AGENT-BASED MODELING AS A TOOL FOR MANPOWER AND PERSONNEL MANAGEMENT

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ABSTRACT

This paper describes the development of a generalized agent-based simulation tool for studying manpower and personnel management behaviors. The subject matter of the simulation are complex organizational behaviors found within United States Navy Manpower and Personnel processes. Behavior of such a complex system is typically associated with a hierarchical structure in which the lowest level agents are characterized by continuous and discrete event-variable dynamics and the highest level agents by heuristically based decision-making mechanisms. The system dynamics approach is used to develop a model that describes the dynamics of a sailor's behavior while he or she is a member of the US Navy. This system dynamics based model constitutes a basic "microscopic" element of an agent-based model of the US Navy's Manpower and Personnel (M&P) systems. Agent-based techniques are used to handle heterogeneity in behaviors and domain descriptions associated with shipboard processes. The results of our work provide strong support for the importance of agent-based modeling approach as a key tool for analyzing M&P systems and policy design.

Keywords:
Complex Adaptive Systems, Agent-Based Modeling and Simulation, Nonlinear Behavioral System Dynamics, Fuzzy Logic Decision-Making.

1 INTRODUCTION

This paper describes the development of a generalized agent-based simulation tool called the Integrated Manpower & Personnel Agent-based Computer Tool (IMPACT). By Manpower & Personnel we mean the collection of processes designed to manage personnel in the Navy. On a large scale, these include the determination of manpower requirements, the budget allocation for fulfilling these requirements (manpower programming), the provision of people to fulfill the requirements (personnel planning), and the distribution of the available personnel. The M&P process is typically perceived at an aggregate level, representing the aggregate flow of people within the personnel planning stage. During personnel planning people are recruited, trained, and 'managed' in communities. These communities serve as a pool of servicemen for fulfilling actual billets in the process of personnel distribution (Trifonov et al., 2005).

Traditional modeling and simulation methods of such systems offer views of macro level behaviors (e.g. modeling that involves general aspects of a system like the average behaviors), which results in losing some detailed aspects of the system (Wild et al., 2003). Even if the effect of single policies on an individual was understood, being able to understand their

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compounding affect on the crew, battle group, or Navy has been left to qualitative measures that leave no room for quantitative prediction much less the ability to react to new processes, technology or changes in personnel assignment. The ability to examine the changes in ships' personnel over time is crucial to designing new ships with new capabilities. Furthermore, understanding the effects of planned military operations on the sailors' community as a whole is crucial to performing shipboard manpower and personnel planning optimally in the long run.

Behavior of such a complex system is typically associated with a hierarchical structure in which the lowest level agents are characterized by continuous and discrete event-variable dynamics and the highest level agents by a logical decision-making mechanisms. The interaction of these different levels, with their different types of information, leads to the representation of system behavioral dynamics by combined discrete/continuous modeling and simulation methodology that supports a *multi-formalism* modeling approach on one hand and its dynamic simulation by Agent-Based techniques on the other hand (Axelrod, 1997), (Bonabeau, 2002), (Epstein & Axtell, 1996).

In addition, the proposed agent-based simulation enables modular model construction giving us the capability to easily extend the model under study. For example, IMPACT is easily adapted for a stochastic simulation optimization procedure which can be thought of as finding a combination of input parameters (e.g. components of different MPT&E policies) that gives the optimal expected response of some objective function that is evaluated by simulation of the Manpower & Personnel agent-based model. The multi-agent based model allows us to study dynamic effects of different detailing policies and different crew assignment strategies, and many other organizational strategies and their positive/negative consequences on an individual sailor's performance, decision-making, motivation etc.. For example, IMPACT allows us to study how optimal crew assignment (i.e., the one that tries to optimize skill set match between sailors and billet requirements) may decrease the negative consequence of boredom and lead to the improvement of a sailor's performance. Integration of a model that describes a sailor's desire to reenlist or separate from the NAVY using a multi-attributes fuzzy logic modeling technique is another example of IMPACT's modularity.

The paper is organized as follows. Section 2, following this introduction, describes the basic properties and structure of MPT&E processes. An agent-based model dynamics and simulation framework for such a system is presented in Section 3, while Section 4 illustrates the results of simulations; Conclusions close the paper.

2 IMPACT: AGENT-BASED MODEL

2.1 Methodology Overview

The purpose of IMPACT is to help with the analysis of the effects of high-level policies on individual sailors and their decision making when it comes to reenlistment. This requires the modeling of macro level processes like recruitment, training, and community management as well as the micro level process of sailors' decision making. Even though such a system can be modeled to a certain extent by following the system dynamics (SD) method alone, it becomes increasingly difficult to solve the problem of heterogeneity when multiple descriptive attributes of sailors influence the dynamics of the system.

The real obstacle to using only system dynamics for the purposes of this model is the existence of implicit feedbacks between the heterogeneous types of sailors in the system. Using SD to model the dynamics of one type of sailor and extrapolating that for other parameterized types is reasonable until we encounter direct dependencies between them. Section 2.3.7 on the Activity Agent is a good description of how that occurs in our specific case, while (Trifonov et al., 2003) provides a detailed discussion of this issue in a more general setting.

On the other hand, the SD approach has significant advantages when it comes to modeling processes that involve soft variables like stress, motivation, and fatigue, which are a central part to the sailor agent representation. It allows us to naturally model the qualitative patterns of dependency between these variables and conveniently link them to exogenous quantitative signals from the external MPT&E process like the current level of workload, time available for sleep, etc.

These two main considerations lead us to use a hybrid approach where the overall simulation is driven by an agent based model, while each individual sailor contains a SD model of some of its states. This allows us to represent the heterogeneity of sailors and the interactions between different types naturally, while at the same time provides for a good representation of intrinsic dynamic states of separate agents. Later sections discuss the details of how the hybrid model operates.

2.2 Model Overview

The IMPACT simulation tool is intended to provide insight into the effects of high-level MPT&E policies on the NAVY's ability to procure "the right kind of sailor to the right place, at the right time". It not only focuses on the population dynamics of sailors as whole, but also on the impact of these policies on the daily life of individual sailors and how these effects in turn feed back to the dynamics of the system. To achieve that, IMPACT includes representations of macro-level actors in the MPT&E system as well as an explicit representation for multiple individual sailors. The model includes agents that represent every major branch of the Navy manpower and personnel system, it takes sailor agents through all phases in the life cycle of enlisted sailors, and allows for natural interactions and information flow to take place between them. Figure 1 illustrates the main components of the MPT&E system that are included in our model.

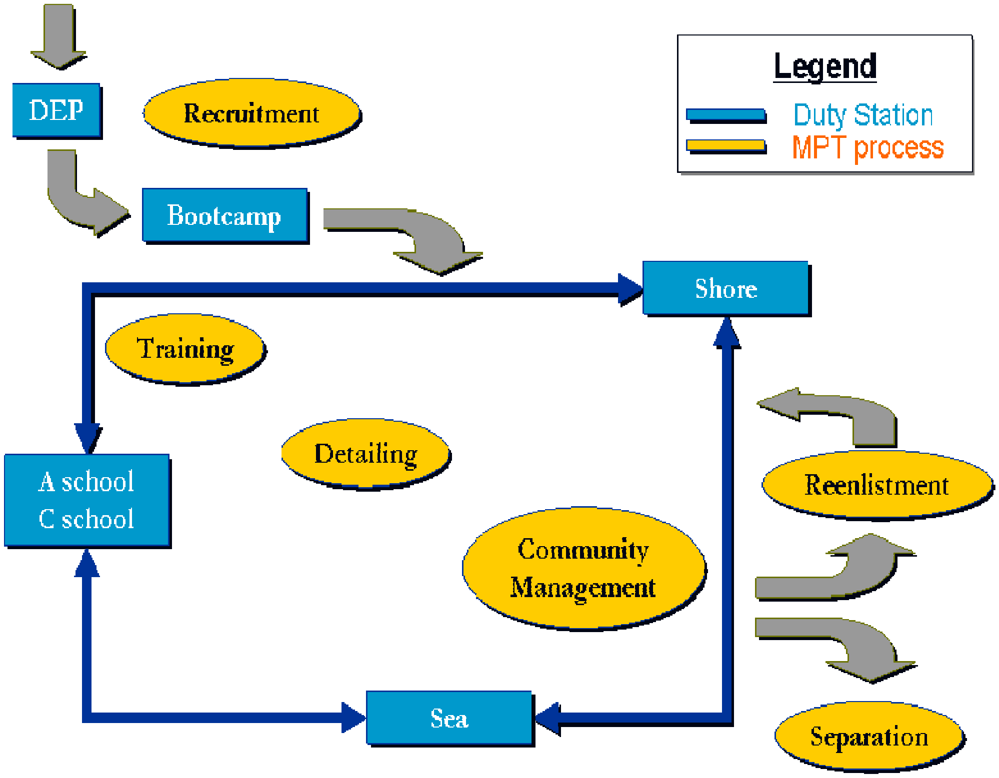


Figure 1: MPT&E components in IMPACT

Rectangles represent different types of duty that a sailor may find themselves on. They describe the states that a sailor may be in relative to the MPT&E ecosystem. The ovals, on the other hand illustrate the different processes that govern the flow of sailors between different duty types.

Sailors enter the system via the recruiting process. A portion of new recruits go through the Delayed Entry Program (DEP) prior to active duty, while the remainder enter active duty and go directly to boot camp. All sailors are given an intended future rating based on a demand signal that is received in the form of an accession plan from the different communities. This mechanism represents the way communities exert relative pressures to the recruitment command for filling their respective needs. Sailors who finish boot camp enter a loop between three different duty types as shown on the figure. From that moment on until they leave the system sailors are either on shore duty, on sea duty, or in training. Depending on A-school seat availability sailors who complete boot camp may go straight to A-school before they go on to sea or shore duty. Sailors who do not enter additional training immediately after boot camp enter the sea-shore rotation as general details (GENDET) until they get a chance to go to A-school to get their designation. Within the simulation, A and C-school class schedules are generated by a training agent, which captures the training process.

The training agent periodically schedules classes with limited availability for both A and C school. Once sailors enter the rotation loop, a detailing process is responsible for choosing the next duty station a sailor will go to. Sailors contact the detailer agent when they enter a detailing window relative to their projected rotation date.

The detailer agent in turn looks at all available requisitions in the system and chooses the most appropriate one for the sailor based on skill match, NEC reutilization, take up month / arrival gap, and activity manning levels. All requisitions in IMPACT are based on the number of total billets authorized. Sea requisitions are based on the vacant billets for the different ships at the time of the detailing request. Each ship generates new requisitions periodically by comparing the current sailors on board, the expected gains over the next period, the expected losses over the next period, and the total number of billets authorized. IMPACT assumes that shore requisitions are unlimited and there is always a shore billet that a sailor can be assigned to. Sea billets on the other hand are per ship, and are defined in the ship manning document (SMD) for each ship. Every billet is described by the required rating, pay grade, and NECs. Billets are organized in departments and divisions. In addition to billets, the SMD specifies all operational watch stations and the departmental workload broken down per division and skill set. Throughout the entire lifecycle of designated sailors they are subject to community management policies. IMPACT's representation of the community management process includes advancement, reenlistment, retirement, and accession planning. Advancements are performed periodically by holding examinations and looking at all components that the Navy uses. The reenlistment process occurs at the end of every enlistment period for each sailor. Communities manage that process by setting SRB (selective reenlistment bonus) levels, HYT (high year tenure) ceilings, CREO (community reenlistment objectives) levels, utilizing a PTS (Perform to Serve) program, and considering recommendations for reenlistment. IMPACT represents all of these details. From a sailor's perspective the decision of whether to reenlist or not is subject to a probability to quit, which is affected by six different factors. Sailors take into account the stress and motivation levels that they experience during sea and shore rotations; their proximity to retirement; their proximity to the HYT ceiling; the SRB level; and the advancement opportunity. All of these factors interact to formulate a final likelihood that the sailor will choose to reenlist for one more term. Even then, they are subject to the community management policies, which may or may not allow the reenlistment to occur. Finally, sailors eventually leave the system through the separation process. A separation event may occur for several different reasons. A sailor may simply choose not to reenlist, in which case they leave the system at EAOS (end of active obligated service). In another occasion, a sailor who otherwise desires to reenlist may not be eligible for retention due to low recommendation marks, or due to lack of vacancies in their community and in the communities in which they have applied for conversion to. Finally, sailors may eventually reach retirement age and leave the system that way.

2.3 The Generic Model Agents

Generalizing from the process description above, each of the components specifying the MPT&E system will be thought as a single agent dynamically interacting with the other ones following prescribed relationships (e.g Sailor Agent, Enlisted Master File Agent, Recruitment Command Agent, Training Command Agent, Community Management Agent, Manning Control Agent, Ship Agent, Assignment Control Agent, etc.). The system agents are represented as hybrid systems that involve both continuous valued and discrete variables. In general, analyzing such complex dynamics is difficult from an analytical point of view as solutions might not exist in closed form. Because of these features, we investigate its dynamics by means of an agent-based approach. That is, within an individual agent, behavioral decisions may be done by evaluation of their dynamics described by general hybrid dynamic models (GHDS). However, the system level behavior is then determined by running dynamics describing the interactions among agents. The integration of GHDS approaches to describe the dynamics of individual agents together with agent-based simulation gives us a mean to study dynamics evolution of large scale interconnected systems in a natural way. We now take a closer look at the structure of agents and agent-based simulation of MPT&E processes.

2.3.1 The Sailor Agent as a General Hybrid Dynamic System Automaton Model

The sailor agent captures the properties and the rules of behavior of a Navy sailor. Sailor agents can be either on the ship at sea, or on shore. They are brought in the system through the recruitment strategy of the on-shore pool agent and can leave the system either by retiring or by declining to reenlist. The defining characteristics of the sailor agent are its rating and pay grade. Higher pay grades mean higher experience for a sailor, while the rating refers to the particular profession (skill set) for which the sailor specializes. Ratings determine the billets to which sailors can be assigned while at sea and therefore determine the watch stations and divisions they work in. The rating and the pay grade can be adjusted through training, which is determined by the training command agent.

The key component of the sailor agent is a new dynamic model of an individual sailor's behavior during his enlistment with the Navy. The model illustrates how psychological factors such as stress and motivation, which are caused by a combination of influences of different US Navy's Manpower, Personnel and Training (MPT) policies (and different levels of required readiness), impact a sailor's performance and his decision to continue to enlist or to leave the Navy. Because of our interest in the dynamics of a sailor's behavior, we examine *performance* as a function of time on task. While on the ship, each sailor agent is assigned to a particular billet and serves on a set of watch stations. This determines the amount of departmental work (number of tasks) that that sailor is able to perform, apart from the required watch standing. We argue here that the task's execution depends on the sailor's skill level, cognitive and emotional factors (e.g. stress, motivation and vigilance) and that our model captures this dynamics.

The individual sailor behavioral model is formulated as a Generalized Hybrid Dynamical System – the system formalism for combined discrete/continuous modeling (Brocket, 1993). This formalism is a combination of two analytical approaches: 1) the discrete event automaton describing discrete phenomena corresponding to discrete states and dynamics such as the dynamics associated with a sailor's rating and pay grade transitions; and, 2) the differential equations system describing the individual sailor behavioral model which is formulated as a set of first order coupled differential equations where causal relationships between behavioral and cognitive variables is modeled in a form of simple linear and nonlinear dependencies. In simulation, the two parts alternate in model execution. While the discrete part executes the state transition at the event times, the continuous part computes the state trajectories in between. The events define discrete changes of the continuous input values. We transform the event segments to piecewise constant segments to accomplishes this. For example, for the sailor agent dynamics the most frequent event transitions (e.g. workload change) occur every seven days while the continuous part describing a sailor behavioral response to such an event (i.e. a piecewise constant segment) computes state trajectories for each day during a week of deployment.

The GHDS framework provides a means to specify the system agent, using mathematical formalism defined for a hybrid automaton model (Brocket, 1993). A hybrid automaton is a system (Brocket, 1993)

$$H = (Q, \Re^n, \Sigma, \Pi, E, \Phi, \Gamma) \tag{1}$$

Q is the finite set of discrete states (e.g. rating with an associated pay grade and NECs: $Q = \{q_{SN}^{E1}, q_{SN}^{E2}, q_{SN}^{E3}, q_{SNBM}^{E1}, q_{SNBM}^{E2}, q_{SNBM}^{E3}, q_{BM}^{E4}, ...\}$ with time based switching points $t_{SN}^{E1}, t_{SN}^{E2}, t_{SN}^{E3}, t_{SNBM}^{E1}, t_{SNBM}^{E2}, t_{SNBM}^{E3}, t_{BM}^{E4}, t_{BM}^{E5}, t_{BM}^{E6}, ...$ indicating the time at which a particular paygarde or rating transition occurs assuming that all necessary requirements for such a transition are met (e.g. years of service and/or required training)), $\Re^n$ is the set of continuous states, and Π is the finite set of discrete events. The finite set of edges, $E \subset Q \times 2^{\Re^n} \times \Pi \times \{\Re^n \to \Re^n\} \times Q$, models the discrete event dynamics of the system. An edge $E \ni e = (q_e, X_e, V_e, r_e, q_e^{'})$ is enabled when the discrete state is in q_e (e.g. a new sailor recruit has a paygrade E1 and rating Seaman-SN q_{SN}^{E1}) and continuous state is in X_e (e.g. current level of stress, motivation, and fatigue). When the transition is taken, the event $V_e \in \Pi$ is accepted, the continuous state is reset according to map r_e. This mapping can simply restart the continuous state from a new set of initial conditions (e.g. the last values of such states at the final time while in q_e stat). Then the system enters discrete state $q_e^{'}$ (e.g. q_{SN}^{E2}). In this representation of discrete event automaton we account not only for the order in which events occur but also for event occurrence times which leads us to a timed discrete event system model. In addition, at any given time state ***q***, the occurrence of an event at a given state can lead to several possible next states. In our model we can select one of these next states according to some perspective set of rules (e.g. checking and planning available spaces in different training schools, requirements for a specific rating skill sets, force shaping requirements, and many other functionalities and rule sets associated with detailing and force shaping policies etc.). We also employ a discrete event controller to model a situation in which sailors can be abruptly "redirected" in their process of skill set – rating build up due to new NAVY strategy initiatives (e.g. force shaping). A discrete event controller for DES is an external discrete event control that disables some events and enables the others.

By modeling a sailor's paygrade and rating/NEC transition dynamics as a discrete event system, an optimal trajectory (e.g. optimal career path that leads to highest paygarde while satisfying sailor's skill set preferences in shortest time) can be derived. The optimal trajectory (or an optimal policy) is the 'best' trajectory (policy) to be followed in order to direct the sailor to go to the final state q_f , that is the state representing the highest paygrade and skill set of choice in during his/her enlistment period.

Finally, $\mathbf{\Sigma} = \{\Sigma_q\}_{q \in Q}$ is the collection of constituent dynamical systems where each $\Sigma_q = \lfloor X_q, \Gamma_q, U_q, \Phi_q \rfloor$ is a dynamical system with inputs describing a sailor's behavior corresponding to a particular discrete state ***q***. Here, the $X_q \subset \Re^n$ are the continuous state spaces and Φ_q are called the continuous dynamics, Γ_q transition system. Continuous- and discrete-time transition system denote the cases where $\Gamma_q = \Re$ (or $\Re_+$) and $\Gamma_q = \mathrm{Z}$ (or $\mathbf{Z}_+$) respectively[1]. $U_q \subset \Re^m$ is the set of piecewise

[1] The symbols **R**, **R+**, **Z**, and **Z+** denote the reals, nonnegative reals, integers, and nonnegative integers, respectively.

constant inputs $u \in U_q$ (e.g. workload assignment per week, motivation stimulus, available sleep time – these inputs will be described in detail shortly). The continuous state evolves according to the differential inclusion $\dot{X}_q(t) \in F_q(\mathbf{q}(t), X_q(t), U_q(t))$, defined shortly in Equations (2)-(5).

In simulation, the two parts alternate in model execution. While the discrete part executes the state transition at the event times, the continuous part computes the state trajectories in between. The events define discrete changes of the continuous input values. We transform the event segments to piecewise constant segments to accomplishes this. For example, for a sailor agent dynamics the most frequent event transitions (e.g. workload change) occur every seven days while the continuous part describing a sailor behavioral response to such an event (i.e. a piecewise constant segment) computes state trajectories for each day during a week of deployment.

The equations governing the time rate change of these basic determinants of the behavior of i[th] sailor with a specific paygrade and rating defined by discrete event state $\boldsymbol{q}$ has the general form of first order nonlinear time-varying differential equations:

$$\dot{x}_i^s(t) = -\gamma_i^s(t)x_i^s(t) + a_i^s(t)x_i^m(t) - b_i^s(t)x_i^s(t)x_i^m(t) + c_i^s(t)x_i^f(t) + \\ + \delta_i^s u_i^{wl} + \sum_{\substack{j \\ i \neq j}}^{N_K \subseteq N} T_{ij}\, g(x_j^s) \tag{2}$$

$$\dot{x}_i^m(t) = \gamma_i^m(t)x_i^m(t) - a_i^m(t)x_i^s(t)x_i^m(t) + \delta_i^a U_i^{perf}(t) + \mu_i^m u_i^{mf} \tag{3}$$

$$\dot{x}_i^f(t) = -\gamma_i^f(t)x_i^f(t) + \delta_i^f u_i^{sf} \tag{4}$$

$$U_i^{perf} = (x_i^s)^p (x_i^m)^q (x_i^a)^r \tag{5}$$

$$\dot{x}_i^{co}(t) = \gamma_i^{co}(t)(U_i^{perf}(t) - x_i^{co}(t)) \tag{6}$$

where continuous states of the sailor behavioral model are: x_i^s is the i[th] sailor stress level (a cognitive state) , x_i^m describes the i[th] sailor state of being motivated and x_i^f is the i[th] sailor "fatigue" state which is caused by job demands and the attention to goals. x_i^{co} is the Commanding Officer's (CO) estimate of the ith sailor performance during his enlistment which is used by the CO to produce recommendations for the ith sailor promotion/demotion.

The inputs to the continuous dynamic model described by Equations (2) to (6), are defined as follows: The i[th] sailor workload factor u_i^{wl} describes the expected workload per unit of time (e.i. per week). This determines the amount of departmental work that a sailor is able to perform, apart from the required watch standing while serving on the ship. The i[th] sailor motivation factor u_i^{mf} represents the effect the current state of a sailor's career has on his/her motivation. The motivation factor is a function of the difference of a sailor's actual paygrade and their expected paygrade. The expected paygrade of a sailor is determined by the minimum time-in-rate requirements for advancement. The ith sailor fatigue factor u_i^{sf} describes the ith sailor available time for sleep per week during different mission types. That is, as less time is available for sleep due to increase workload the sleep factor is closer to its maximum value of 1 which adversely affects a sailor's fatigue level.

It is important to note that these inputs are determined based on the definition of a ship and an initial pool of available sailors, as well as a list of sailor types that could exist, which in turn are a direct consequence of the applied MPT&E polices (e.g. recruitment, training and retention, assignment and distribution of personnel). It is through these inputs that our sailor model directly interacts with the other agents in the system. During the simulation we account for situations when not all billets are necessarily filled by sailors. This increases the expected work per manned billets, because the division is still responsible for the same amount of work. When a sailor does not have enough available time to complete all the expected work, he/she has less time for sleep which increases her/his fatigue over time. Increase in the level of workload and correspondingly in a sailor's fatigue level causes stress to build up, in turn stress and performance influence motivation, Equations (2) and (3) .

Stress (x_i^s) can be defined as a state of tension that is created when a person responds to the demands and pressures that come from work, family and other external sources, as well as those that are internally generated from self imposed demands, obligations and self-criticism. The state variable describing the stress level for an individual sailor is designated as x_i^s, whose time rate of change is given by Equation (2). $\gamma_i^s(t)$ is the time-varying coefficient that describes the i[th] sailor ability to cope with stress generated during his or her enlistment period. In addition to effects on the individual, stress has also been shown to negatively impact group functioning. When stressed, an individual's communication effectiveness may likely be reduced (Driskell, Carson, and Moskal, 1988). To capture the group affect on individual sailor stress we include the following term $\sum_{j,i\neq j}^{N_K \subseteq N} T_{ij}\, g(x_j^s)$ which represents the impact on the i[th] sailor stress level "received " from sailors within a team of sailors ($N_K \subseteq N$) with whom the i[th] sailor's interacts, which is described by the nonlinear function $g(x_j^s)$ which depends on a state of stress of the jth sailor, x_j^s. We also assume that an individual's stress is positively affected by an individual's motivation, for example, a sailor who is achieving his or her career goals of progressing through the enlisted ranks. We express this phenomena by adding the negative feedback term $b_i^s(t)x_i^m(t)x_i^s(t)$ in Equation (1). Stress builds up in response to work environment pressure (e.g. increase in fatigue level and workload) which is described by addition of the positive feedback element $c_i^s(t)x_i^f(t)$ and $\delta_i^s u_i^{wl}$, respectively Equation (1) and is relieved in the absence of the work environment pressure.

Motivation: Motivation is an internal state or condition that serves to activate or energize goal-oriented behavior and give it direction (Revelle,1993). The state variable describing the motivation level for an individual sailor is designated as x_i^m x_i^s, whose time rate of change is given by Equation (2). $\gamma_i^m(t)$ is the time-varying coefficient that describes the i[th] sailor's self motivation to reach predetermined stages of his or her career goals before his Projected Rotation Date (PRD). Equation (2) also indicates that motivation is affected by high level of job demands, $a_i^m x_i^s x_i^m$. Motivation builds up in response to increase in the level of individual performance measure $\delta_i^a U_i^{perf}$ and is affected by the current state of a sailor's career described by addition of the positive feedback element $\delta_i^m u_i^{ml}$, Equation (2).

Fatigue: Human fatigue generation depends upon the complex interplay of several distinct factors. These factors include sleep quality and quantity, circadian, environmental stressors (these include: thermal environment, mechanical environment, auditory environment, visual environment, toxic environment, combat environment), health, etc. Their effects on fatigue are often interacting and complex. In this research we model individual sailor fatigue dynamics very simplistically. The i[th] sailor's fatigue dynamics is described as a first order differential equation with the input, Equation (5), where $\gamma_i^f(t)$ is the time varying coefficient that describes the i[th] sailor's ability to cope with different levels of fatigue during his or her enlistment period (e.g. cumulative measure of sleep quality and quantity, circadian and environmental stressors). Fatigue builds up in response to work environment pressure (e.g. decrees in available time for sleep) which is described by addition of the term $\delta_i^f u_i^{sf}$ through which the piecewise continuous input – sleep factor u_i^{sf} - affects the i[th] sailor's fatigue state.

When fatigue builds up as the sailor works for long periods under extreme stress– during which time, sleep deprivation is an absolute given–fatigue adversely affect a sailor's contribution to his/her mission performance.

Performance: Performance is *focused behavior* or *purposeful work* (Rudman, 1998, p. 205). In our model, U_i^{perf} denotes the individual sailor performance which is dependent on the work context (Mitchell, 1997; Siders, 1997). This implies that the model must therefore include a simulated work environment of the United States Navy Manpower & Personnel (M&P) systems. For our purposes it is sufficient to model a Navy battlegroup that consists of a number of heterogeneous NAVY platforms and their interaction with the available supply of sailors through the MPT process as outlined in details in Section 2. Following the performance formulation presented in (Revelle, 1993) we define the explicit form of the direct measure of individual performance, Equation (4), to be dependent on cognitive and emotional factors (e.g. stress, motivation and fatigue). Also, an individual's performance influences dynamics of the individual sailor's cognitive and emotional factors. The model captures the *Yerkes-Dodson law* (Yerkes & Dodson, 1980) which predicts an inverted U-shaped function between stress and performance. Either, too little stress or too much stress has a negative affect on the sailor (Zoethout et al., 2006).

2.3.1.1 Analysis of the Model: Stability Analysis

The model, given by Equations (2)-(5), postulate certain basic behavioral actions on the part of the actors, namely, the individual sailors and the MPT authority. What is important in this description is that a particular sailor's overall performance during his time on the sea may become significantly altered if the strength of any one of these factors becomes great enough (exceeds the critical threshold). In this case, the system may become unstable to the "stimulus" being imposed, for example, the critically undermanned ship increases the expected work per manned billets causing the stress to build up and leading to extended exposure to stress which eventually results in performance degradation. It is therefore, important to know the range of values for which the sailor dynamic behavioral model is stable, and from the point of view of the decision maker, it is important to know the range of values of the parameters at which the system is most sensitive to change, so that a timely policy initiative may be made to effect a desired change and also to be aware when an unwanted change may be likely to occur. In other words, for which values of the parameters of the system should the decision maker be alerted to a likely significant change of system performance and in what direction is this change going to occur? Also, what "perturbation" must be imposed upon the system to affect its performance in a desired way? The proposed mathematical formalism for modeling MPT&E system allows us to address the above mentioned issues by applying mathematical stability analysis for such a hybrid interconnected time-varying dynamics system (Garagic et al., 2006).

2.3.1.2 Modeling A Sailor's Separation decision process using Fuzzy Logic

The model outlined in the preceding sections captures the dynamics of sailor recruitment, training and retention, as well as their performance during missions as influenced by cognitive and emotional factors. From a sailor's perspective the decision of whether to reenlist or not is subject to a probability to quit, which depends upon the complex interplay of several distinct factors. These factors include a sailor's stress and motivation levels that he experiences during sea and shore rotations; his proximity to retirement; his proximity to the HYT ceiling; the SRB level; and the advancement opportunity. One way to capture uncertainties of this decision process, which are associated with complex interactions between the above mentioned factors, is to employ Fuzzy Logic Control methodology (Zadeh, 1965) to formulate a final likelihood that the sailor will choose to reenlist for one more term. Then, this fuzzy logic based decision module is integrated within the agent-based simulation formalism and is dynamically invoked during the simulation each time a sailor is at the end of his enlistment period (Garagic, et al. 2006). Analogously to the design of fuzzy controllers (Passion and Yurkovich, 1998), we divide this process into three processes: fuzzification, inference, and defuzzification. Before we proceed further in defining the fuzzy decision controller in terms of the above-mentioned processes, we introduce first the necessary notations. Let X_i be a set of the universe of discourses associated with the six factors that influence the ith sailor decision space. Let Z_i be the universe of discourse associated with the ith sailor decision space (e.g . ith sailor preference to reenlist). For convenience of notation we omit the use of index i indicating the i[th] sailor and we make a note that the fuzzy decision controller is imbedded in the model of every individual sailor. In a fuzzy system, any input and output variable with range *X* and *Z* is represented by a set of linguistic terms *L*(*X*) and *L*(*Z*) (e.g. large, medium, and small). Let F and G be fuzzy convex mappings representing a process of fuzzification and inference, while D denotes a continuous mapping (defuzzification) that produces a crisp numerical value from a fuzzy set, a cardinal measure of the ith sailor decision to reenlist, Equation (6). First, we define the mappings F,G, and D. The fuzzification process is used to characterize the imprecision or uncertainty in which capacity each of the six factors affect the sailor's decision to reenlist. In order to characterize any measurement over *X* symbolically, let *L*(*X*) be a set of linguistic terms. For example, the set *Ls* (*X*)={small, medium, large} could be used to represent the symbolic values of the ith sailor stress level. The meaning over *X* of a symbol *L* (*X*) is characterized, for all factors that belong to asset *X* by its membership function, denoted $\mu_{T(X,L)}(X_S \in X), s=1,..6$, where the mapping *T*(*X*, *L*) associates any value of the universe of discourse of $X_S \in X, s=1,..6$ with its symbolic value $L_S(X_s)$. The fuzzy meanings of small, medium, large, etc. are represented by the membership functions $A_l^s, l=1,2,...M$ for each of the six factors $X_S \in X, s=1,..6$ and $B_k^{'}, k=1,2,...K$. The subscripts *l* and *k* represent the numbers of membership functions used to cover the universe of discourse of the *s*[th] factor that influence the decision to reenlist of the i[th] sailor and the universe of discourse associated with the i[th] sailor decision space, respectively. For example, the set of symbols for the first (*s=1*) factor (e.g. i[th] sailor stress level) of the i[th] sailor is $A_l^1 = \{\text{small,medium,large}\}, l=1,2,3$. A fuzzy controller scheme is given by the commuting diagram of Equation (6),

$$\begin{array}{ccc} x \in X & \xrightarrow{g} & z \in Z \\ F \downarrow & & \uparrow D \\ \left[\mu_{A1}(x),......,\mu_{A_M}(x)\right] \in [0,1]^M & \xrightarrow{G} & \left[\mu_{B_1^{'}}(z),......,\mu_{B_M^{'}}(z)\right] \in \aleph^M \end{array} \qquad (7)$$

Fuzzy inference map depends on the representation of the set of rules, called rule base. It is a finite set of linguistic statements that allows us to incorporate heuristic knowledge of a possible intent of a sailor. Here, the fuzzy controller has M rules of the form

$$\text{RULE}_i : \text{ IF } x_i^1 \text{ is } A_j^1 \text{ AND ....AND } x_i^6 \text{ is } A_j^6 \text{ THEN } z \text{ is } B_k \quad , \quad j \in \{1,.....,M\} k \in \{1,..,K\} \tag{8}$$

For example, if a sailor has a "medium" level of stress and is close to his retirement then likelihood that this sailor will re-enlist is "large". The inference rule $\aleph^M$ is a cross product of the space of fuzzy sets on Z. The most widely used inference rule computes $\mu_{B_i^{'}}(z) = \min\{\mu_{A_i}(x), \mu_{B_i}(z)\}$, for all $z \in Z$, and defuzzifies using the centroid: $z = \left(\sum_{i=1}^{M} \bar{z}^i \mu_{B_i^{'}}(\bar{z}^i)\right) \Big/ \left(\sum_{i=1}^{M} \mu_{B_i^{'}}(\bar{z}^i)\right)$, where $\bar{z}^i$ equals the centroid of $\mu_{B_i^{'}}(z)$: $\bar{z}^i = \left(\int_Z z\mu_{B_i^{'}}(z)dz\right) \Big/ \left(\int_Z \mu_{B_i^{'}}(z)dz\right)$. The defuzzification process produces a crisp numerical value from a fuzzy subset of the universe of discourse of the ith sailor decision space. The crisp numerical value is a cardinal measure of the ith sailor likelihood to reenlist (e.g. it can be a value between [0,1], where 1 means 100% likelihood to reenlist) .

As a simple example to illustrate this idea, consider the following situation in the context of an individual sailor decision process of selecting to reenlist or separate from the NAVY. For the sake of illustration, we assume that a sailor's decision to reenlist or separate is a function of only two factors, his stress level and motivation at the time the decision process is invoked (Note that the IMPACT tool utilizes six factors to determine each individual sailor, within the pool of available sailors, decision whether to reenlist or separate from the NAVY). We define first a rule base which contains a fuzzy logic quantification of the factors (stress and motivation) that affect the decision process as well as fuzzy logic quantification of the decision space variable. For the sake of simplicity we have assigned to each of the factors and the output decision variable three linguistic terms L(X)={small, medium, large}, that is, $L_1(x^s) = \{\text{small,medium,large}\} = \{A_1^1, A_2^1, A_3^1\}$ where x^s is the ith sailor stress state which dynamics is given by Equation (1); $L_2(x^m) = \{\text{small,medium,large}\} = \{A_1^2, A_2^2, A_3^2\}$ where x^s is the ith sailor stress state which dynamics is given by Equation (2). Each of these linguistic terms is specified with a membership function of trapezoidal or triangular shape (symmetrically distributed on the universe of discourse of the factors that influence the ith sailor decision process) $\mu(x^s) = \{\mu_{A_1^1}(x^s), \mu_{A_2^1}(x^s), \mu_{A_3^1}(x^s)\}$ and $\mu(x^m) = \{\mu_{A_1^2}(x^m), \mu_{A_2^2}(x^m), \mu_{A_3^2}(x^m)\}$, respectively. The shape and distribution of the membership functions on the universe of discourse of the player strategy can be used to reflect certain constraints and rules imposed upon that strategy. On the other hand, we have assigned three linguistic terms for the ith sailor decision variable , z , $L(z) = \{\text{small,medium,large}\} = \{B_1^{'}, B_2^{'}, B_3^{'}\}$ where each of these linguistic terms is specified with a membership function of triangular shape (symmetrically distributed), Figure 2.

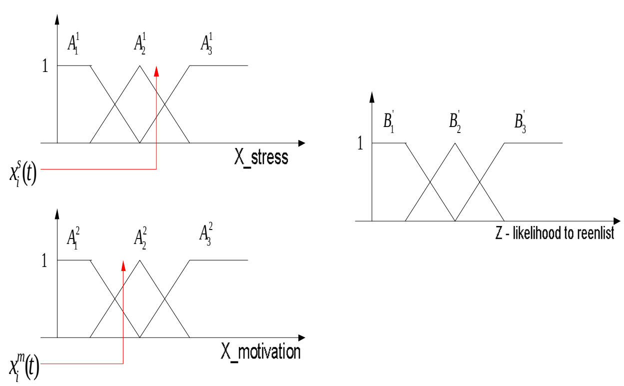


Figure #.

We assume that the ith sailor stress level is $x_i^s(t = t_d)$ (e,g. 70% of its max. level) and the ith sailor motivation level is $x_i^m(t = t_d)$ at the time $t = t_d$ when the ith sailor is asked to make a decision regarding his reenlistment. We compute the ith sailor likelihood of reenlistment/separation by executing the three processes of fuzzification, inference, and defuzzification. The fuzzification process amounts to finding the values of the input membership functions for inputs $x_i^s(t = t_d), x_i^m(t = t_d)$. Using Figure 1, we see that $\mu_{A_2^1}(x^s(t)) = 0.6, \mu_{A_3^1}(x^s(t)) = 0.4$ *and* $\mu_{A_1^2}(x^m(t)) = 0.3, \mu_{A_2^2}(x^m(t)) = 0.7$. Inference Mechanism: Determining Which Rules to Use. We define the fuzzy rules which describe heuristic knowledge of how the two factors affect the sailor's decision to reenlist. Then, the inference mechanism is used to determine which rules to use and to quantify each of these rules with fuzzy logic; we find that the rules, Equation (7), that are on are the following:

(1) IF $x_i^s(t=t_d)$ is "medium" (A_2^1), AND $x_i^m(t=t_d)$ is "medium" (A_2^2), THEN likelihood of reenlistment $z_i(t=t_d)$ is "medium" $(B_2^{'})$

(2) IF $x_i^s(t=t_d)$ is "medium" (A_2^1), AND $x_i^m(t=t_d)$ is "small" (A_1^2), THEN likelihood of reenlistment $z_i(t=t_d)$ is "medium" $(B_2^{'})$

(3) IF $x_i^s(t=t_d)$ is "large" (A_3^1), AND $x_i^m(t=t_d)$ is "small" (A_1^2), THEN likelihood of reenlistment $z_i(t=t_d)$ is "small" $(B_1^{'})$

(4) IF $x_i^s(t=t_d)$ is "large" (A_3^1), AND $x_i^m(t=t_d)$ is "medium" (A_2^2), THEN likelihood of reenlistment $z_i(t=t_d)$ is "medium" $(B_2^{'})$

Note that we have at most two membership functions overlapping in this example. We will never have more than four rules at one time. For example, the conclusion reached by rule (1); using the minimum to represent the premise and the product operation to represent the implication of the fuzzy rule, we have

$\mu_1^B(z(t_d)) = \min\{\mu_{A_2^1}(x^s), \mu_{A_2^2}(x^m)\}\mu_{B_2^{'}}(z) = 0.6\mu_{B_2^{'}}(z)$. Defuzzification operates on the implied fuzzy sets produced by the inference mechanism and combines their effects to provide the most likely outcome of a sailor's decision. We use the center of average defuzzification method to compute the ith sailor fuzzy likelihood of reenlistment e.g. defuzzification of the active rules (1)-(4) results in likelihood of reenlistment of $z = \left(\sum_{i=1}^{M} \bar{z}^i \mu_{B_i^{'}}(\bar{z}^i)\right) \Big/ \left(\sum_{i=1}^{M} \mu_{B_i^{'}}(\bar{z}^i)\right) = 0.44$, Fig. 3.

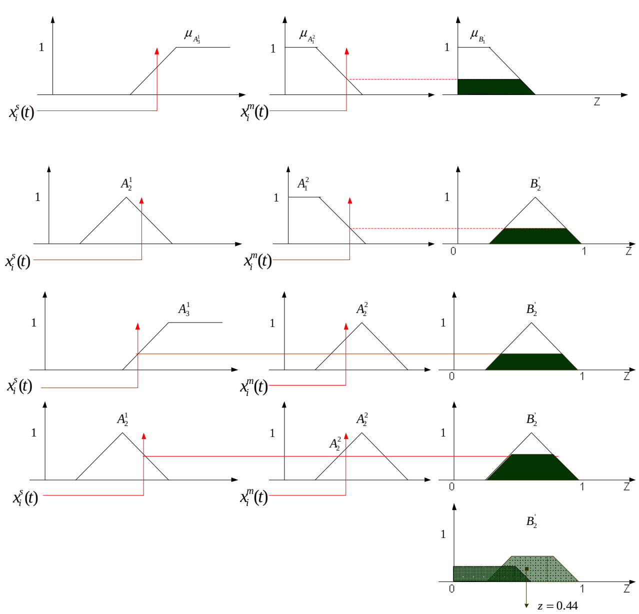


Figure #.

Note that the proposed fuzzy decision controller models only an individual sailor desire to reenlist or separate from the NAVY. However, sailors are subject to the community management policies outlined in Section 2.2.5, which may allow the reenlistment to occur, or not. Our Agent-Based model captures this behavior as well.

2.3.2 Enlisted Master File Agent

The Enlisted Master File Agent (EMFA) serves a relatively simple but nevertheless important role. It is the repository for all sailor agents during the course of a simulation. Its responsibility is to provide a centralized location for all sailor agents and take care of the book-keeping that is necessary in a dynamic population of agents. Every new sailor agent that enters the system via the recruitment process is registered with the EMFA and is removed from the population when that sailor becomes a subject to the attrition processes that are part of the model.

2.3.3 Recruitment Command Agent

The Recruitment Command Agent (RCA) encapsulates the rules that represent the recruitment process in the Navy. It operates against a fixed goal for the total population size of the Navy and activates itself when the current population level is below the prescribed goal. The RCA assumes an infinite supply of recruits and generates new sailor agents on demand.

In the process of creating a new sailor agent the RCA determines whether the sailor will begin their Navy career as a general detail (GENDET) or will attend A-school before entering the sea-shore rotation. The RCA determines a sailor's future designated rating by analyzing a demand signal that each community produces. Depending on the relative demand for sailors between the different communities, the RCA chooses probabilistically in which direction to channel the new sailor agent.

Once these two choices are made, the RCA compiles the initial list of duty stations that the sailor will visit. If the sailor is classified as a GENDET then they are immediately dispatched to boot-camp. On the other hand, when a sailor must go to A-school, the RCA contacts the Training Command Agent for the current availability of classes in the sailor's chosen area. Once an available class is identified, the sailor's orders are designed so that they visit boot-camp immediately prior to the start of the class. Any time that remains between the beginning of boot-camp and the day the sailor is recruited, the sailor spends in the Delayed Entry Program (DEP).

Finally, the RCA serves as the DEP duty station. This means that it contains the logic for accounting for all sailor agents that are currently in DEP. Whenever DEP duties for a sailor expire, they move on to the next duty station, according to their list of orders.

2.3.4 Training Command Agent

The Training Command Agent (TCA) is responsible for maintaining boot-camp, A-school, and C-school classes and their schedules. The TCA periodically schedules classes and makes them available to the RCA and the Assignment Control Agent for sending sailors to training. A and C-school classes are scheduled based on user-defined frequencies, while boot-camp classes are assumed to be available at all times. The user also specifies the duration and the capacity for each individual A/C school class that the TCA controls.
The TCA serves as the sailor duty location for boot-camp, A-school, and C-school classes. It manages the list of all sailors that are in training at all times during the simulation.

2.3.5 Community Management Agent

The community management process is represented by a Head Community Management Agent (HCMA) and multiple instances of the Community Management Agent (CMA). The HCMA is responsible for the advancement, reenlistment, retirement, and accession planning in the system.

The advancement process follows current Navy procedures in great detail. Different pay grade levels have their advancement examinations performed at user-defined periods, while the process itself accounts for time-in-rate (TIR) requirements, vacancies, sailor performance evaluations, and all components of the final multiple score (FMS) formula. Our approach allows us to keep track of the standard score (SS), the performance mark average (PMA), the passed-not-advanced (PNA) points, the service in pay grade (SIPG) time, and the total length of service (LOS). These elements are added up in a user defined weighted sum for every different pay-grade level.

In managing the reenlistment process, the HCMA encapsulates logic for high year tenure (HYT) ceilings, a full blown perform-to-serve (PTS) application process, and selective reenlistment bonus (SRB) incentives. To accomplish this, the HCMA uses the help of one CMA for every rating that exists in the system. Every CMA is capable of computing the current reenlistment objectives (CREO) as well as SRB levels. Based on these indicators, the HCMA drives the PTS process and provides reenlistment incentives to sailors.

The retirement process is fairly simple. When a sailor reaches retirement age they make a probabilistic decision as to whether they desire to serve beyond retirement or they will separate. Finally, the HCMA handles the accession planning process by compiling the demand signals from each CMA and producing a plan that the RCA can use in the recruitment process.

2.3.6 Manning Control Agent

The role of Manning Control Agents (MCA) is to account for all ships and shore bases that are available in the system and to manage deployment cycles for sea activities. Our model assumes that there is an unlimited supply of shore billets, while sea billets are strictly defined for each ship. Ships are deployed based on a user-defined deployment cycle, where the user has the ability to choose the length of deployments and the time between deployments.

2.3.7 Activity Agent

Activity agents represent sailor duty stations, which have billets on them. A billet is a definition for a position that needs to be filled on board a ship. Billets are described by rating, pay grade, and a list of NECs (special skills) that a sailor must have in order to be eligible for the position. Billets are organized in divisions, which in turn are organized in departments. We call this the departmental structure of the activity. In addition to billets, this structure also accounts for the workload that needs to be accomplished by sailors that are on board. Workload is organized per division and is split into workload records. Each workload record is described by rating, pay grade, and NEC, which specify the minimum qualifications of a sailor that can work on it and the size of the workload in hours per week.

Although sailor agents perform departmental work on every duty station, the sea activity agent (ship agent) is the only duty station that engages sailors in non-nominal workload patterns as well as watch-standing activities. The heterogeneous nature of the sailor agent is key here because it allows for the rich dynamics that take place on board ships. By having multiple attributes like rating, pay grade, and NECs, sailor agents can be matched against specific positions on each ship. Since the work is organized by division, sailors that happen to be in the same division are responsible for the same set of workload records, constrained by their individual qualifications. When there are shortages of sailors on the ship due to the dynamics of the MPT&E process, a reduced amount of sailors have to handle an increased amount of workload. This effect is exacerbated for senior sailors since they have higher qualifications and can work on most workload records in their division. When billets for junior sailors are empty, senior sailors have to work extra hours, which in turn influences their stress and motivation dynamics, leading to changes in their reenlistment decision making.

Apart from departmental workload, ships also include operational workload. This is time spent by sailors on manning watch stations and is independent from departmental work. Furthermore, operational workload takes priority as it pertains to the actual mission and operation of the vessel.

A watch station is described by a skill set (rating, pay grade, NEC) but is often more general in its qualification requirements than billets. Together with the fact that operational workload takes priority, this allows for sailors from different divisions, with different skill sets to be assigned to the same watch station when shortages occur. This translates into another mechanism by which shortages of one kind of sailor may affect the life of sailors that are with a completely different profession. Ships allow for sailors of one heterogeneous sub-type to affect the dynamics of the sailor population in another community. A shortage of one kind of sailors translates in exacerbated workload patterns for sailors of other kinds, which in turn affects decision making and eventually reenlistment patterns.

Finally, activity agents are responsible for posting requisitions for their billets based on their expected needs. Periodically each activity agent will analyze its current crew and will balance it against its expected gains and expected losses using a simplified mechanism similar to the Navy's enlisted distribution and verification report (EDVR) system. Based on the results, the activity will post the necessary requisitions with the Assignment Control Agent.

2.3.8 Assignment Control Agent

The Assignment Control Agent (ACA) is responsible for the detailing process in the simulation. It manages a list of requisitions at all times and responds to sailor agent requests for orders.
Whenever a sailor's current duty approaches its end, the sailor agent will contact the ACA with a request for new orders. The ACA manages the sailor's sea-shore rotation cycle by choosing from sea billets, shore duty, and training for each sailor.

When GENDET sailors have completed several rotations after boot camp they are typically considered for A-school classes. If no class is available at the time, the sailor is sent over for another sea-shore rotation. Designated sailors on the other hand, are considered for C-school classes after every sea-shore rotation, depending on class and seat availability. The

ACA matches sea requisitions to sailors based on several criteria. First, the match between the sailor's skill set and the billet requirements is determined. This is done based on rating, pay-grade, and NEC requirements. Next, the matching requisitions are sorted by current activity manning, take-up-arrival gap, and NEC reutilization.

3 SIMULATION RESULTS

In this section, we discuss potential use of agent-based simulation for the analysis of Shipboard Manning and Personnel Behavior and policy design for Manpower & Personnel (M&P) systems of the United States Navy. The simulations have been conducted using the IMPACT simulation tool built using Java programming language, which object-oriented architecture is particularly suited to run agent-based simulations.

In addition to building a realistic model of the MPT&E processes and dynamics, as described in details in previous sections, the current version of the tool integrates and utilizes the actual ship billets for the fully manned NAVY ships, described in the Ship Manning Documents (SMDs) for DDG51- guided missile destroyer; FFG7- guided missile frigate, and CG47 - guided missile cruisers NAVY ships. The IMPCAT tool enables the user to configure and simulate large variety of scenarios involving different levels of complexity.

In this section we will present simulation results for scenarios that involved a small NAVY battlergroup composed of multiple DDG51, CG47 and FFG07 ships (3 ships total). The simulation implements more than 270 billets on each ship for missions with different ship readiness levels. We used realistic Billets, Watch stations and workload assignment according to SMDs and corresponding to DDG51, CG47 and FFG07 SMDs. The sailor pool size was approximately 1100 strong and included all paygrades, ratings and NECs. We also included into the ABM simulation a realistic cost model which accounts for Basic Pay per pay grade; Costs of A-school, C-School and Boot Camp. Note, that during the simulations we allowed ships to be deployed if undermanned. This option can be easily disabled in the tool and the user can specify the minimum level of manning required for the ship deployment. The length of simulation can be adjusted to be between one to ten years with a time step of one week for MPT&E process dynamics while the time step for an individual sailor behavioral dynamics is one day. The tool implements detailed MPT processes, described in Section 2. It is also important to point out that, in all simulations we have utilized the same initial conditions for each of the agents in order to make the various numerical investigations completely comparable. The full sweep of relevant combinations of parameters will be conducted in our ongoing research and presented in upcoming publications.

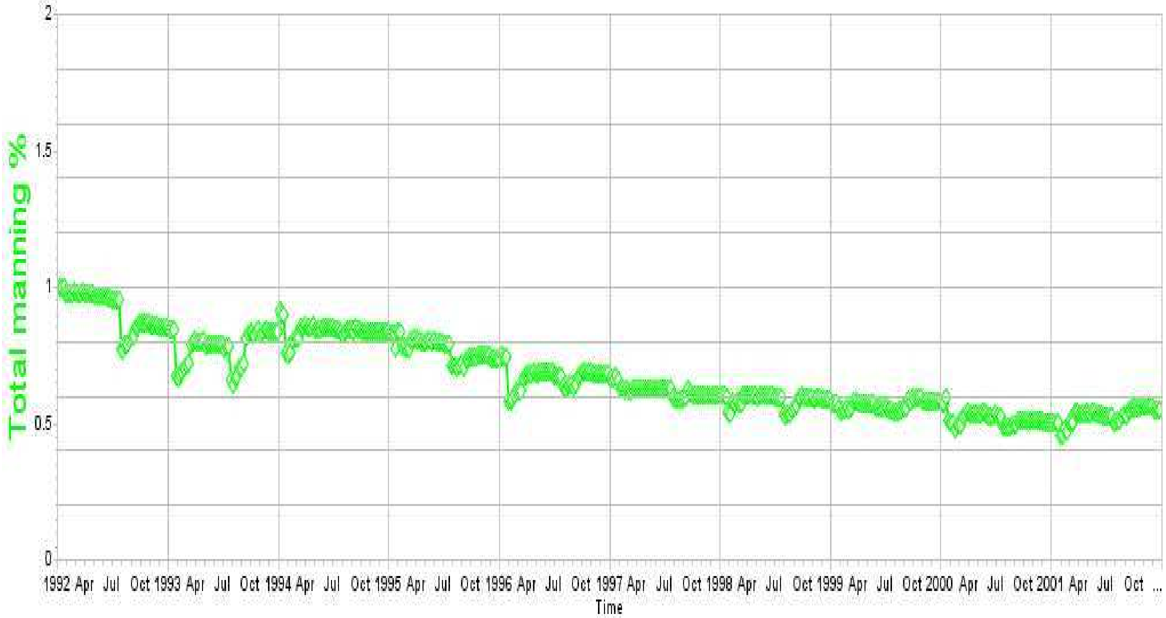
Two case studies were evaluated in simulations. ***The first case study*** involved four sample scenarios which were simulated based on manipulation of two key parameters, length of deployment cycle and percentage of crew "refreshment". We were interested in analyzing the impact of decreasing the periods between deployments. For example, compare the behavior of the model when the 6 month deployment window is used versus a deployment plan that the ship would be ready to sail immediately following a brief maintenance period (i.e. 1 month). Also, within these scenarios we tested the impact of keeping about half of the crew onboard but completely changing out the other half after redeployment. That is, there is a core ship's crew that runs the ship but about half the crew is dependent on the particular mission, air crew for air missions, etc.

In Figure 2, we show aggregated simulation results for a scenario involving three ships and a pool-size of 1100 sailors while at sea with 6 month deployment cycle and 50 % crew refreshment. The decreasing level of manning, Figure 2.a., causes increase in the workload that sailors are responsible for which eventually shortens the time available for sleep, Figure 2.b., which in turn adversely affects the stress and fatigue of sailors, Figure 2.c. As the sailors are more stressed out and exposed to persistent fatigue while at sea, the significant degradation in their motivation and performance is evident, Figures 2.c. and 3.a. The 6 months deployment cycle helps reduce the level of stress as the sailors are allocated to the shore duties, Figure 1.c. During these simulation runs we assumed that ships can be deployed even if undermanned. The significant drop in manning occurs sometime during the 4^{th} year of deployment, Figure 2.a., which causes degradation in performance due to increasing level of stress and fatigue, which stabilizes at a new equilibrium state for stress, fatigue and motivation. That is, the sailors adapt to operate under increased level of stress and fatigue caused by shortage of manning. Our model captures a sailor's behavior in which too little stress has an inert effect on the sailor, while too much has a hypereffect, Figure 4. Figure 4, shows the relationship between the performance and stress level of a sailor ID 491 with ET (Electronic Technician) rating and E5 paygrade while at sea. The model captures the *Yerkes-Dodson law* which predicts an inverted U-shaped function between stress and performance. Figure 3.b. shows the number of sailors which were allowed to quit the NAVY and it was computed using the fuzzy logic based decision tool from Section 3.1.2.

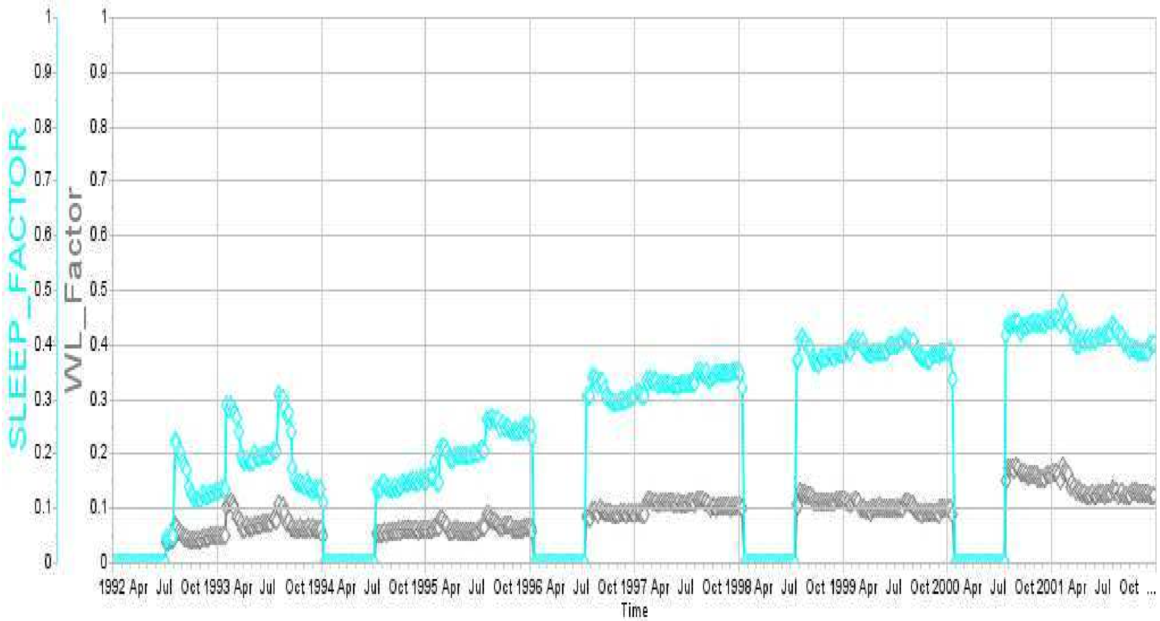
We were also interested in showing the impact of decreasing the periods between deployments and how they are affected by the crew "refreshment" strategy. Figure 5. shows the aggregated level of stress in the case of a deployment plan that the ship would be ready to sail immediately following a brief maintenance period (i.e. 1 month) with and without crew "refreshment". In general, the sailors experience higher level of stress and fatigue compared to the 6 month deployment cycle, Figure 6., and do not recover very well after they are sent to shore duties. That is, they do not significantly reduce their stress lebel before they are send back to the sea duty, which eventually leads to performance degradation. The impact of keeping about half of the crew onboard but completely changing out the other half after redeployment shows that this strategy positively affected overall system behavior for both cases of deployments. The stress level was significantly decreased for the case of the frequent deployment plan, Figure 5. This strategy had a smaller affect on overall sailors behavior when the 6 month deployment cycle plan is used since the time buffer of 6 month of onshore duties provides sailors with sufficient time to release significantly reduce their stress levels and fatigue before going on the next sea duty, Figure 6.

The capability of our model to simulate situations like these is very important from the point of view of a decision maker so that a timely policy initiative may be instituted to effect a desired change and also to inform the user when an unwanted change may be likely to occur. In other words, the user is able to test which system parameter values will likely cause the significant change in system performance and in what direction is this change going to occur. The IMPACT tool is, also capable of retaining all information associated with agents so that analyst can easily extract any individual states and data belonging to individual agents.

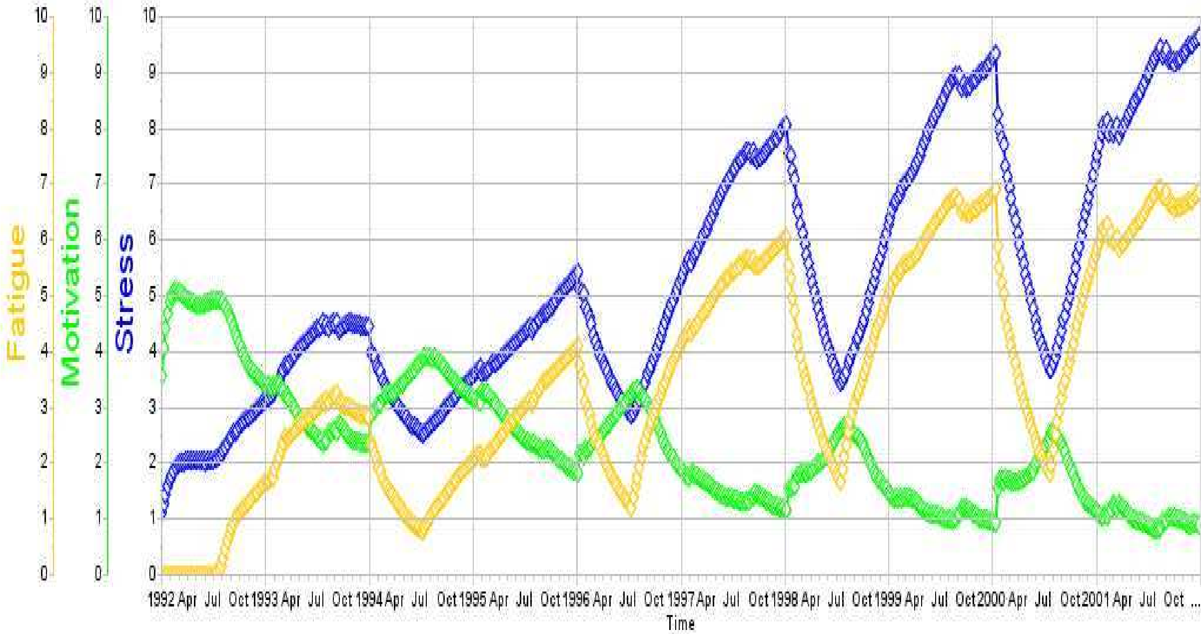
The second case study involved analyzing an optimal billet configuration so that the crew remains within a desired performance range after a specified manning reduction. That is, given a fixed manning level, determine the best billets to man so as to minimize the crew cost and manning level, maximizing performance while satisfying constraints imposed by NAVY an hierchical structure with respect to crew's paygrade and rating across a given time period. This optimization problem was formulated as a constraint multiobjective integer programming problem and solved using Genetic Algorithm Optimization. The details of the Genetic Algorithm based solver for this type of optimization problem will be disclosed in our upcoming publications. Five optimization scenarios were simulated using a single ship, Figures 7. and 8. : i) optimization based on minimization of cost and manning; ii) optimization based on minimization of cost and manning while satisfying required NAVY hierarchy with respect to sailor's rating and paygrade; iii) optimization based on minimization of cost and manning, maximization of performance, and finally iv) optimization which accounted for all above mentioned objectives (e.g. minimizing cost and manning, maximization of performance while fulfilling NAVY hierarchy constraints). The output of each of these optimization processes produced a reduced optimal SMD with respect to defined objectives, which was then used to produce simulation results shown in Figures 7. and 8. . It is also important to note, that in the case of optimization scenarios iii) and iv) we employed a simulation optimization procedure that gives the optimal expected response of the objective function defined in terms of the performance measures generated as the outputs of the simulation. Figure 7. compares the aggregated level of stress for a fully manned ship (nominal response – red line) with level of stress of the undermanned ship (e.g. with a minimum of 80% manning), in which SMDs were optimized based on four different objectives. If we optimize SMD with respect to case i) the optimizer will generate the least expensive crew which is also the least experienced one. This in turn, will increase an overall level of stress by almost 61%, than in the case of the fully manned ship since inexperienced sailors will be spending more work hours learning how to do tasks which are out of the scope of their qualifications, Figure 7.. On the other hand if we optimize the undermanned ship configuration with respect to objectives defined for case iv) we can achieve a very small degradation in the overall stress level (e.g. only about 7.14% increase in the stress level compared to the fully manned ship –blue line with stars, Figure 7.) and a relatively small increase in fatigue of the undermanned ship crew, Figure 8., (e.g. 34.6% increase in the fatigue level compared to the fully manned ship – blue line with stars). Thus, optimizing undermanned ship crew configuration which explicitly accounts for performance of individual sailors has a great potential to reduce cost and manning with minimal impact on the overall effectiveness of the crew.


Total manning %
2
1.5
1
0.5
0
1992 Apr Jul Oct 1993 Apr Jul Oct 1994 Apr Jul Oct 1995 Apr Jul Oct 1996 Apr Jul Oct 1997 Apr Jul Oct 1998 Apr Jul Oct 1999 Apr Jul Oct 2000 Apr Jul Oct 2001 Apr Jul Oct ...
Time

(a)

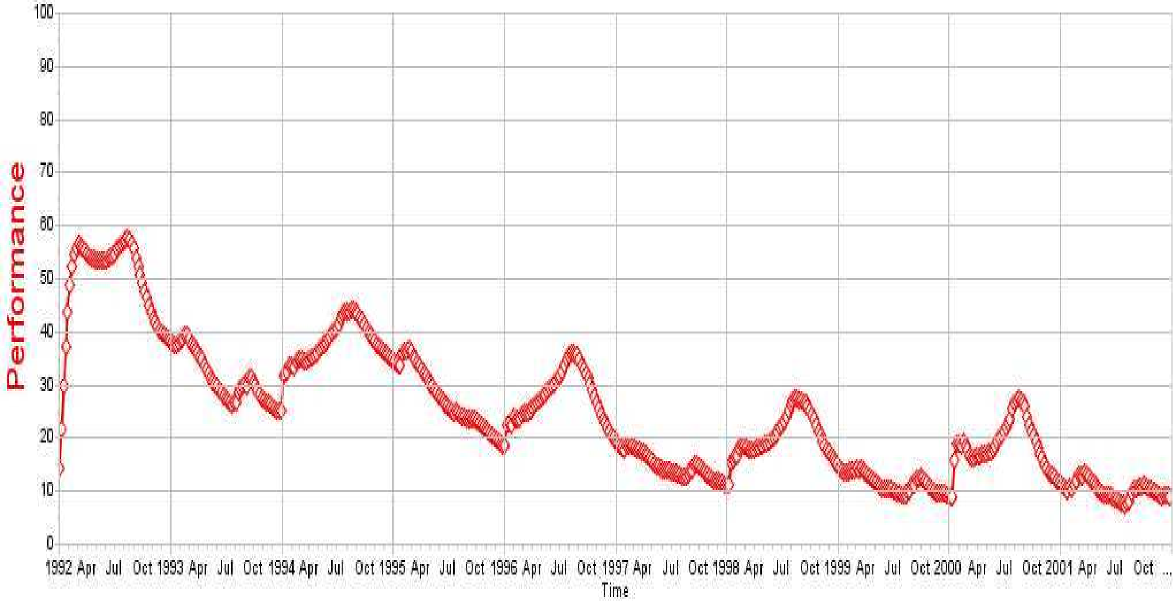

SLEEP_FACTOR
WL_Factor
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1992 Apr Jul Oct 1993 Apr Jul Oct 1994 Apr Jul Oct 1995 Apr Jul Oct 1996 Apr Jul Oct 1997 Apr Jul Oct 1998 Apr Jul Oct 1999 Apr Jul Oct 2000 Apr Jul Oct 2001 Apr Jul Oct ...
Time

(b)

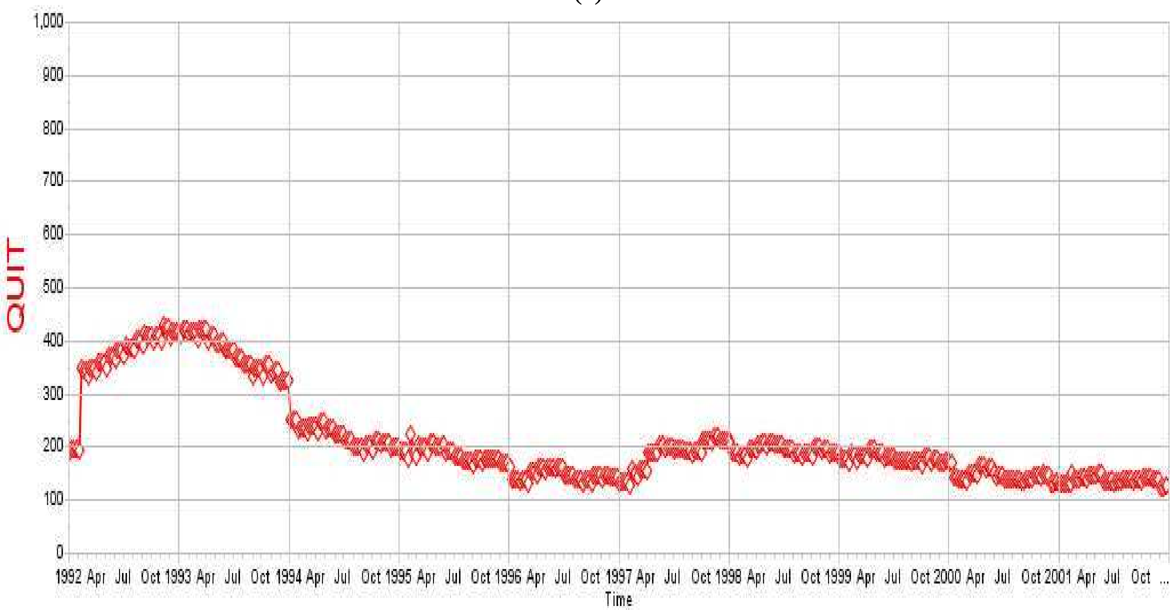


(c)

Figure 2: Aggregated simulation results for Pool-Size of 1100 sailors while at sea with 6 month deployment cycle and 50% crew refreshment. (a) Total manning level; (c) Aggregated workload and sleep factor inputs affecting sailors behavior; (d) Aggregated Stress, Fatigue and Motivation.



(a)



(b)

Figure 3: Aggregated simulation results for Pool-Size of 1100 sailors while at sea with 6 month deployment cycle and 50% crew refreshment. (a) Total performance; (b) Total number of sailors who quit the NAVY during the simulation period.

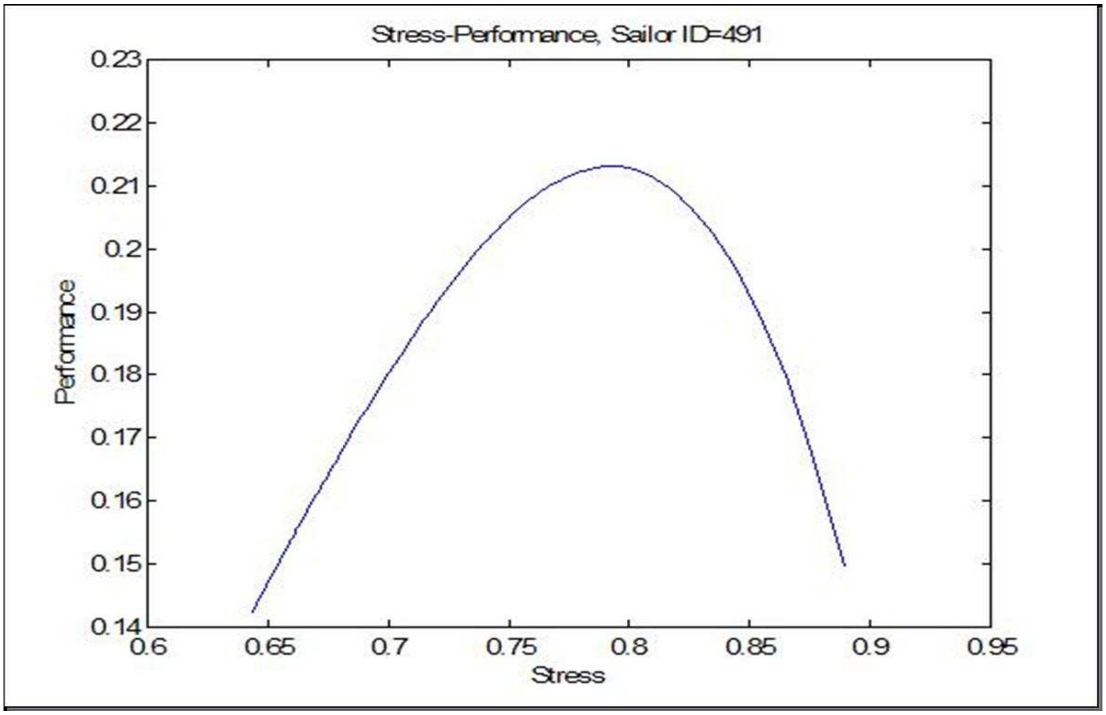


Figure 4: Performance versus Stress level of a sailor ID 491 with ET (electronic Technician) rating and E5 paygrade while at sea. Performance and Stress are normalized to be on an interval between [0,1].

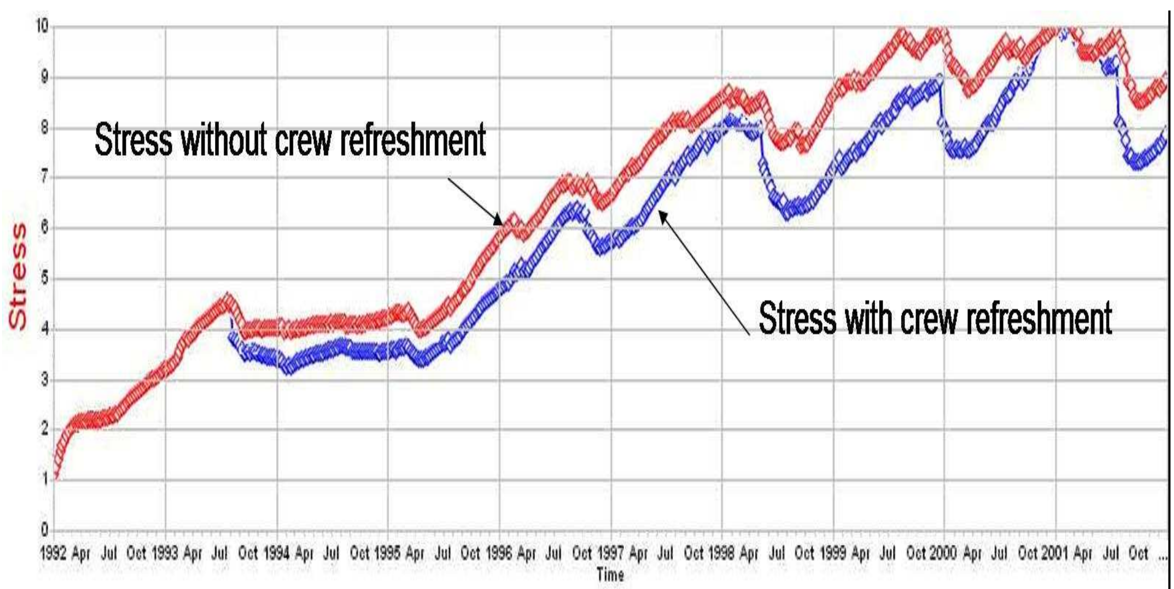


Figure 5: The impact of crew refreshment policy on aggregated level of stress with the 1 month deployment window.

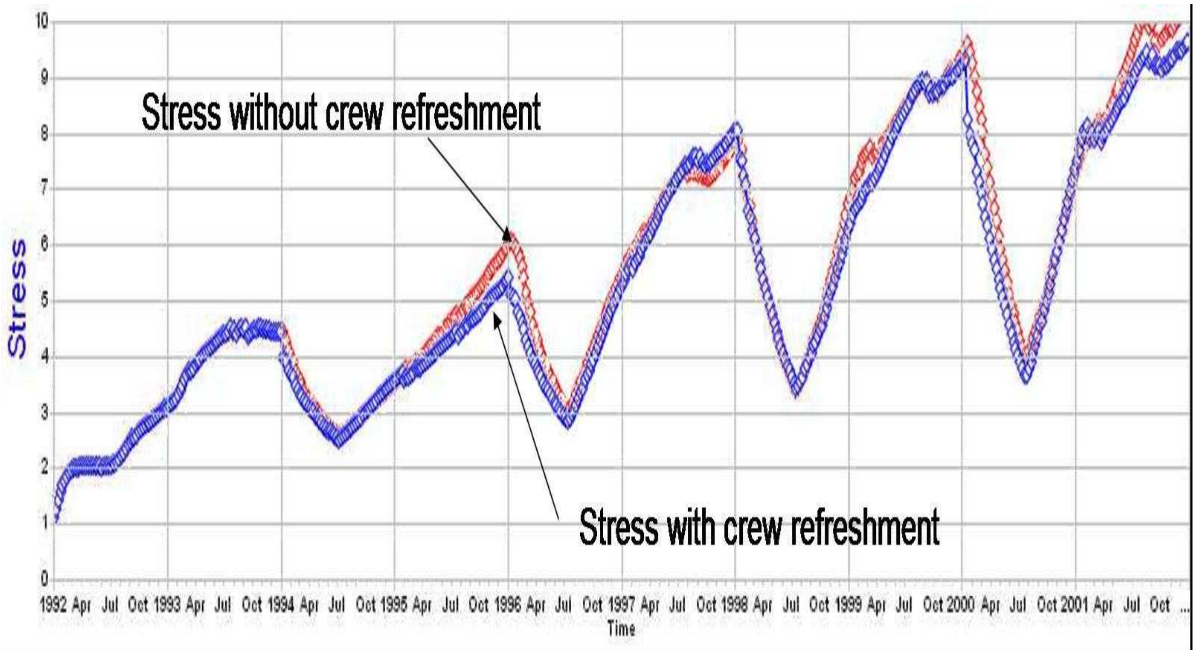


Figure 6: The impact of crew refreshment policy on aggregated level of stress with the 6 month deployment window.

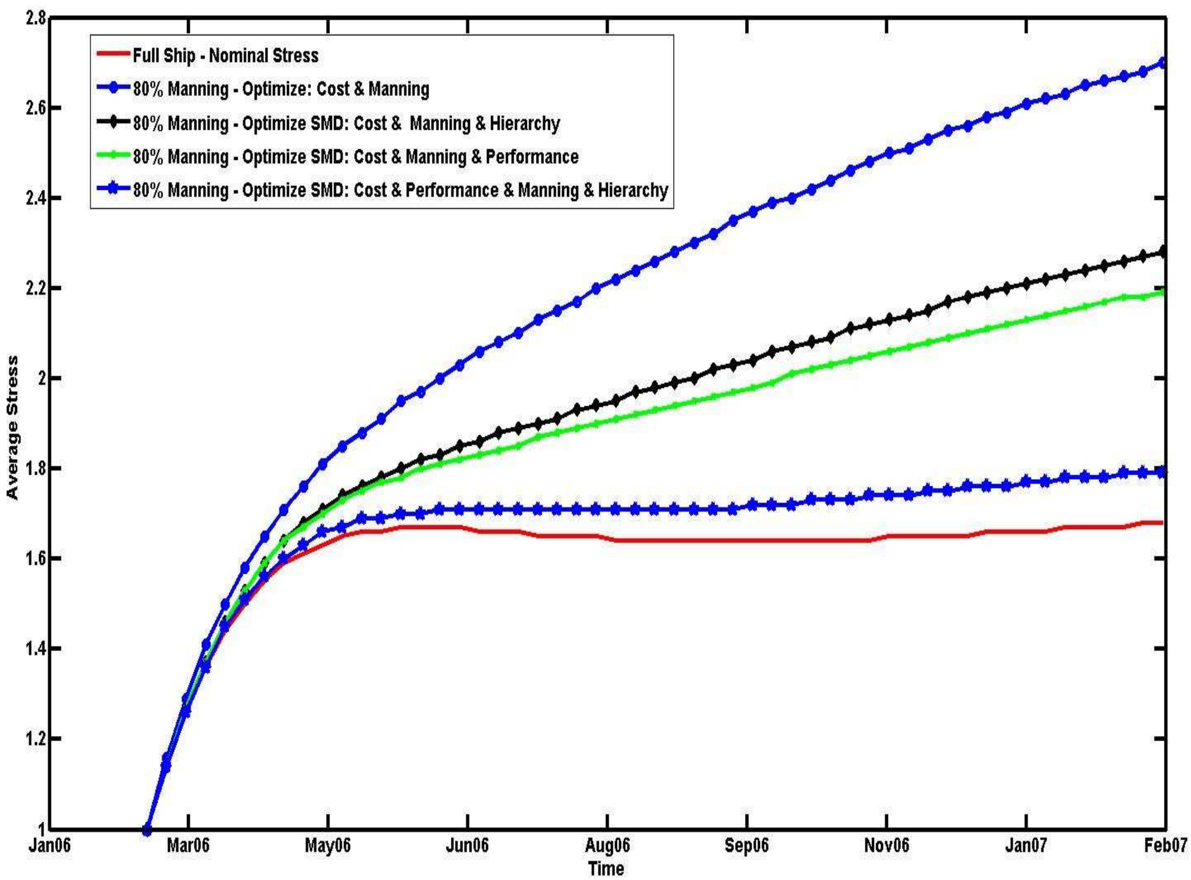


Figure 7: Aggregated Stress Level for 4 cases of Billet configuration Optimization.

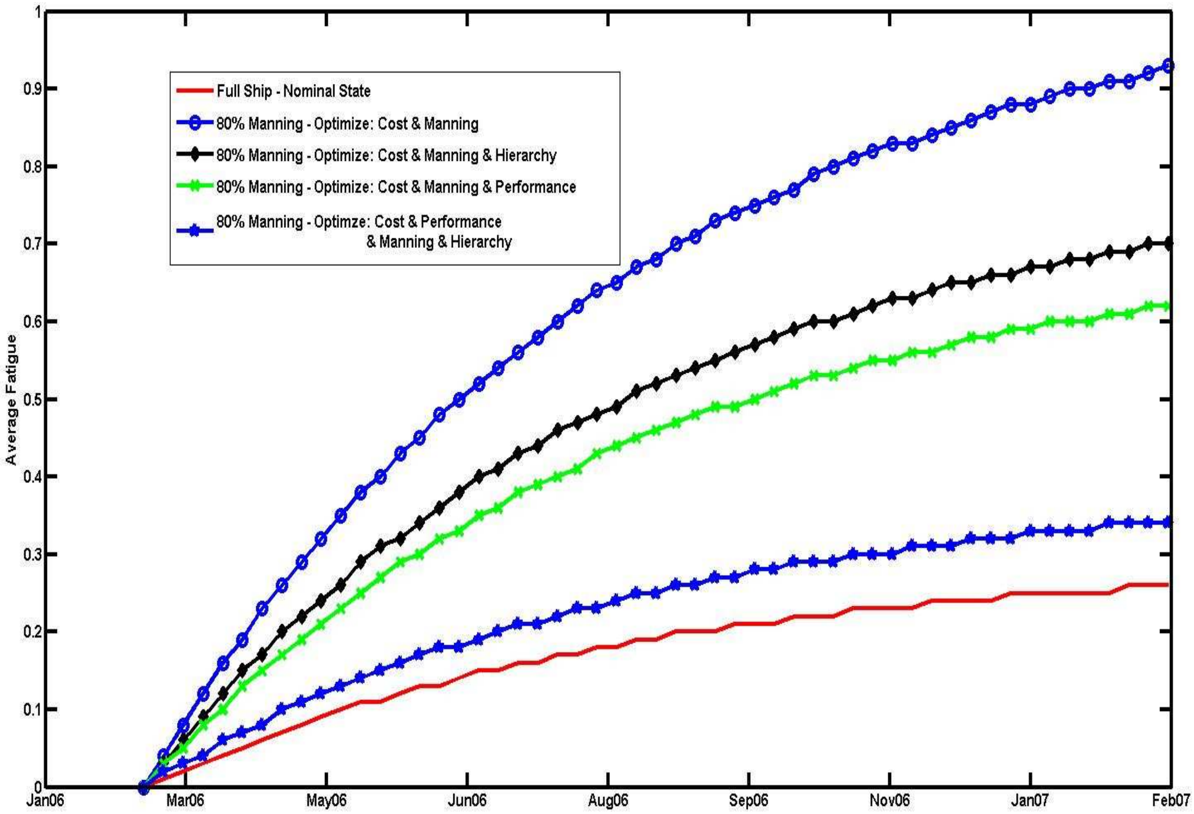


Figure 8: Aggregated Fatigue Level for 4 cases of Billet configuration Optimization.

4 CONCLUSIONS AND FUTURE WORK

In this work, we described the development of a generalized agent-based simulation for analyzing complex organizational behaviors and interactions of NAVY Shipboard Manpower & Personnel (M&P) Behaviors (Integrated Manpower & Personnel Agent-based Computer Tool - IMPACT). The system agents were represented as hybrid systems that involve both continuous-valued and discrete variables. We investigated dynamics of M&P behaviors by means of an agent-based approach. That is, within individual agent, behavioral decisions may be done by evaluation of their dynamics described by general hybrid dynamic models (GHDS). However, the system level behavior is then determined by running dynamics describing the interactions among agents.

The results of our work provide strong support for the importance of our quantitative modeling approach as a key tool for analyzing M&P systems and policy design. The model captures a surprising degree of complexity, and exhibits *emergent* behaviors not unlike those seen in the real Navy. Agent-based models are ideally suited to investigate the dynamics of complex systems of this type. The considerable advantage of the agent-based representation is its capacity to retain all information associated with the variability and interdependency between attributes of those units which might otherwise become lost if aggregate quantities were formed directly from individual data. One additional advantage of ABMs is that they tend to scale favorably. The model we have described here is a sound foundation for a more detailed model that captures many more aspects of the real Navy M&P system.

In our ongoing research we are extending this model to replicate an entire fleet. Through these enhancements, we will be able to test the impact of various M&P policies. We expect our tool to offer several benefits to the Navy, including the ability to design new policies for existing ships or new ships; the ability to understand the impact of shipboard technologies to increase automation; and the ability to study the impact of various interventions on sailor retention. The model also promises to be useful for personnel management in the commercial sector

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