# NAVAL POSTGRADUATE SCHOOL

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# THESIS

**OPTIMIZING NAVY RESERVIST ASSIGNMENTS**

by

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Every three months, roughly 2,000 Navy Reserve Sailors apply to billets. Currently, a time-intensive manual process is used to assign reserve Sailors to billets. This thesis develops a Python-based decision support tool called the Reserve Applied Sailor Model (RASM) to facilitate this process. RASM maximizes number of assignments while considering four goodness-of-fit metrics: unit type, locality, and Sailor and command preference. While teams of assigners currently assign one or a few Sailors at a time, RASM considers all possible assignments and all metrics at once. Each metric is assigned a weight. While there are established default weights, users can input weights, and weights between metrics can vary between assignment iterations based on priorities for each cycle. The model structure is designed to remove subjectivity and bias in assignments and to ensure reproducibility in results. Compared to the manual process, RASM assigns more Sailors, assigns higher percentages of Sailors in favorable metric categories, and completes a three-week assignment task in under two minutes. The time required to input data for RASM, validate its output, and implement the resulting assignment is approximately one week. RASM will optimize fit and fill and will speed up the assignment process within each quarterly cycle, yielding manpower savings. This work will benefit the entire Navy Reserve and will produce tangible increases in lethality and warfighting readiness.

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**OPTIMIZING NAVY RESERVIST ASSIGNMENTS**

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Submitted in partial fulfillment of the
requirements for the degree of

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# ABSTRACT

Every three months, roughly 2,000 Navy Reserve Sailors apply to billets. Currently, a time-intensive manual process is used to assign reserve Sailors to billets. This thesis develops a Python-based decision support tool called the Reserve Applied Sailor Model (RASM) to facilitate this process. RASM maximizes number of assignments while considering four goodness-of-fit metrics: unit type, locality, and Sailor and command preference. While teams of assigners currently assign one or a few Sailors at a time, RASM considers all possible assignments and all metrics at once. Each metric is assigned a weight. While there are established default weights, users can input weights, and weights between metrics can vary between assignment iterations based on priorities for each cycle. The model structure is designed to remove subjectivity and bias in assignments and to ensure reproducibility in results. Compared to the manual process, RASM assigns more Sailors, assigns higher percentages of Sailors in favorable metric categories, and completes a three-week assignment task in under two minutes. The time required to input data for RASM, validate its output, and implement the resulting assignment is approximately one week. RASM will optimize fit and fill and will speed up the assignment process within each quarterly cycle, yielding manpower savings. This work will benefit the entire Navy Reserve and will produce tangible increases in lethality and warfighting readiness.

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# LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| CNRFC | Commander, Navy Reserve Force Command |
| CO | Commanding Officer |
| FY | Fiscal Year |
| IRR | Individual Ready Reserve |
| JO | Junior Officer |
| MNA | MyNavy Assignment |
| NEC | Navy Enlisted Classifications |
| NOLH | Nearly Orthogonal Latin Hypercube |
| OSO | Operational Support Officer |
| PM | Project Manager |
| Q | Quarter |
| RASM | Reserve Applied Sailor Model |
| RESFOR | Reserve Forces |
| RFAS | Reserve Functional Area and Sex |
| RFMT | Reserve Force Manpower Tools |
| SELRES | Selected Reserve |
| TAR | Training and Administration of the Reserves |

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## EXECUTIVE SUMMARY


There are currently 45,345 Navy Reserve Sailors (U.S. Navy Reserve 2022). Reserve Sailors served crucial roles during major American wars, and the placement and readiness of reserve Sailors is relevant for wartime and peace. Unlike in active duty where service members are assigned to billets by individual detailers, reserve Sailors are assigned to billets by a team of assigners. A team of roughly 15 Training and Administration of the Reserve (TAR) Sailors are active-duty personnel at Navy Reserve Forces Command who assign reserve Sailors to billets, and there is currently no automated process to assign reserve Sailors to billets. Reserve Sailors are assigned to billets every quarter, or every three months, during an assignment cycle. There are various phases of the assignment cycle, but this thesis focuses on the selection phase.

This thesis develops the Reserve Applied Sailor Model (RASM) to assign enlisted reserve Sailors who apply to billets every quarter. Due to the availability of data, RASM cannot assign junior officers, and it can only assign Sailors who applied to billets. About 2,000 Sailors apply every quarter. Teams of assigners separately assign one or a few Sailors at a time. A linear program considers all assignments at once. Additionally, a linear program can account for all metrics at once. RASM maximizes number of assignments while taking into consideration Unit Type, Locality, and Sailor and command preferences. Unit type is the type of unit a billet belongs to: operational or readiness. Reserve Sailors can live wherever they want, and the locality of a billet is determined based on a 100-mile threshold from a Sailor to a billet. Sailor Preference and Command Ranking represent the Sailor and command preferences respectively. Each metric is assigned a weight. While there are established default weights, users can input weights, and weights between metrics can vary between assignment iterations based on priorities for each cycle.

RASM requires a pre-processing program and optimization program that are both implemented in Python. The pre-processing program utilizes an application file, which contains all the applications in a cycle. The pre-processing file also addresses the status of an application. If a status deems a Sailor assigned to a billet, all other applications by the Sailor or to the billet are removed from the dataset. The optimization program uses Pyomo

version 5.7.3 (Hart. et al. 2017) package and solves with the COIN-OR branch and cut (CBC) Solver version 2.10.8.

Most of the results of this thesis focus on Q2 FY22 and Q3 FY22. They are the first two assignment cycles that included Command Ranking as a metric. 2,000 Sailors applied in Q2 FY22 and 1,936 Sailors applied Q3 FY22. Regardless of metric weight variations, RASM assigns 116 more Sailors in Q2 FY22 and 166 more Sailors in Q3 FY22 compared to what was accomplished in manual hand-assignments. Additionally, RASM assigns Sailors in higher percentages in favorable metric categories for all four metrics. Across all four metrics for both cycles, RASM assigns 3.6% more Sailors on average with default metric weights. Although this thesis mainly focuses on the assignment results for Q2 FY22 and Q3 FY22, RASM produced comparable results in Q4 FY21 and Q1 FY22.

The model structure of RASM is designed to remove subjectivity and bias in assignments and to ensure reproducibility in results. Assigners can also utilize RASM with weight variations to produce different assignments for the same cycle and compare results. It currently takes assigners three weeks to assign applied Sailors to billets. Running both the pre-processing and optimization programs for RASM is completed in two minutes on average. The time required to input data for RASM, validate its output, and implement the resulting assignment is approximately one week. RASM will optimize fit and fill, speed up the process within each quarterly cycle, and yield manpower savings. This work will benefit the entire Navy Reserve and will produce tangible increases in lethality and warfighting readiness. It will be implemented immediately in the next cycle of Sailor assignments and is expected to be expanded to junior officer assignments, pending the availability of data.

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# I. INTRODUCTION

## A. HISTORY

The U.S. Navy Reserve plays an integral role in the United States Navy and military. It was established in 1915 to prepare for “America’s inevitable entry into World War I” (Naval History and Heritage Command [NHHC] 2015). By the end of World War I, Navy Reserve Sailors outnumbered active-duty personnel. Initially, only Navy veterans were able to join the reserve component. Since then, eligibility has expanded to allow a greater, more diverse force. Initiatives like Navy Reserve Officer Training Corps and Aviation Cadet Program broadened the talent pool and gave Americans more opportunities to serve in the reserves. By the end of World War II, all reserve Sailors were called into active duty, and the total number of activated reserve component forces outnumbered regular Navy Sailors by 5 to 1 (NHHC 2015). Since then, the reserve component has remained smaller than the Active Component, but reserve component has still contributed to every major war since its creation. By the end of the Korean War, 140,000 Navy Reserve Sailors were serving on active duty (NHHC 2015). During the Cold War, 40 Navy Reserve Training ships were activated, and 3 Reserve Squadrons mobilized (NHHC 2015). The Vietnam War had 2 Reserve Seabee battalions and 3 Naval Air Reserve squadrons mobilized (NHHC 2015). Operation Desert Shield and Desert Storm deployed 20,000 Reserve Sailors (NHHC 2015). Over 70,000 reserve Sailors were mobilized in Iraq, Afghanistan and worldwide to support the Global War on Terror (NHHC 2015).

While America is not currently involved in any major conflict or war, Navy Reserve Sailors are prepared to serve while leading civilian lives. The training and placement of Navy Reserve Sailors are pertinent. This thesis details the development of Reserve Applied Sailor Model (RASM). RASM is a linear program, and it acts as a supplemental tool that provides recommendations considering all assignments at once. The placement and readiness of Navy Reserve Sailors is relevant for wartime and peace. In the 2020 Navy Reserve fighting instructions, Commander Navy Reserve Force (CNRF) states:

> WARFIGHTING READINESS IS PRIORITY ONE: We are focused unambiguously on warfighting readiness. It is my number one and only

> priority-period. We will generate the combat power and critical strategic depth the Navy requires to prevail in conflict in an era of great power competition. That's our job, and why we exist. All else is secondary. (U.S. Navy Reserve 2020)

## B. CURRENT PROCESS

There are currently 45,345 drilling reserve Sailors at 139 reserve units across the country (U.S. Navy Reserve 2022). Unlike in active duty where service members are assigned to billets by individual detailers, reserve Sailors are assigned to billets by a team of assigners over a 3-month process during an assignment cycle. Each billet is a 3-year term. There are about 15 assigners in the N1 Department at Navy Reserve Forces Command (RESFOR). The current process is suboptimal as reserve Sailors are assigned one at a time by teams of different assigners. CNRF highlights areas of improvement in his 2020 Navy Reserve fighting instruction: "Refine reserve assignment policies, processes, and procedures to best support manning Navy's Selected Reserves billets. Examine detailing options in addition to current slating processes." (U.S. Navy Reserve 2020) The processes of the U.S. Navy Reserves need to adapt to current times, and an automated personnel assignment tool is necessary. The automation of Navy Reserve personnel assignments will increase efficiency, contribute to manpower savings, and ensure a more-capable Navy force.

## C. CONTRIBUTIONS AND OUTLINE

This thesis details the development of the Reserve Assigned Sailor Model (RASM) to optimize the assignment of Navy Reserve Sailors. Chapter II provides background information, including the timeline and current process in which Navy Reserve Sailors are assigned to billets, and a literature review. Chapter III describes the RASM model and its supporting software. Chapter IV analyzes the results of the model's assignments for each metric of interest, and Chapter V is the conclusion.

Our findings indicate that RASM can provide substantial improvements in the quality of reserve Sailor assignments, as well as the time required to produce these assignments. Notably, the pre-processing and RASM optimal assignments can be obtained in under 2 minutes. Compared to what is accomplished manually, RASM assigns a larger volume of Sailors and assigns Sailors in more favorable assignment categories. The time required to input data for RASM, validate its output, and implement the resulting assignment is approximately one week. This is a significant improvement over the current three weeks to gather data for the manual assignment process, make assignments manually, and validate and implement the manual solution.

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# II. BACKGROUND

## A. NAVY'S RESERVE COMPONENT

Drilling Navy Reserve Sailors actively serve one weekend per month and two weeks per year. As necessary, reserve Sailors can expect to occasionally enter an active-duty status and deploy. This category of the U.S. Navy Reserve is the Ready Reserve, and the Ready Reserve is comprised of Selected Reserves (SELRES), Training and Administration of the Reserves (TAR) personnel, and the Individual Ready Reserve (IRR) (U.S. Navy 2022). While the focus of this thesis is SELRES, both TAR and IRR personnel are involved in the assignment process. TAR Sailors are full-time Active Duty service members stationed at reserve units to perform training and administrative duties (U.S. Navy 2022). For example, the personnel assigners at RESFOR are TAR Sailors. Members in the Individual Ready Reserve previously had naval service, but they do not have a mandatory monthly or annual service. They can be in inactive or active status, and active Individual Ready Reserve Sailors can voluntarily perform active-duty service (U.S. Navy 2022). The U.S. Navy Reserves is mostly comprised of drilling reserve Sailor in SELRES. Following is the description of drilling Navy Reserve Sailors and units:

> These are designated Navy Reserve Sailors who are available for recall to Active Duty status. They serve as the Navy's primary source of immediate manpower. They typically fulfill the traditional service commitment of one weekend a month and two weeks a year. They receive many of the same benefits and perform many of the same duties as their Active Duty counterparts. This includes people on initial Active Duty for training. (U.S. Navy 2022)

It is imperative for drilling Navy Reserve Sailors to be assigned in billets and units that make the most out of their training and qualifications. In addition to this, assignments should contribute to an all-around stronger force that fulfills individual and organizational needs. The Chief of Navy Reserve Forces instructs the Reserve Component to "divest capabilities and capacities that do not support validated Navy requirements or do not explicitly train to mobilization billets" (U.S. Navy Reserves 2020). This addresses the different types of billets within units that reserve Sailors can be assigned to. A service member can be assigned to an operational or readiness unit, and the Navy Reserves prioritizes operational units. While all reserve component billets support warfighting readiness, an operational unit can deploy as an entire entity. Along with a Sailor's capabilities, the billets they can be placed into are limited by their Reserve Functional and Sex (RFAS) code or Navy Enlisted Classification Code (NEC). RFAS codes determine whether a service member can be assigned to a billet based on the billet's rank, rate, or gender requirements. NEC codes are special job qualifications and experiences that a service member need in order to be assigned to a billet. Lastly, Sailors can be prevented from being assigned to a billet based on disqualifiers determined by their Individual Mobilization Status (IMS) codes, Manpower Availability Status (MAS) codes, or security clearance codes. IMS and MAS are administrative and medical disqualifiers that prevent Sailors from being assigned (Spitnale 2021). Navy Reserve Sailors are assigned to billets over a 3-month period, or cycle. The section B describes the assignment cycle and its various stages.

## B. ASSIGNMENT CYCLE

### 1. Assignment Databases

There are two main website database interfaces in which Sailors and junior officers apply to billets: MyNavy Assignment (MNA) and Reserve Force Manpower Tool (RFMT). The description of the MNA database is as follows: "MyNavy Assignment (MNA) is designed and used by Sailors, Command Career Counselors, and command personnel. The Web-based system allows Sailors to view available jobs and make their own applications or make applications through their Command Career Counselor" (MyNavy HR 2022). The dataset for the applications of enlisted personnel is acquired via MNA. Contrary to this, the applications for junior officers can only be accessed and utilized through RFMT. While MNA provides exportable data that reflects all Sailor-to-billet applications, RFMT does not provide a discernable dataset for junior officers. Junior officers are only assigned by assigners clicking through a website user interface. Because of this, we focus on assigning enlisted reserve Sailors with RASM.

### 2. Assignments Based on Rank

The assignment processes for enlisted Sailors, junior officers, and senior officers all differ based on the website interface that they utilize and the assigners who detail them. Unlike Sailors and junior officers, senior officers do not utilize a website interface to apply for billets due their small number and command-specific billets. They communicate directly with assigners throughout their entire assignment process. They are assigned to leadership billets within reserve unit commands. Sailors, as mentioned in the previous paragraph, utilize MNA, and junior officers utilize the JOAPPLY interface on RFMT. Sailors and junior officers apply for billets using their respective website-interfaces on the front end, and assigner teams make selections on the back end. The timeline and strenuous process in which Sailors and junior officers are assigned to billets is depicted in the calendar in Figure 1. Figure 1 reflects the assignment cycle for the first quarter (Q) of Fiscal Year (FY) 2022.

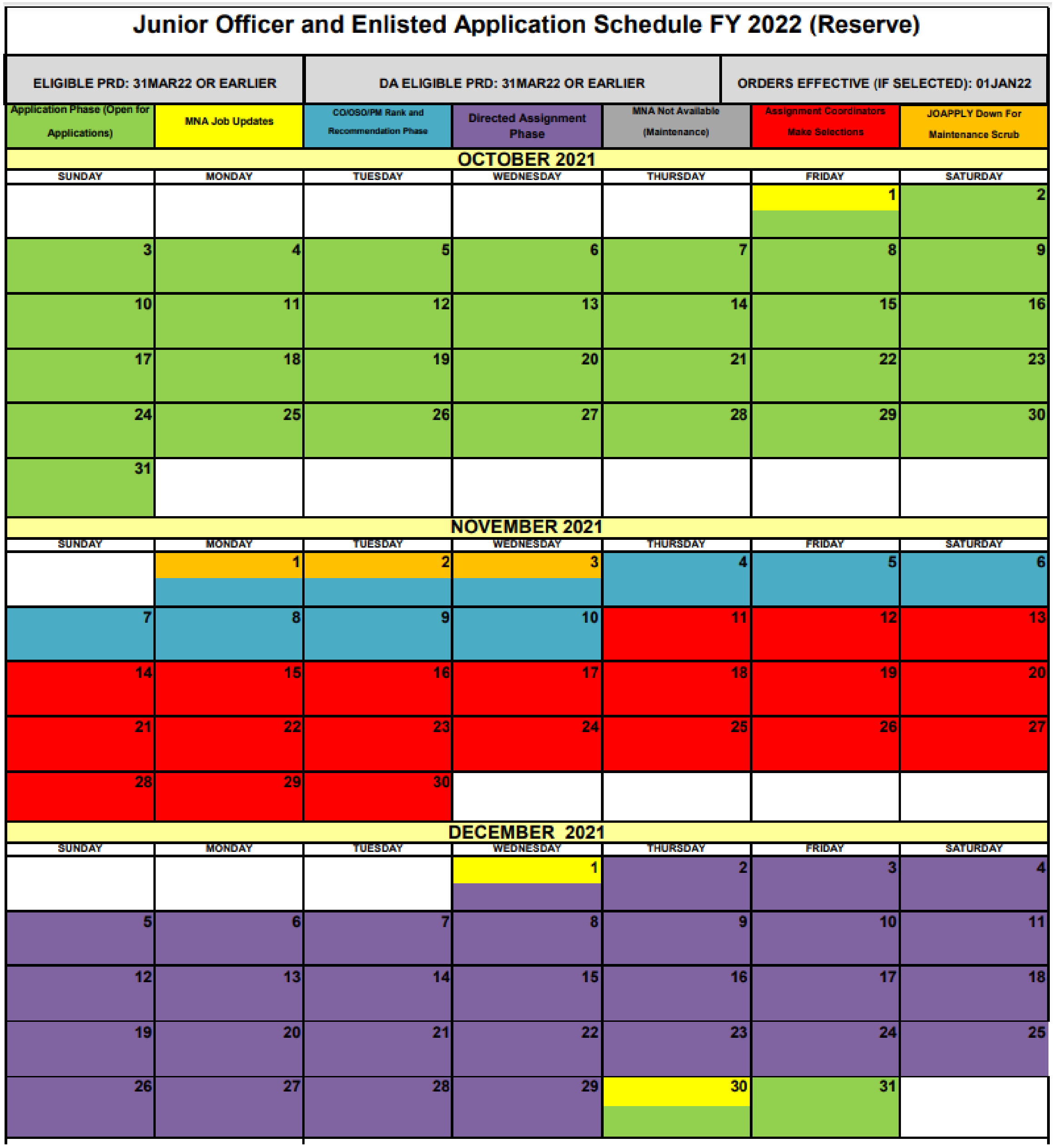


Figure 1. Q1 FY 2022 Assignment Cycle. Source: MyNavyHR (2021)

The assignment cycle consists of four main phases:

1. Application Phase: At the beginning of every quarter, Sailors who are currently due for a new billet can apply for their preferred billet. Roughly 2,000 Sailors apply every cycle (Spitnale 2021). Sailors can only apply to billets if they have the qualifying RFAS and NEC codes. While it is not

mandatory for a Sailor to apply for a billet, it would behoove them to do so. It would be advantageous for them to apply for a favorable billet and accessible location for their next Command. Otherwise, they will be assigned during the Direct Assignment Phase.

2. Commanding Officer (CO)/Operational Support Officer (OSO)/Program Manager (PM) Rank and Recommendation Phase: Once Sailors or junior officers apply to a billet, the CO, OSO, or PM of that respective command can give a "Command Comment" or ranking for each service member. Prior to this project, a Command's sentiment toward a service member was only expressed through a written statement. Historically, the written statement was intended to give only a positive endorsement for a service member who applied to their unit. Now, commands can give Sailors a quantitative ranking. This change was implemented to accommodate the optimization model and provide a quantitative variable for command preference. However, only two cycles of results are analyzed due to the availability of this data.

3. Selection Phase: Only Sailors who apply to billets are assigned during this phase. This thesis optimizes, improves, and expedites this 3-week process. Due to the availability of datasets, RASM can only assign Sailors in this phase of the cycle. This thesis analyses the results of the last two cycles since Command Ranking was only implemented the last two cycles.

4. Direct Assignment: Sailors who did not apply or were not assigned to a billet during the Selection Phase are directly assigned. So far, no discernable dataset determines possible billets for Sailors in this phase. Similar to the process in which assigners assign junior officers to a billet, directly assigned service members are assigned through a user-interface. Additionally, Sailors can only be assigned to billets if they have the qualifying RFAS and NEC codes.

## C. LITERATURE REVIEW

A substantial body of literature describes models and techniques for personnel assignment. This thesis focuses on assigning reserve Sailor personnel using multiple criteria to determine the quality of a solution. Previous works that optimize personnel assignments, finances, and infrastructure have been studied to develop this thesis.

Enoka (2011) developed the Marine Security Guard Assignment Tool (MSGAT) to assign Marines to serve as security personnel at various nationwide embassies. Default weights are assigned to the attributes of each assignment, and the user, or assigners, have the ability to change the weights of each attribute. RASM adapted the same user-input. Like MSGAT, RASM was developed to effectively reduce manpower hours, increase efficiency, and optimize assignments. While the results of MSGAT were measured with focus on particular attribute weights, the assignments of Sailors using RASM was explored with a wide range of weight combinations. Similar to the MSGAT's ability to input weights, Alger (2019) provided the same user ability in his model.

Alger (2019) utilizes Ground Officer Assignment Tool (GOAT) to assign Marines to ground billets. He explains that GOAT gives assigners "the added flexibility of testing multiple sample solutions in a short period of time and seeing the comparative cost" (Alger 2019). RASM also gives assigners the ability to see different Sailor assignments for different priorities in a short amount of time. RASM adapts GOAT's weights and penalty scheme to assign a cost to each assignment. Alger utilizes ghost Marine and Billet limitations to ensure feasibility; RASM utilizes "supersource" and "supersink" nodes to accomplish this. The supersource and supersink nodes allow Sailors and billets to be unassigned and still allow an assignment to be feasible. Unlike both Enoka's MSGAT and Alger's GOAT formulation, RASM does not allow the user to specify Sailor-billet assignments. Rather, the assignment of a Sailor to a particular billet is done in the cleaning of the data.

Martinez (2021) refined the Marine Corps' tool to assign the best fit military occupational specialty (MOS) to recruits by creating the Modernized Recruit Distribution Model (M-RDM). While the current process predominantly assigns based on school seat's availability, Martinez's model improvements include, "minimizing idle time spent between training schools, maximizing goodness of fit pairings, and ensuring the assignments over the course of a year are approximately achieving M&RA staffing goals" (Martinez 2021). Martinez calculates a goodness-of-fit score, as determined by ASVAB scores, in his objective function. He also utilizes adjustable penalties for the recruits under target, recruits over target, Marine awaiting training, and the goodness-of-fit score (Martinez 2021). This gives assigners the flexibility to prioritize metrics based on the needs of an iteration of recruits' MOS assignments. Like Martinez's M-RDM model, RASM utilizes penalties for the input and calculated data in its objective function, and assigners have the ability to change metric weights when assigning reserve Sailors to billets.

Goudyrev (2019) develops a support tool for manpower assignments. Goudyrev explains, "this tool augments decision making by analyzing potential movers in groups and maximizing their personal preferences while minimizing the number of government-funded geographic relocations" (Goudyrev 2019). He assigns a weight for every mover-job combination. The weight is determined by the mover's ordered preference for all the jobs. While Goudyrev's model considers one metric, RASM utilizes four metrics and also four metric weights. Additionally, Goudyrev utilizes "ghost" movers to have an equal number of movers for every job. This ensures a feasible solution. The ghost mover weights are higher than the most undesirable preference for a job. For example, if five jobs are available, the ghost weights are 6. Similar to his model's ghost weights, RASM utilizes pseudo arcs to allow a feasible solution for every model run. Likewise, RASM's pseudo arc penalties for all metrics are higher than the most undesirable circumstance.

Hooper and Ostrin (2012) aim to minimize the monetary expenses incurred by the Marine Corps when a service member and their family move to another permanent duty station. Like RASM, their thesis utilizes a linear program for personnel assignment. However, their objective function measures the personnel monetary cost for the assignments of Marines. They explain, "the Marine Corps has long been successful in assigning its available personnel inventory to vacant billets. However, by our research, it has not done so while minimizing the assignment costs faced by the Marine" (Hooper and Ostrin 2012). When assigning Marines to a new permanent duty station, their model utilizes four metrics similar to those in RASM: military occupational specialty, billet vacancies, duty station preference, and seniority. While these metrics are utilized in their model's constraints, RASM includes similar metrics in its objective function with tunable weights. Hooper and Ostrin aim to reduce monetary cost. Although RASM is also a linear program, its objective function focuses on the quality of every assignment while also aiming to assign all Sailors who applied to a billet.

Nganga (2020) develops various models to optimally assign U.S. Marine Corps (USMC) officers to billets. First, he studies the methods of other branches' billet assignment processes and website interfaces. Next, he creates different objective functions to demonstrate tradeoffs for valuing different metrics. He considers the financial cost of assigning a Marine to a billet, and he considers Marines' preferences. Nganga explains, "Data from a subset of the aviation community were collected and processed to develop optimization models that balance two goals: permanent change of station cost, and Marines' priorities" (Nganga 2020). He utilizes a Weighted Sum Method for Assignment Model (WESMAM) and Hierarchical $\varepsilon$-Constraint Method Assignment Model (HECMAM) for two multi-objective models. While RASM does not utilize a hierarchical method to consider metrics sequentially, the weight sum method is adapted in the RASM tool. Furthermore, a tunable weight options allows users to consider all metrics but to prioritize certain ones.

Renosto (2019) develops a mixed integer linear model called the Installation Readiness Optimization Model (IROM) to optimize the Marine Corps' infrastructure portfolio and establish readiness goals for Marine Corps Installation Command. While RASM utilizes continuous variables to assign personnel, IROM utilizes two binary variables to represent whether a facility is demolished and whether a facility is recapitalized. Renosto explains the goal of her tool as follows: "the MILP objective is to maximize readiness subject to budget constraints, where readiness is defined by the Facility Condition Index (FCI) and Mission Dependency Index (MDI)" (Renosto 2019). Unlike Hooper and Ostrin (2012), Renosto utilizes a monetary constraint. Lastly, Renosto's model allows user input. She explains, "IROM allows the user to change input values and factors to reflect Marine Corps policies and campaign plans which assist in recommending financial expenditures… by specifying levels of sustainment, demolition, and restoration." (Renesto 2019). Similarly, RASM allows users to input metric weights to change the priority of Sailor and billet considerations in the objective function.

Rincon (2020) develops the AOC matching system (AOC-MS) to designate U.S. Army Medical Service Corps (MSC) officers to specialized areas of concentration (AOCs). For phase I of his model, Rincon uses officer assignment and educational data to predict AOC aptitude and to recommend matches between officers and AOCs. He determines that multinomial logistic regression is the best-performing machine learning classifier. For phase II of his model, he utilizes an integer linear program to "decide designations based on mutual preferences between officers and AOCs as well as manpower target fill rates" (Rincon 2020). Similarly, RASM aims to do the same thing by meeting the desires of Sailors and billet commands. By utilizing different measures of effectiveness, Rincon determined that his models, "outperformed the current process while performing similarly to each other" (Rincon 2020). Likewise, RASM assigns more Sailors than what was accomplished manually, regardless of the weighting scheme.

Brown, Dell, and Wood (1997) express guidelines for persistent, accurate results in the development of a model. They state, "a previously optimal solution, or a slight variation of one, may still be nearly optimal in a new scenario and managerially preferable to a dramatically different solution that is mathematically optimal" (Brown, Dell, and Wood 1997). While RASM does not currently employ any persistence-related functionality, this could easily be incorporated in future versions in a manner similar to that employed by Enoka (2011). Brown, Dell, & Wood warn that many papers focus on achieving an optimal solution rather than how an optimal solution is implemented (Brown, Dell, and Wood 1997). The results of RASM were not measured in a vacuum as they are compared across different runs and historic results, and the model will run alongside manual assignments in the next cycle.

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# III. MODEL: METHODOLOGY

## A. METRICS IN THE ASSIGNMENT PROCESS

Four main metrics determine the quality of an assignment of a reserve Sailor to a billet: Unit type, Locality, Command Ranking, and Sailor Preference. The RASM model expresses these metrics via penalties, which combine to form an overall cost associated with assigning a particular reserve Sailor *s* to a particular billet *b*. We now describe each of these metrics in more detail, including the penalty values associated with particular outcomes.

<u>Unit Type</u>: Each unit is distinguished as an operational or readiness unit. For reasons mentioned in the Chapter II, an operational unit is prioritized per policy and leadership guidelines. Operational units are distinguished by "NR" in the unit name. Table 1 shows the RASM penalty $U_b$ associated with a billet *b* for each of the two different unit types.

Table 1. Unit Penalties

| Unit Type | $U_b$ |
|---|---|
| Operational | 1 |
| Readiness | 2 |

<u>Locality</u>: Locality is determined by a 100-mile threshold, and a local assignment is preferred over a cross-assigned assignment. When a Sailor applies to a billet, the mileage from the Sailor's home of record to the billet's unit is populated. Anything less than or equal to 100 miles is deemed as a local unit. Additionally, Sailors can apply for a cross-assign waiver. This waiver would deem a cross-assigned billet application equivalent to a local billet. Table 2 demonstrates the penalties penalty $L_{s,b}$ associated with the two different locality outcomes that are possible for a given Sailor *s* and billet *b*.

Table 2. Locality Penalties

| Locality | $L_{s,b}$ |
|---|---|
| Local | 1 |
| Cross-Assigned | 2 |

Command Ranking: Command Rankings represent a command's sentiment toward a Sailor who applied to them. After service members apply to a billet, the respective command has the opportunity to rank the service member on a scale of 1* (worst) to 5* (best). This scale was placed recently employed in lieu of the "Command Comments" section of an application that was previously utilized. The Command Comments section is a verbal description of how favorable a service member is viewed by the command, and commands are instructed to only provide positive remarks. In the Command Ranking numerical system, commands can now express negative sentiment toward an applicant. Additionally, multiple Sailors can receive the same rank from the same command. For example, a command can give multiple service members a 5* ranking for the same billet in a single application cycle. Likewise, a command may give out 1* ranking to all service members who applied for their billet. Since it is optional for commands to rank Sailors who applied, only a little over 30% of applications received rankings in the data we received. A default value of 3* is given to any application that did not receive a Command Ranking. Table 3 expresses the Command Ranking penalty $C_{s,b}$.

Table 3. Command Preference Penalties

| Command Preference | $C_{s,b}$ |
|---|---|
| 5* | 1 |
| 4* | 2 |
| 3* | 3 |
| 2* | 4 |
| 1* | 5 |

Note: 3* is default if no rank is given

Sailor Preference: Each service member can apply for up to ten billets, distinguishing their ordered preference for each billet. A preference of 1 denotes a Sailor's most desired billet. Likewise, a preference of 10 is a Sailor's least desired billet (assuming they do apply to 10 billets). Typically, Sailors only apply to three billets (Spitnale 2022). Table 4 shows the penalty $P_{s,b}$ associated with Sailor Preferences

Table 4. Sailor Preference Penalties

| Sailor Preference | $P_{s,b}$ |
|---|---|
| 1 | 1 |
| 2 | 2 |
| 3 | 3 |
| 4 | 4 |
| 5 | 5 |
| 6 | 6 |
| 7 | 7 |
| 8 | 8 |
| 9 | 9 |
| 10 | 10 |

## B. RESERVE APPLIED SAILOR MODEL

The assignment of Sailors to billets can be modeled using a network model. This guarantees an integer optimal solution when solved with the simplex algorithm, even when using continuous decision variables (Ahuja, Magnanti, and Orlin 1993). Each Sailor *s* and billet *b* is represented by a node in the network. An arc (*s,b*) exists between every Sailor *s* who applied to a billet *b*. Sailors can only be assigned to billets that they applied to, and unassigned Sailors will move onto the Direct Assignment phase of the selection process, where a manual assignment will occur. A fit cost is calculated based on the weighted metric values for every Sailor-to-billet application, and this cost is assigned to arc (*s,b*) and denoted as $cost_{s,b}$. The objective function of RASM aims to minimize the total cost of all the assignments. Constraints ensure that every Sailor is assigned to one billet, and every billet receives one Sailor. In order to ensure feasibility, RASM uses a "supersource" Sailor node and a "supersink" billet node. All unassigned Sailors will be assigned to the supersink, and all unassigned billets will be assigned the supersource. The supersource node is connected to every billet node, and every Sailor node is connected to the supersink. Arcs incident to the supersource and supersink have a fit cost strictly higher than the cost corresponding to the most unfavorable outcome for every metric. Figure 2 illustrates an example network with three Sailor nodes and four billet nodes. Black arcs denote Sailor applications. For clarity, we show arcs incident to the supersource and supersink in grey. Bold arcs have positive flow in an optimal solution. Note that although every Sailor applied to at least one billet, and every billet received at least one application. In this example network, it is impossible to assign every Sailor to a billet. Sailor 2 is unassigned, while billets 2 and 3 are unfilled.

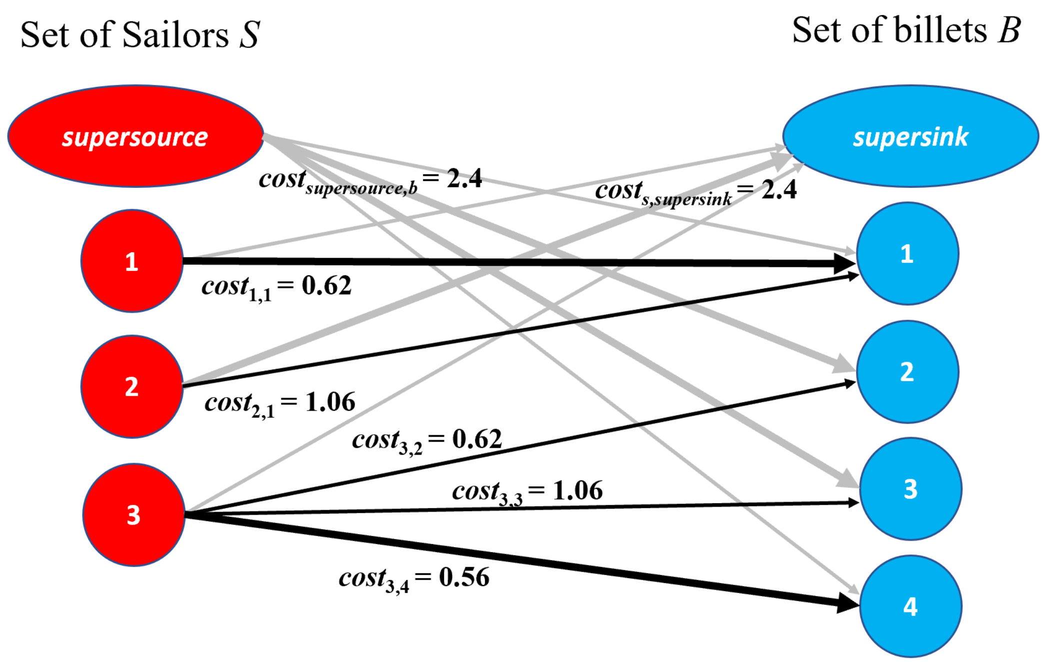


Figure 2. Example Network

The mathematical formulation of RASM is as follows:

**Indices and sets:**

| | |
|---|---|
| $s \in S$ | sailors |
| $b \in B$ | billets |
| $(s,b) \in APPLIED$ | sailor $s$ applied fill billet $b$ |

**Input data [units]:**

| | |
|---|---|
| $U_b$ | unit type cost of billet $b$ (1 if Readiness, 2 if Operational) [unitless] |
| $D_{s,b}$ | distance between sailor $s$ and billet $b$ [miles] |
| $C_{s,b}$ | command ranking of sailor $s$ for billet $b$ (1-5, with 1 being best) [unitless] |
| $P_{s,b}$ | preference of sailor $s$ for billet $b$ (1-10, with 1 being best) [unitless] |
| $W_{unit}$ | weight given to unit type cost [unitless] |
| $W_{locality}$ | weight given to locality cost [unitless] |
| $W_{command\_pref}$ | weight given to command preference cost [unitless] |
| $W_{sailor\_pref}$ | weight given to sailor preference cost [unitless] |

**Calculated data [units]:**

$$L_{s,b} = \begin{cases} 1 & \text{if } D_{s,b} \leq 100 \\ 2 & \text{if } D_{s,b} > 100 \end{cases}$$ locality cost for sailor $s$ and billet $b$ [unitless]

$$\text{cost}_{s,b} = \begin{cases} W_{unit} * U_b + W_{locality} * L_{s,b} + W_{command\_pref} * C_{s,b} + W_{sailor\_pref} * P_{s,b} & \text{if } s \neq \text{supersource and } b \neq supersink \\ W_{unit} * 3 + W_{locality} * 3 + W_{command\_pref} * 6 + W_{sailor\_pref} * 10 & \text{if } s = \text{supersource or } b = supersink \end{cases}$$

overall cost of assigning sailor $s$ to billet $b$ [unitless]

**Decision variables:**

$ASSIGN_{s,b}$ assign sailor $s$ to billet $b$ (nonnegative)

**Formulation:**

$$\min_{ASSIGN} \quad z = \sum_{(s,b)\in APPLIED} cost_{s,b} ASSIGN_{s,b}$$

$$\text{s.t.} \quad \sum_{\substack{s: \\ (s,b)\in APPLIED}} ASSIGN_{s,b} = 1 \qquad \forall b \in B - supersink \qquad (1)$$

$$\sum_{\substack{b: \\ (s,b)\in APPLIED}} ASSIGN_{s,b} = 1 \qquad \forall s \in S - supersource \qquad (2)$$

$$ASSIGN_{s,b} \geq 0 \qquad \forall (s,b) \in APPLIED \qquad (3)$$

## C. METRIC WEIGHTS

RASM includes weight metrics to allow a user to select which metrics to prioritize in each model run. Leadership of the assignment staff at N1 RESFOR tend to prioritize Unit Type and Locality due to Navy Reserve policy. However, individual assigners tend to focus on Command Ranking and Sailor Preference since they interact and communicate with the reserve Sailors daily throughout the assignment process. The model structure is designed to remove subjectivity in assignments and to ensure reproducibility in results. For simplicity's sake, the weights can be thought of percentages and should add up to 1. A higher weight signifies a greater importance for a particular metric during an assignment cycle. Weights between metric can be viewed as their relative importance. Weights also give the user a mechanism to determine the best possible performance with respect to a given metric during an assignment cycle. Specifically, that metric's weight can be "maxed out" -- held to one -- while all other metrics are held to zero. (Note that this particular weight scheme can lead to solutions that are not Pareto optimal and should only be utilized to determine the best possible performance for a single metric in a given assignment cycle, and not to produce an assignment to be used in practice.) Of course, any other weight distribution can be utilized. There is an inherent tradeoff and art when utilizing the optimization model and establishing the weights for each metric.

The personnel assignment team at RESFOR have established the default weights in Table 5 when assigning service members to billets. Assigners can also tune the weights of the objective function based on the priorities for a given assignment cycle.

Table 5. Default Metric Weights

| metric | Weight Notation | Default Weight |
|---|---|---|
| Unit Type | $W_{unit}$ | 0.4 |
| Locality | $W_{locality}$ | 0.3 |
| Command Ranking | $W_{command\_pref}$ | 0.2 |
| Sailor Preference | $W_{sailor\_pref}$ | 0.1 |

In order to establish the best possible performance with respect to each metric, the weight distributions in Table 6 can be used. In this situation, a metric's weight would equal 1 while all other weights equal 0, thus a metric's weight is "maxed out." As stated before, these weights can result in dominated solutions and should only be used to determine the best possible performance with respect to a given metric, and not to produce actionable assignments.

Table 6. Max Metric Weights

| Max Unit | Max Local | Max Command Ranking | Max Sailor Preference |
|---|---|---|---|
| $W_{unit} = 1$ | $W_{unit} = 0$ | $W_{unit} = 0$ | $W_{unit} = 0$ |
| $W_{locality} = 0$ | $W_{locality} = 1$ | $W_{locality} = 0$ | $W_{locality} = 0$ |
| $W_{command\_pref} = 0$ | $W_{command\_pref} = 0$ | $W_{command\_pref} = 1$ | $W_{command\_pref} = 0$ |
| $W_{sailor\_pref} = 0$ | $W_{sailor\_pref} = 0$ | $W_{sailor\_pref} = 0$ | $W_{sailor\_pref} = 1$ |

## D. UTILIZATION OF THE TOOL

### 1. Pre-Processing Program

Input files are read into Python and manipulated using the Pandas library. The pre-processing, or data cleaning process, takes less than 45 seconds to run on average. Every application has an associated status. An application's status determines whether a Sailor was previously assigned to the applied billet. If a status deems a Sailor already assigned to a billet, all other applications by the Sailor or to the billet are removed from the dataset.

#### *a. Inputs*

Application File: This file contains the information for all applications of the cycle. Sailor Preference and Locality are determined from this file.

Billet File: This file contains information for all billets and their respective commands. A billet's Unit Type is determined from this file.

Sailor File: Although the information is not translated into the optimization file, it identifies potential IMS, MAS, or Security Clearance disqualifiers for every reserve

Sailors. Sailors are not removed from the application file; rather, they are flagged in different output file.

IMS/MAS/Security Clearance Disqualifier Table: This CSV file identifies all current IMS, MAS, or Security Clearance disqualifier codes. Assigners can edit this file as policies regarding disqualifiers change. As with the Sailor File, Sailors are not removed from the application file if this file contains a disqualifier.

#### *b. Outputs*

Optimization-Ready File: In this CSV file is the necessary information from the Application file and the Unit Type that each billet belongs to. Only this file will be input into the optimization model.

Ineligible Sailors File: CSV file identifies all potentially ineligible Sailors and their respective IMS, MAS, and Security Clearance disqualifiers. Sailors' applications, however, are not removed from the Optimization-Ready file. This is due to the volatility of policy changes and the fact that a Sailor's eligibility information may not up to date. This allows assigners to cross-reference whether Sailors are actually ineligible, after which assigners can remove their applications prior to running the model.

Billet Discrepancies: CSV file that identifies all billets that were not identified in the Billet Input File. Since the billets' Unit Type cannot be identified, all applications are removed from the Optimization-Ready File.

### 2. Optimization Program

RASM's inputs and outputs are as follows.

#### *a. Input*

Optimization-Ready Application File: CSV file contains the input data and quantitative penalty for all metrics.

### *b. Output*

Optimized Assignments: CSV file containing optimal Sailor-billet assignments. Unassigned Sailors are also flagged at the end of the file.

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# IV. ANALYSIS

We implemented RASM in Python using the Pyomo version 5.7.3 (Hart. et al. 2017) package on a 64-bit HP Spectre x360 with 8 GB RAM and solve with the COIN-OR branch and cut (CBC) Solver version 2.10.8. We first compare RASM's results to historical results from the Q2 FY22 and Q3 FY22 assignment cycles. The Q2 FY22 assignment cycle contained 2,000 Sailors. The resulting RASM model utilizes 7,522 decision variables and 2,266 constraints, and it solves in less than 15 seconds. The Q3 FY22 assignment cycle contained 1,936 Sailors. The RASM model utilizes 7,305 decision variables and 2,248 constraints, and it also solves in less than 15 seconds.

## A. Q2 FY22 ASSIGNMENT CYCLE RESULTS

Table 7 illustrates the number of Sailors assigned by RASM and the percent similar RASM's assignments were compared to the historical manual assignment for the Q2 FY22 assignment cycle. The leftmost column depicts the historical results of the manual assignment process, while the remaining columns represent RASM's results for the default metric weights (shown in Table 5) and maximum weight for each individual merit (shown in Table 6). The model makes the same number of assignments for each setting of the weights. For all settings, RASM assigns 116 more Sailors than the manual process.

Similarity is calculated by counting the number of times RASM made the same assignment as was made by manual hand-assignments, divided by the total number of Sailors that were manually hand-assigned. This calculation is conservative because it does not account for Sailors with identical characteristics. For example, if Sailor A and Sailor B both have the same attributes with respect to a particular billet, but RASM assigns Sailor A to the billet while the hand-assignment assigns Sailor B, we treat the assignment as different in our calculation.

Table 7. Q2 FY22 Model Performance

| | Manual Hand-Assignments | Default Weights | Max Unit | Max Local | Max Command Ranking | Max Sailor Preference |
|---|---|---|---|---|---|---|
| Number of Sailors Assigned | 1,799 | 1,915 | 1,915 | 1,915 | 1,915 | 1,915 |
| % Similar to Original Assignments | | 79.71% | 65.81% | 67.54% | 75.49% | 73.93% |

Table 8 provides further detail on the performance of RASM with respect to each metric. As in Table 7, we compare the historical manual assignment from Q2 FY22 to the assignments resulting from RASM's default weight setting shown in Table 5 and each of the "maxed out" weight settings shown in Table 6. Each row of the table represents a particular metric; in the rightmost column, we show the best possible performance for that metric resulting from the corresponding "maxed out" weight setting. The percentage assigned out of the 2,000 possible Sailors is depicted in each cell, and the number in parentheses represents the total number of Sailors assigned. In this table we only include the most favorable outcome for each metric (e.g., Sailors receiving their highest-ranked billet). The Appendix describes the results of all outcomes for each metric.

Table 8. Q2 FY22 Metric Results

| Metric | Manual Hand-Assignments | Default Weights | Max Weights |
|---|---|---|---|
| Operational Units | 23.30% (466) | 26.85% (537) | 29.20% (584) |
| Local Assignments | 42.90% (858) | 45.70% (914) | 47.55% (951) |
| 5* Command Ranking | 27.05% (541) | 25.7% (514) | 27.95% (559) |
| 1st Sailor Preference | 64.40% (1,288) | 71.1% (1,422) | 77.75% (1,555) |

As the table indicates, the default RASM weights result in improved outcomes relative to the manual assignment for every metric except Command Ranking. The manual assignment assigns 27.05% of the 2,000 applicants to a command that gave them a top ranking; this is very close to the best possible percentage of 27.95% and reflects the assigners stated inclination to satisfy command preferences. Recall that the Command Ranking metric does not explicitly maximize the number of Sailors given a top ranking by a command; rather, it considers rankings on a scale from 1* to 5*. As the Appendix shows, RASM also assigns significantly more Sailors to commands that gave them 4* and 3* rankings. Recall that a 3* ranking is used as a default when a command does not enter a ranking for a Sailor; about 70% of applications received a 3* ranking in this dataset.

## B. Q3 FY22 ASSIGNMENT CYCLE RESULTS

In Q3 FY22, 1,936 Sailors applied. In this cycle of assignments, RASM assigns 166 more Sailors than were assigned in the manual process. Table 9 depicts the number of Sailors assigned by RASM and the percent similar RASM's assignments were compared to the historical manual assignment for that cycle. Table 10 provides further detail on the performance of RASM with respect to each metric.

Table 9. Q3 FY22 Model Performance

| | Manual Hand-Assignments | Default Metrics | Max Unit | Max Local | Max Command Ranking | Max Sailor Preference |
|---|---|---|---|---|---|---|
| Number of Sailors Assigned | 1,691 | 1,857 | 1,857 | 1,857 | 1,857 | 1,857 |
| % Similar to Original Assignments | | 78.65% | 65.52% | 68.18% | 74.04% | 72.62% |

Table 10. Q3 FY22 Metric Results

| Metric | Manual Hand-Assignments | Default Weights | Max Weights |
|---|---|---|---|
| Operational Units | 23.86% (462) | 28.46% (551) | 30.42% (589) |
| Local Assignments | 41.27% (799) | 44.89% (869) | 46.64% (903) |

| Metric | Manual Hand-Assignments | Default Weights | Max Weights |
|---|---|---|---|
| 5* Command Ranking | 27.32% (529) | 28.25% (547) | 30.06% (582) |
| 1st Sailor Preference | 61.36% (1,188) | 69.32% (1,342) | 76.91% (1,489) |

Unlike the last cycle, RASM assigns more 5* command ranked Sailors with default metrics and with max Command Ranking weight. While the model was not able to assign more 5* Command Ranking Sailors in the last cycle, the variability of Command Ranking is explored in later plots. In Q3 FY22, RASM is successful in assigning more Sailors in the favorable category of each metric with default weights and even more so when only considering that specific metric. The plots in Section D explore the variability of metric assignment across all metric weights for objective function of RASM.

## C. PREVIOUS ASSIGNMENT CYCLE RESULTS

To further explore the performance of RASM, we now consider the assignment cycles from Q4 FY21 and Q1 FY22. Since the Command Ranking quantitative feedback was not yet collected during these cycles, we consider only Unit Type, Locality, and Sailor Preference. Depicted in Table 11, the manual hand-assignment process assigned 84% of Sailors in Q4 FY21 and 89% in Q1 FY22. RASM assigned around 95% in both quarters. This demonstrates the increase of assignments when using RASM. The subsequent tables, Table 12 and Table 13, provide further details on the performance of RASM with respect to each metric on the past cycles.

Table 11. Model Results of Q4 FY21 and Q1 FY22

| Quarter Fiscal Year | Number of Sailors Applied | Percentage Manually Hand-Assigned | Percentage Assigned Default Weights |
|---|---|---|---|
| Q4 FY21 | 2,157 | 84.23% (1,817) | 94.62% (2,064) |
| Q1 FY22 | 2,003 | 89.11% (1785) | 95.66% (1916) |

Table 12. Q4 FY21 Metric Results

| Metric | Manual Hand-Assignments | Default Weights | Max Weights |
|---|---|---|---|
| Operational Units | 26.05% (562) | 28.51% (615) | 33.94% (732) |
| Local Assignments | 35.98% (776) | 38.66% (834) | 41.63% (898) |
| 1st Sailor Preference | 53.50% (1,154) | 68.75% (1,483) | 70.38% (1,518) |

Table 13. Q1 FY22 Metric Results

| Metric | Manual Hand-Assignments | Default Weights | Max Weights |
|---|---|---|---|
| Operational Units | 25.76% (516) | 27.96% (560) | 31.90% (639) |
| Local Assignments | 40.34% (808) | 42.39% (849) | 44.28% (887) |
| 1st Sailor Preference | 61.26% (1,227) | 72.09% (1,444) | 73.64% (1,475) |

## D. SENSITIVITY ANALYSIS

In this section, we further explore RASM's performance on the Q2 FY22 and Q3 FY22 assignment cycles using weights generated via nearly orthogonal Latin hypercubes (NOLH) (Sanchez 2021). The NOLH's "space-filling" design produces a wide range of weight variations. For each of the four metric weights, the NOLH produced varied weights between 0.0001 to and 1. The weight variations were produced using a Ruby program file (Sanchez 2021), and 113 different weight variations were produced. The following plots demonstrate the variability in outcomes among the 113 different weight variations. Each plot's vertical axis is scaled to capture the variation range of the metric being considered. The horizontal axes represent the 113 weight variations that were produced by the NOLH simulation and inputted into RASM. Before considering our four main metrics, we first examine the similarity of RASM assignments to manual assignments.

### 1. Similarity

The similarity of RASM's assignments to the manual hand-assignment for Q2 FY22 and Q3 FY22 is depicted in Figure 3 and Figure 4 respectively. For both quarters, RASM's assignments are as low as 73% and as high as 81% similar to manual assignments. With default weights, RASM makes 79.71% of the same assignments for Q2 FY22 and 78.65% for Q3 FY22.

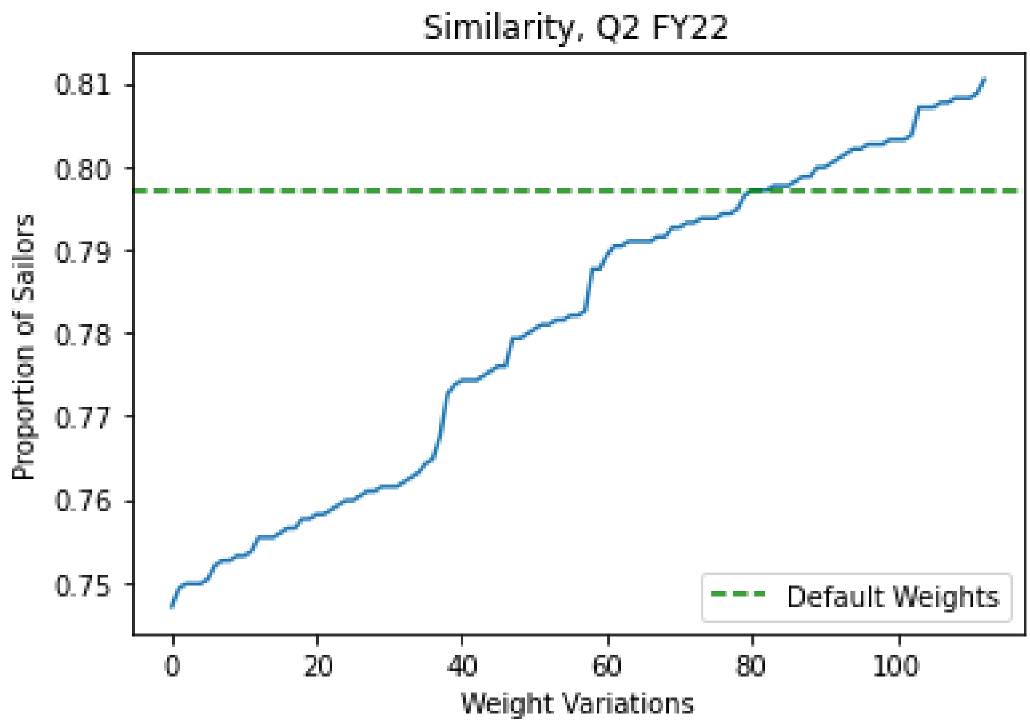


Figure 3. Proportion of Sailors Similar to Manual Hand-Assignments in Q2 FY22

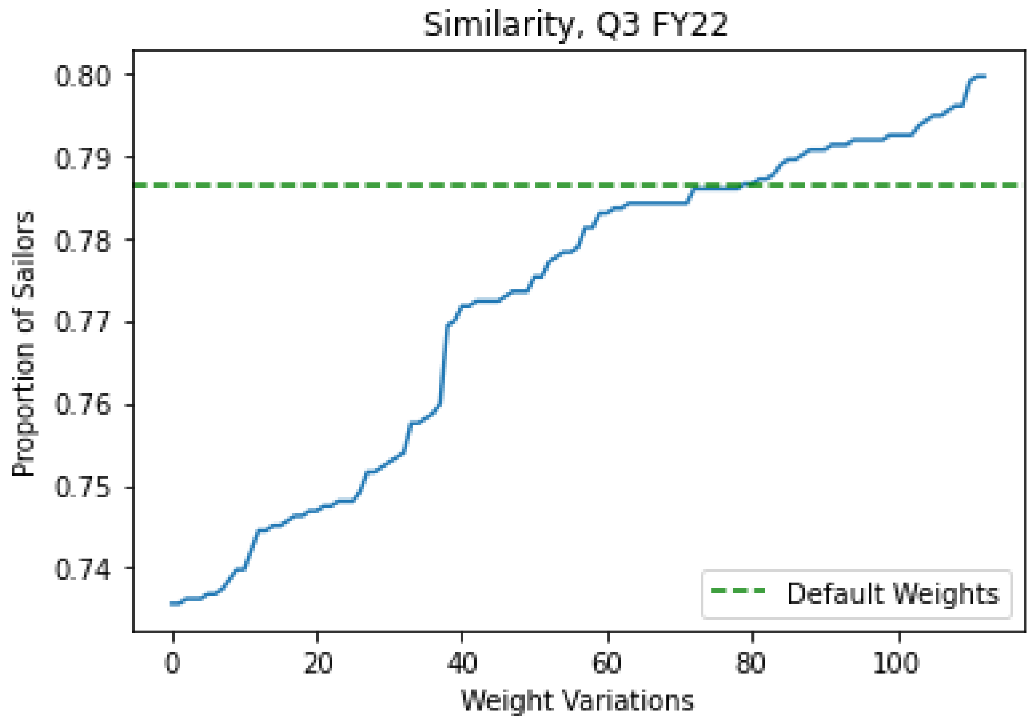


Figure 4. Proportion of Sailors Similar to Manual Hand-Assignments in Q3 FY22

While manual assignments are sub-optimal, there can be value in determining which metric weights produce the most similar results compared to what was completed by hand. Despite Unit type having the highest priority in RASM's default weights, a large weight for the Command Ranking metric produces the most similar results. As established by the assigning team at RESFOR, Unit Type is the most important metric. However, assigner reward high performing or highly sought-after Sailors. Assigners manually assign these Sailors first. High performing Sailors are determined by their "Command Comment" write up on their application. Sailors are typically given a 5* Command Ranking upon receiving a positive endorsement in the Command Comment section on their application, but command sentiment toward Sailors is only prioritized by the Command Ranking metric weight. RASM does not assign these highly sought-after Sailors first, but this step can be enforced in the model by manually assigning these Sailors before running RASM. Assigners can adjust the weights, remove arcs to other billets for which those Sailors applied, or change the status of an application prior to the pre-processing of the data. If a status deems a Sailor assigned to a billet, all other applications by the Sailor or to the billet are removed from the data. RASM accounts for application status changes as Sailors are assigned and the tool is run iteratively throughout the assignment cycle.

The remaining plots show RASM's performance on the four primary metrics by showing the percentage of Sailors assigned to the most favorable category for each metric: operational for Unit Type, local for Locality, 5* for Command Ranking, and 1st for Sailor Preference. This is calculated by dividing the number of Sailors assigned into the most favorable category using RASM by the total number of Sailors who applied in the cycle.

### 2. Unit Type

The first metric that will be addressed is Unit Type, and it is represented in Figure 5 and Figure 6. Unit type is the metric with the highest priority. Some of the NOLH weights gave Unit type a low weight, yet still assigned a higher proportion of Sailors to operational units than the manual hand-assignment. RASM assigned between 24% and 29% of Sailors to operational units for Q2 FY22 and between 25% and 30% of Sailors for Q3 FY22. There is an approximate 5% range of operational units that RASM can assign a Sailor when varying the metric weights. This is a key finding for RESFOR since leadership and policy dictate that assigning Sailors to operational units is the highest priority.

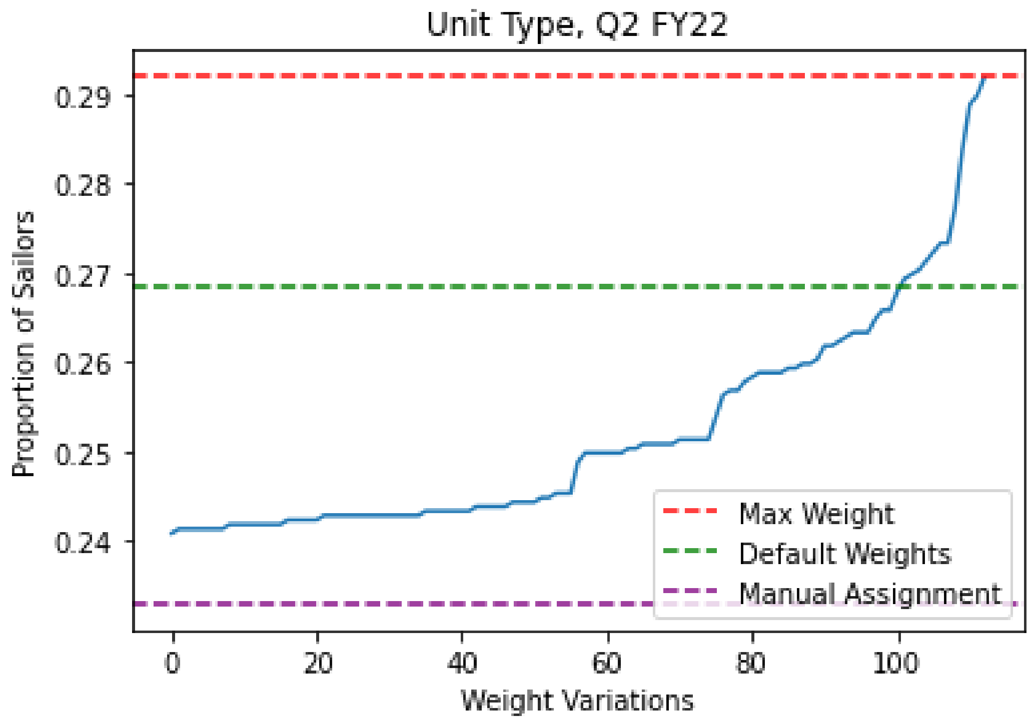


Figure 5. Proportion of Sailors Assigned to Operational Units in Q2 FY22

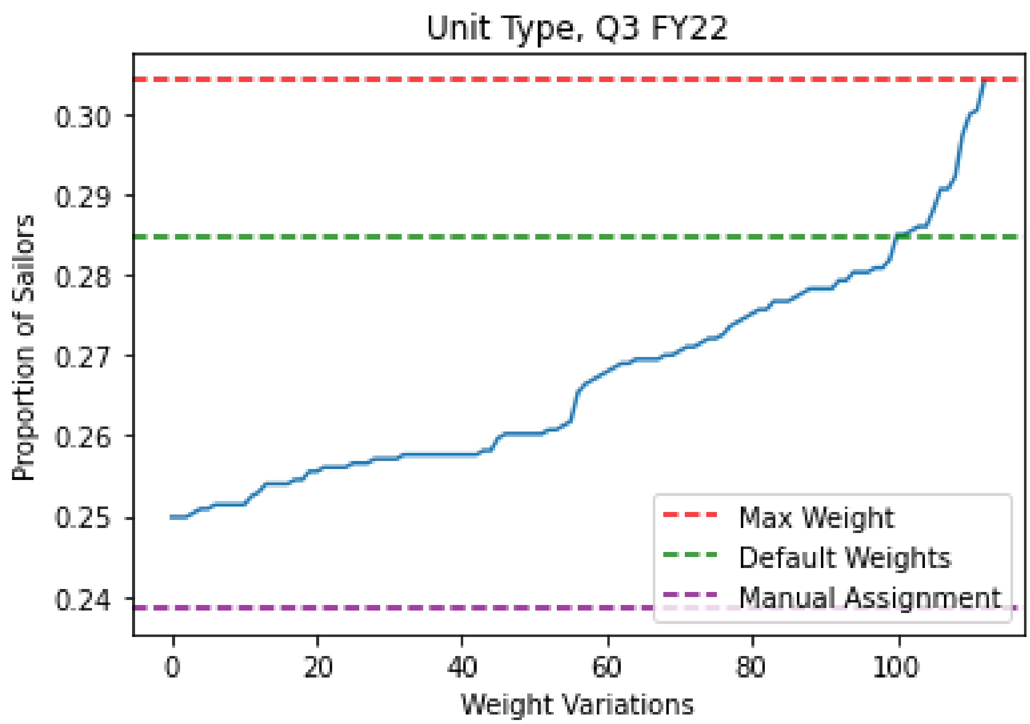


Figure 6. Proportion of Sailors Assigned to Operational Units in Q3 FY22

### 3. Locality

The metric with the second highest priority is Locality, and the assignment percentages are depicted in Figure 7 and Figure 8. Locality is the second most important metric since it is both cost effective and time effective for Sailors to be assigned to a local unit. RASM assigns between 44% and 47% of Sailors to local assignments in Q2 FY22 and between 43% and 46% in Q3 FY22. All attempted metric weight configurations in RASM assigned more Sailors to local units than the manual assignment.

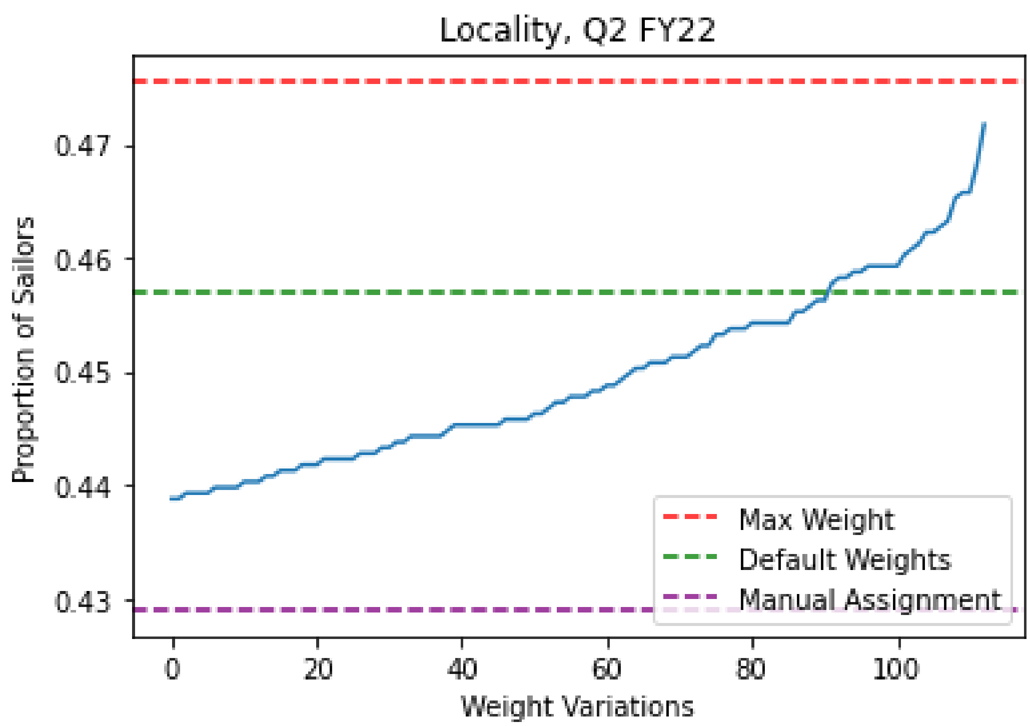


Figure 7. Proportion of Sailors Assigned to Local Units in Q2 FY22

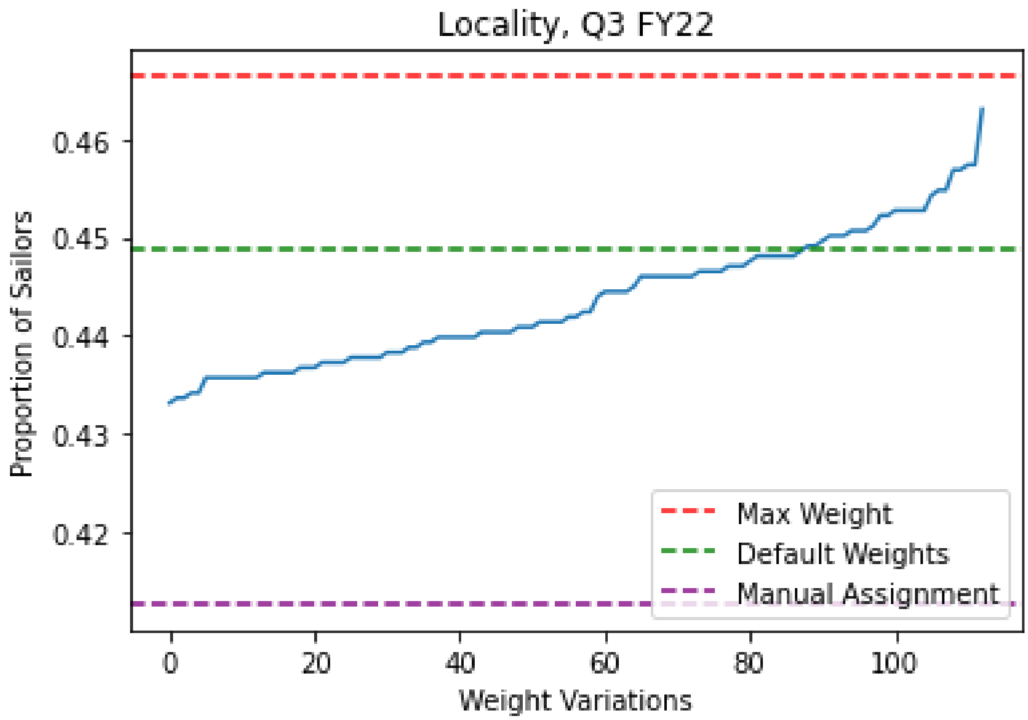


Figure 8. Proportion of Sailors Assigned to Local Units in Q3 FY22

#### 4. Command Ranking

The third most important metric is Command Ranking, and the plots of 5* command ranked assignment variations illustrate the most surprising metric performance. They are depicted in Figure 9 and Figure 10. As mentioned in Chapter III, only about 30% of Sailors' applications receive a Command Ranking. Because of this, there is high variability when measuring the success of the Command Ranking metric. The default weights in Q2 FY22 do not assign as many Sailors to commands that gave them 5* as what is accomplished manually. Contrary to this, both the default weights and maxed Command Ranking weight in Q3 FY22 assign more 5* command ranked Sailors compared to what is done manually. There are two resolutions to combat the variability of the success of Command preference weight. First, RESFOR can encourage more command participation to give Sailors a ranking, so that 70% of Sailors' applications will not receive the default 3* rating. Second, highly sought-after or high performing Sailors, as distinguished by Command Comments, can be manually assigned prior to running the optimization model.

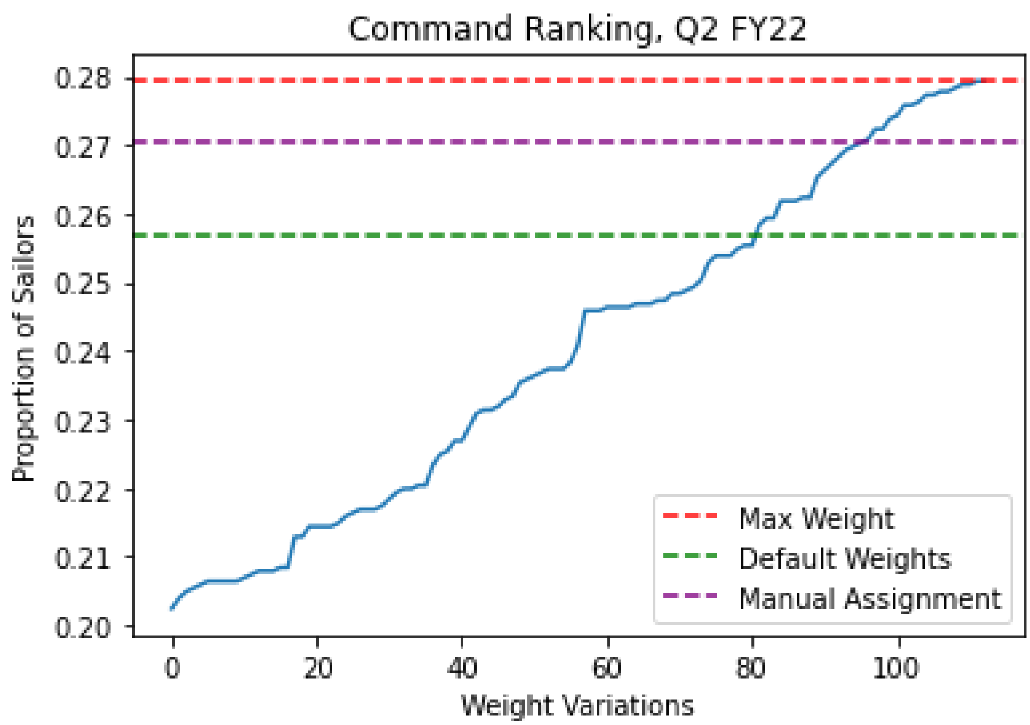


Figure 9. Proportion of 5* Command Ranked Sailors Assigned in Q2 FY22

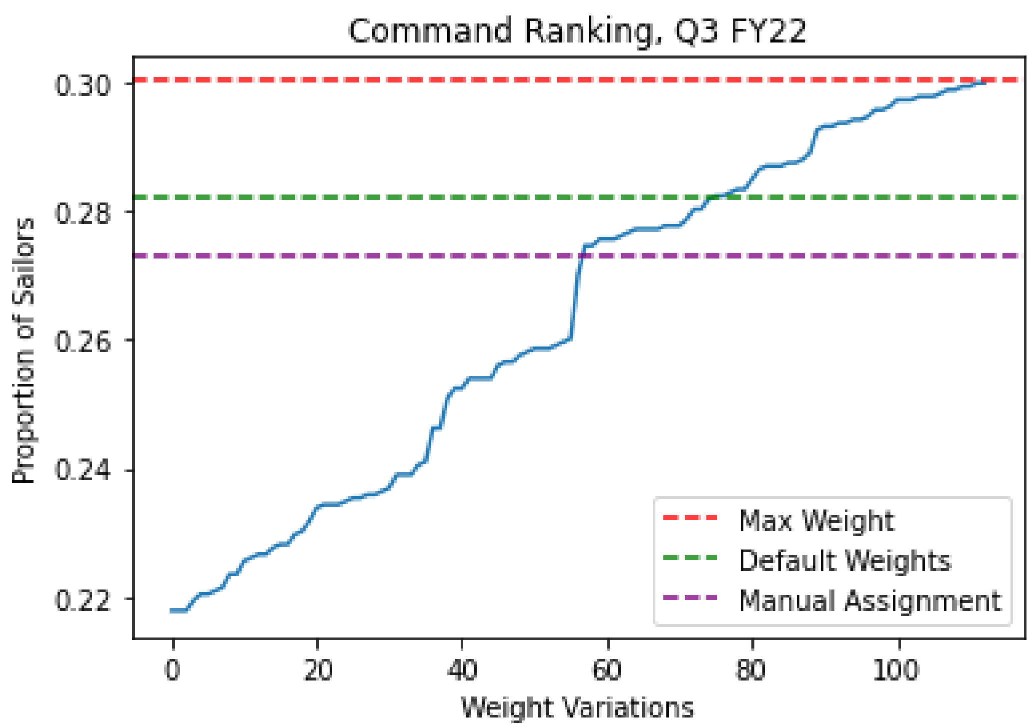


Figure 10. Proportion of 5* Command Ranked Sailors Assigned in Q3 FY22

### 5. Sailor Preference

Sailor Preference is the metric with the lowest priority, and it was the metric with the largest scales of potential values (1-10). Figure 11 and Figure 12 depict the variability of Sailors assigned to their most preferred billet. With every attempted weight configuration, RASM assigns more Sailors to their most preferred billet compared to what was accomplished in manually. Additionally, Sailor Preference had the widest spread of assignment percentages to the most favorable outcome among the four metrics. RASM assigns approximately 68–78% of Sailors to their most preferred billet in Q2 FY22, and it assigns approximately 66–77% in Q3 FY22. The performance of the Sailor Preference metric is not surprising since most Sailors apply to only three billets (Spitnale 2021).

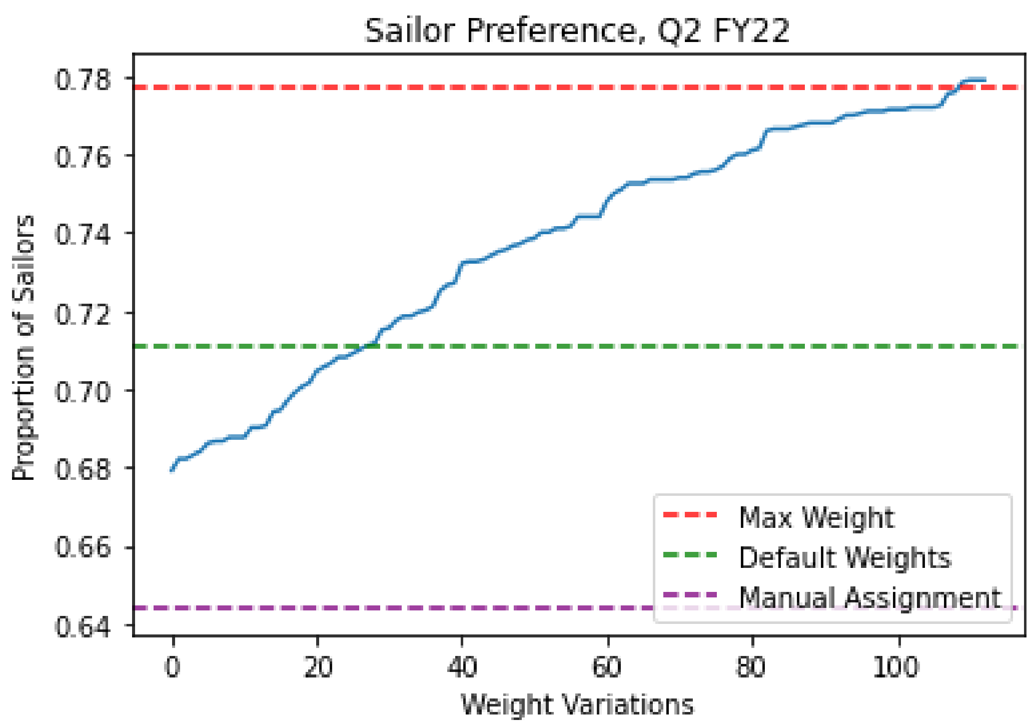


Figure 11. Proportion of Sailors Assigned to 1st Preference in Q2 FY22

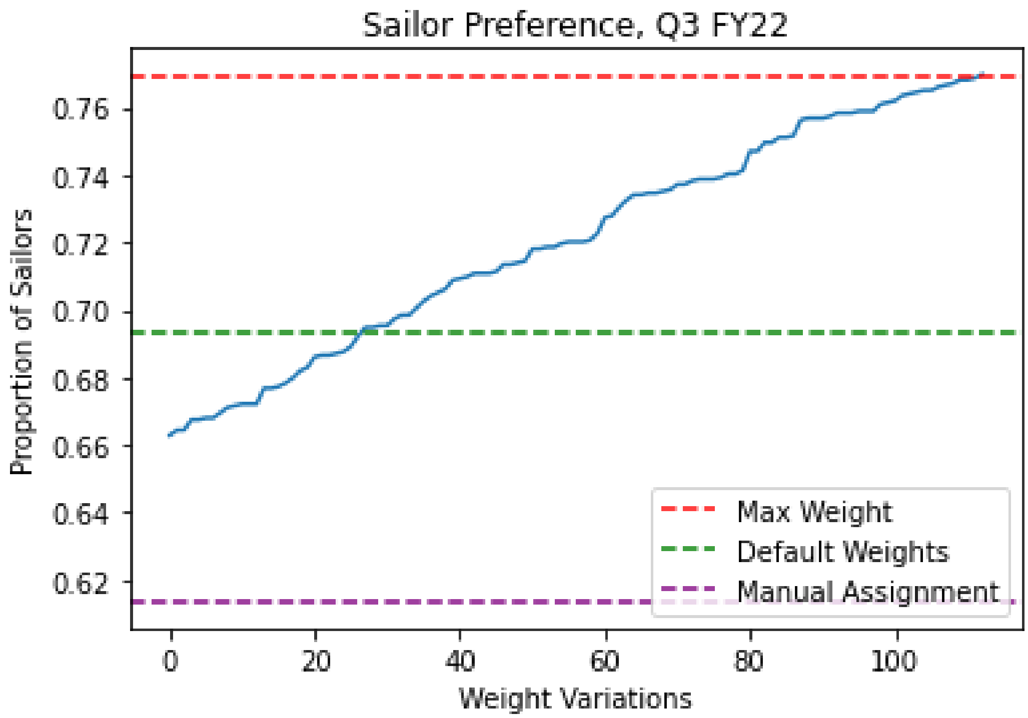


Figure 12. Proportion of Sailors Assigned to 1st Preference in Q3 FY22

# V. CONCLUSION AND RECOMMENDATIONS

## A. CONCLUSION

This thesis details the development of the Reserve Applied Sailor Model (RASM) tool to aid the U.S. Navy Reserve in its placement of personnel. RASM is a Python-based linear program. It is the first automated process that assigns reserve Sailors to billets. Unlike in active duty, reserve Sailors are assigned by a team of assigners each quarter, or every three months, at Navy Reserve Forces (RESFOR) Command. Unlike the current manual process, RASM considers all possible assignments and all metrics at once. The model structure is designed to remove subjectivity and bias in assignments and to ensure reproducibility in results. Assigners can also utilize RASM with weight variations to produce different assignments for the same cycle and compare results. Compared to the manual process, RASM assigns more Sailors, assigns higher percentages in favorable metric categories, and it completes a three-week assignment task in under two minutes. The time required to input data for RASM, validate its output, and implement the resulting assignment is approximately one week.

## B. IMPLEMENTATION

RASM serves as a supplemental tool that provides recommendations considering all assignments at once. It will be implemented immediately in the next cycle of Navy Reserve assignments. RESFOR intends to utilize RASM initially after billet applications close and then iteratively as necessary. Assigners at RESFOR have the option to manually assign positively endorsed Sailors as determined by Command Comments first before utilizing the tool. Any extraneous circumstances can also be addressed in the "optimization-ready application file" before utilizing the optimization tool. For instance, assigners can designate applications with cross-assigned billets as a local billet in the if a Sailor receives the qualifying waiver. RASM will save countless manpower hours throughout every assignment cycle and ensure readiness of the U.S. Navy Reserves.

## C. FUTURE WORK

RASM currently only assigns enlisted reserve Sailors who applied to billets. The automated process cannot currently be implemented for junior officers due to data limitations. The application file, which is the main input file for RASM, is retrieved from the MNA database. So far, no discernable application dataset exists for junior officers. Junior officers utilize the RFMT website database interface to apply to billets. If a similar, exportable file is created, RASM can be extended to junior officer assignments.

While RASM assigns Sailors to billets based on the quality of an application, it does not assign based on an "exact match" criterion of a Sailor's job experience and skillset. An exact match criterion would measure a Sailor's fit for a billet based on their rate, rank, RFAS code, and NEC code. If a quantifiable dataset is created to represent these parameters, assignments can be completed based on the exact match criterion. Additionally, this would allow Sailors to be directly assigned to a billet, regardless of if they applied to a billet for the cycle.

Lastly, a persistence feature can be added in RASM. When a Sailor is assigned to a billet, RASM removes all applications by the Sailor and to the billet using the pre-processing file. However, a persistence feature can allow those removed applications to remain as possible solutions. A user-defined persistence parameter can limit the assigned Sailors or billet that can change when utilizing RASM.

# APPENDIX. MAX METRIC WEIGHTS

These tables demonstrate the variation of Sailor assignments across all metrics when one of the metrics is assigned a max weight of 1 and all other weights are assigned 0. (As previously stated, a weight of 0 can result in a solution that is not Pareto optimal, since it may be possible to achieve better performance with respect to the metric that received zero weight without sacrificing performance in the other metrics.) Each cell is the proportion of Sailors assigned in a particular condition for a given metric. The first row of each table represents the most favorable condition of each metric. Followed by a less favorable condition. From top the bottom, the rows represent the metrics in descending condition preference. The last row is the proportion of Sailors not assigned. The columns represent the type of iteration of assignments. The left column is what was accomplished by manual hand-assignments. The middle column is the assignment of RASM with default metrics. The right column is the assignment of RASM while only considering the respective metric.

Table 14. Q2 FY22 Unit Type Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Unit |
|---|---|---|---|
| Operational | 23.30% (466) | 26.85% (537) | 29.20% (584) |
| Readiness | 66.65% (1,333) | 68.90% (1,378) | 66.55% (1,331) |
| Not Assigned | 10.05% (201) | 4.25% (85) | 4.25% (85) |

Table 15. Q3 FY22 Unit Type Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Unit |
|---|---|---|---|
| Operational | 23.86% (462) | 28.46% (551) | 30.42% (589) |
| Readiness | 63.48% | 67.46% | 65.50% |

| | | | |
|---|---|---|---|
| | (1,229) | (1,306) | (1,268) |
| Not Assigned | 12.65% (245) | 4.08% (79) | 4.08% (79) |

Table 16. Q2 FY22 Locality Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Local |
|---|---|---|---|
| Local | 42.90% (858) | 45.70% (914) | 47.55% (951) |
| Cross-Assigned | 47.05% (941) | 50.05% (1,001) | 48.20% (964) |
| Not Assigned | 10.05% (201) | 4.25% (85) | 4.25% (85) |

Table 17. Q3 FY22 Locality Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Local |
|---|---|---|---|
| Local | 41.27% (799) | 44.89% (869) | 46.64% (903) |
| Cross-Assigned | 46.07% (892) | 51.03% (988) | 49.28% (954) |
| Not Assigned | 12.65% (245) | 4.08% (79) | 4.08% (79) |

Table 18. Q2 FY22 Command Ranking Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Command Ranking |
|---|---|---|---|
| 5* | 27.05% (541) | 25.7% (514) | 27.95% (559) |
| 4* | 2.25% (45) | 2.80% (56) | 3.0% (60) |
| 3* | 58.20% (1,164) | 64.65% (1,293) | 62.6% (1,252) |
| 2* | 0.50% (10) | 0.4% (8) | 0.4% (8) |
| 1* | 1.95% (39) | 2.20% (44) | 1.80% (36) |

| | | | |
|---|---|---|---|
| Not Assigned | 10.05% (201) | 4.25% (85) | 4.25% (85) |

Note: 3* is default if no rank is given

Table 19. Q3 FY22 Command Ranking Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Command Ranking |
|---|---|---|---|
| 5* | 27.32% (529) | 28.25% (547) | 30.06% (582) |
| 4* | 2.27% (44) | 2.22% (43) | 2.01% (39) |
| 3* | 55.79% (1080) | 62.86% (1217) | 61.98% (1200) |
| 2* | 0.36% (7) | 0.52% (10) | 0.15% (3) |
| 1* | 1.60% (31) | 2.06% (40) | 1.70% (33) |
| Not Assigned | 12.65% (245) | 4.08% (79) | 4.08% (79) |

Table 20. Q2 FY22 Sailor Preference Assignment Variation

| | Manual Hand-Assignment | Default Weights | Max Sailor Preference |
|---|---|---|---|
| 1st | 64.40% (1,288) | 71.1% (1,422) | 77.75% (1,555) |
| 2nd | 10.65% (213) | 12.1% (242) | 10.15% (203) |
| 3rd | 5.35% (107) | 5.2% (104) | 3.60% (72) |
| Not Assigned/ Other Preference | 19.60% (392) | 11.60% (232) | 8.50% (170) |

Table 21. Q3 FY22 Sailor Preference Assignment Variation:

| | Manual Hand-Assignment | Default Weights | Max Sailor Preference |
|---|---|---|---|

| | | | |
|---|---|---|---|
| 1st | 61.36% (1,188) | 69.32% (1,342) | 76.91% (1,489) |
| 2nd | 10.95% (212) | 12.65% (245) | 10.43% (202) |
| 3rd | 5.37% (104) | 5.84% (113) | 3.82% (74) |
| Not Assigned/ Other Preference | 22.31% (432) | 12.19% (236) | 8.83% (171) |

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