706		1.653411	
P(T<=t) two-tail	0.149004		0.108701		0.134844	
t Critical two-tail	1.97253		1.972203		1.973303	

C. COMPARISON WITH PAST RESULTS

All comparable results are generally consistent with earlier research. Linear programming as the matching mechanism introduces the disadvantage of blocking pairs but finds solutions with a higher percentage of matches and a higher average command utility for P1 billets. The significantly better performance of the DA for the P2/3 billets in terms of average utility found by Lo and How (2002) is reversed in the "money" scenario. This opposite trend is even more significant with doubled preference list lengths. Although it is hardly possible to predict a trend from two values only, the trade-off between preference list length and percent matches found in other research with the deferred acceptance algorithm is again visible.

With the generally similar results as in previous simulations it seems to be appropriate to infer the same earlier shown superiority (Robards, 2001) over the average human matched detailing for NEDSim as a simulation tool. The results from the sensitivity analysis should provide a good approximation for the real world assignment process.

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VII. CONCLUSIONS AND RECOMMENDATION

A. CONCLUSION

Independent from the matching procedure used, the results of the sensitivity analysis give strong evidence that a Navy that is mainly interested in saving money and reducing expenses for an Assignment Incentive Pay will yield much lower overall utility from the sailors matched to billets. A strong emphasis on minimizing AIP, costs prevents matches with higher qualified sailors and reduces the command utility the Navy receives from the matched sailors. On the other hand, a comparably low weight on the AIP cost factor enables matches with higher command utility than an equally weighted utility function. This is especially valid in the case of the P1 billets, where the pool of sailors is matched to a limited number of billets. The advantage of the "quality" scenario over the "money" scenario is smaller for the P2/P3, billets but still shows a remarkable 15.7% improvement in case of the LP results.

The higher performance in terms of average percent matches under the "quality" scenario, compared with the "money" scenario, is only obvious with a doubled preference list length. Here, "quality" accounted for a 61.6% increase in average percent matches (21 percentage points) under the deferred acceptance algorithm for P2/3 billets, which indicates a more than significant improvement of the assignment process.

When employing the linear program as a matching algorithm, the scenario "quality" produced significantly lower blocking pairs for P2/3 billets.

In general, the scenario "quality" outperforms the scenario "money" over all the chosen measures of performance; the AIP cost is the only downside. The command utility function included the monetary aspects of the AIP from the Navy's standpoint; the average command utility increased, indicating the more qualified sailors outweighed the AIP cost, given the utility function used here.

Consequently, from a simulation perspective, introducing AIP will lead me to predict a more successful matching process and a higher utility derived for the Navy.

This will be especially valid if the Navy emphasizes the quality of the matched sailors over the possible AIP expenses.

B. RECOMMENDATIONS

The primary recommendation from this research is to emphasize the quality and performance of a sailor and to pay AIP at a sufficient level to attract qualified sailors. In a closed bidding procedure, the matched sailor might be attracted by AIP but may not be the sailor with the highest overall utility to the Navy. Therefore the AIP caps need to be high enough to attract the right applicants.

Although the results of this study are significant and leave little room for misinterpretation, they are derived from the Enlisted Personnel assignment process in a simulation environment. As mentioned earlier, the current process does not use automated assignment procedures like linear programming or the deferred acceptance algorithm. However, if the internal decision process follows the same underlying preference factors the real world results might not be too different from the virtual environment of this simulation.

Another interesting aspect might be the psychological affect of a low or high command weight on the AIP portion as simulated by the "quality" and "money" scenarios. A sailor who expects that the Navy does not emphasize limiting the money it spends for AIP might be more likely to enter maximum bids in the AIP bidding process, and therefore increase the overall expenses for the incentive. On the other hand, a Navy that is very much interested in saving AIP money might discourage some sailors from bidding altogether. These effects could very well influence the real life results, but they are well beyond the capabilities of NEDSim, and therefore beyond the scope of this paper.

C. AREAS FOR FURTHER RESEARCH

As a further step to examine the effect of an assignment incentive pay on the overall utility of the Navy, a real world validation of the simulation results is certainly appropriate. The econometrician's model should have a sailor's productivity measure as the dependent variable and the level of the AIP as well as the sailor's perception of the appropriateness of the AIP level among the explanatory variables. Another approach could use retention rates as the dependent variable. This would be a much easier approach, but it also wouldn't be as close to the Navy's utility function as using sailor productivity.

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APPENDIX: ACRONYMS

AIP	Assignment Incentive Pay
BUPERS	Bureau of Personnel
CAN	Center For Naval Analyses
CCCs	Command Career Counselors
CINCLANTFLT	Combat Commander Atlantic
CINCPACFLT	Combat Commander Pacific
CINCUSNAVEUR	Commander in Chief U.S. Naval Forces Europe
CNO	Chief of Naval Operations
CNPC	Commander Navy Personnel Command
DIMS	Distributive Incentive Management System
DOD	Department of Defense
EAIS	Enlisted Assignment Information System
EB	Enlistment Bonus
EMF	Enlisted Master File
EPMAC	Enlisted Placement Management Center
EPRES	Enlisted Personnel Requisition system
Global CONOPS	Global Concept of Operations
JASS	Job Advertising and Selection System
MCA	Manning Control Authority
MPT	Manpower, Personnel and Training
NEC	Navy Enlisted Code
NMP	Navy Manning Plan

NPC	Navy Personnel Command
NPRST	Navy Personnel Research, Studies & Technology
OPNAV	Staff of Chief of Naval Operations
PCS	Permanent Change of Station
PRD	Projection Rotation Date
SRB	Selective Reenlistment Bonus
TFMMS	Total Force Manpower Management System
BMF	Billet Master File

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