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Navy Enlisted Detailing Marketplace Assignment Algorithm

Warren Sutton, Sarah Wilson, and Rachel Townsley

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Abstract

The Navy is implementing the Detailing Marketplace Assignment Policy, which will lead to shorter tours and more frequent assignments for enlisted sailors. Through this study for Navy Enlisted Placement Management, PERS-4013, CNA has developed an assignment algorithm to assist detailers with assignments. The assignment algorithm is based on a non-parametric operations research technique called data envelopment analysis. This annotated briefing presents the modeling approach, provides results on a sample graphical user interface, and explains how the Navy can expand its understanding of sailor and command preferences with synthetic preferences.

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Approved by: **June 2022**

Ann Parcell, Director
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Executive Summary

In this document, we present a Navy enlisted assignment algorithm and a method to generate synthetic preferences. The assignment algorithm is unique in that it allows us to combine multiple metrics with different dimensions into a single score. The scoring is developed as a two-way evaluation of sailors and commands. This evaluation allows sailors to score all the available jobs from their perspective and allows the commands to score all the available sailors for their jobs. The two-way evaluation produces a composite score that is used in an assignment algorithm to maximize the composite score for an assignment slate.

The current enlisted distribution process does not allow sailors or commands to evaluate every potential candidate requisition—doing so would be arduous and impractical. So, we present a method to create synthetic preferences based on the preferences that the sailors and commands have already provided. The synthetic preferences metric provides easily assessable information to sailors and commands to help them identify other potential assignments or candidates for requisitions without additional information and could also be integrated into future versions of our algorithm.

Lastly, we recommend how to integrate our algorithm into the enlisted distribution system and identify additional data to collect to make the system more robust. We highlight the need for quantitatively understanding the additional demand on detailers resulting from the new Detailing Marketplace Assignment Policy (DMAP) and the need for business rules for implementing our proposed assignment algorithm. In the future, the assignment process could benefit from incorporating more specific sailor geographic preference data and would benefit from commands expressing generalized preferences before individual sailors apply for their billets.

Background

Study Sponsor: Navy Enlisted Placement Management, PERS-4013

- The Detailing Marketplace Assignment Policy (DMAP) is intended to improve sea manning.
- DMAP will require more frequent sailor assignments, leading to the need to expand automation of the assignment process.
- Currently, the Navy relies on detailers to broker negotiations with sailors and commands for orders.
- The Navy seeks to establish a Detailing Marketplace to improve the quality of enlisted assignments and the ease of making them.

To improve sea manning, the Navy is making significant changes to the sailor assignment process. The DMAP comprises these changes. Under DMAP, sailors are expected to have shorter tours and require more frequent orders. As a result, expanded automation of the enlisted detailing process will be required [1].

Although a system exists to capture sailor preferences and command comments electronically, it relies heavily on individual detailers to negotiate orders with sailors and is insufficient to support DMAP. The Navy is establishing the Detailing Marketplace as a new electronic platform to engage enlisted sailors in the detailing process to facilitate the goals of DMAP.

Our sponsor, Enlisted Placement Management (PERS-4013), asked CNA to support the transition to DMAP by building an assignment algorithm to assist the detailers.

Study objectives

1. Develop an algorithm to assist detailers in making assignments.
2. Identify key factors and metrics in determining match quality.
3. Recommend improvements to the distribution process data collection methods.

The primary objectives of this study are to support the Detailing Marketplace by developing an algorithm to assist detailers in making assignments, identifying key metrics for measuring assignment quality, and recommending additional data to collect to support the Detailing Marketplace.

Key players in enlisted distribution process

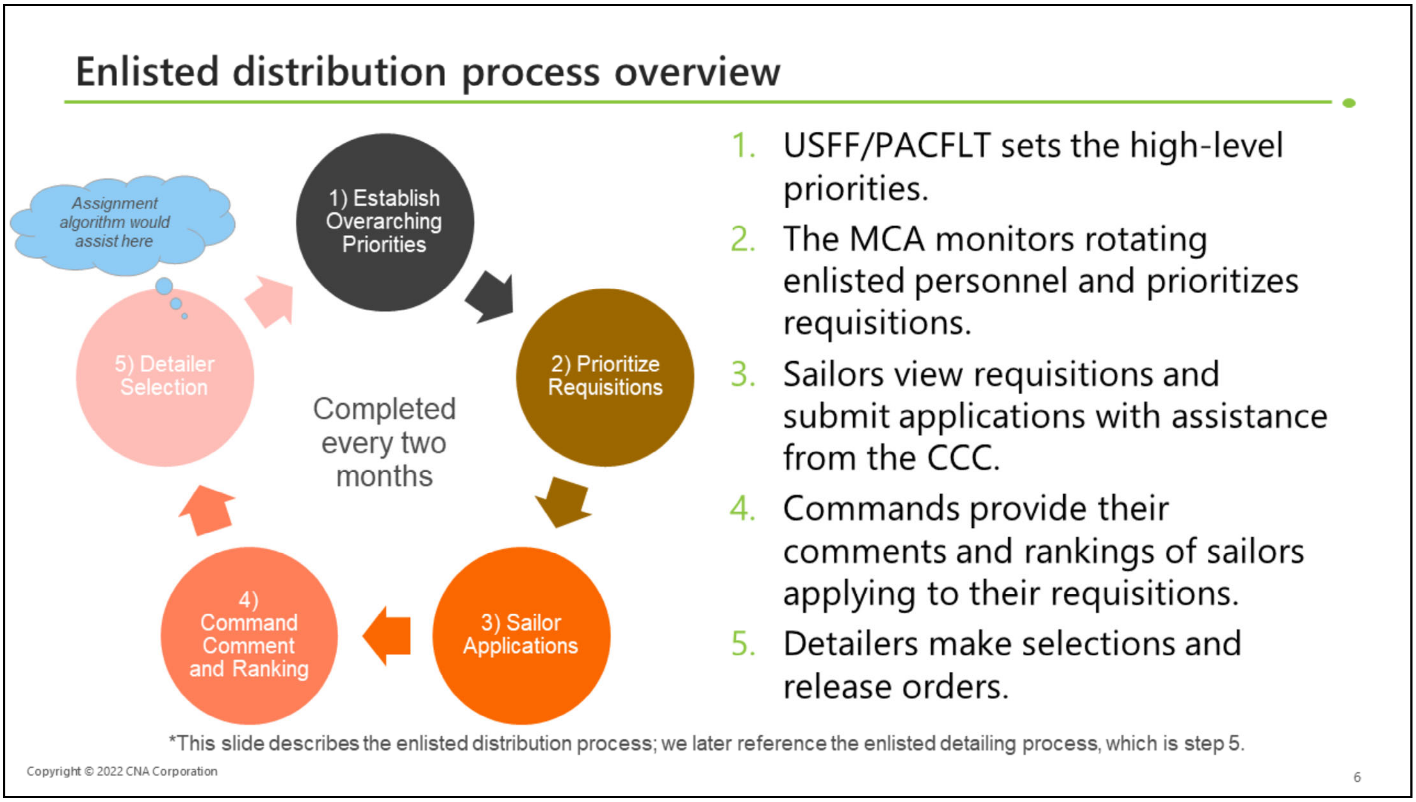
The enlisted distribution process relies on several key players to fulfill roles.

Player	Principle Role(s)
US Fleet Forces Command (USFF)/ US Pacific Fleet (PACFLT)	• Set overarching manning priorities
Manning Control Authority (MCA)/Millington	• Manage the enlisted distribution process • Prioritize requisitions (i.e., billets that need to be filled soon) given fleet priorities and sailor availability
Sailor	• Express preferences through applying for requisitions • Work with the command career counselor to understand the strengths and weaknesses of assignment possibilities • Negotiate with the detailer for final orders
Command Career Counselors (CCC)	• Help sailors navigate the enlisted detailing process • Assist sailors in applying for requisitions
Commands	• Provide input/rank sailors who apply to their requisitions
Detailer	• Assign sailors to available requisitions • Handle special cases (e.g., exceptional family members, limited deployability)

In the existing Navy enlisted distribution process, several key players have important roles. The jobs (or billets) available for assignment are represented in the form of requisitions (called "reqs"). The Navy projects when billets will become vacant based on the planned rotation date of the incumbent sailor or an anticipated loss of a sailor to the Navy. This projection ensures that billets are filled immediately, when possible. Because the number of requisitions usually outnumbers the available sailors, the requisitions are ranked by "need to fill" based on fleet priorities and sailor availability.

Sailors who have an upcoming rotation date can review the available requisitions and signal their interest by applying to their preferred requisitions. To inform their requisition rankings, sailors should work with their CCC to understand the pros and cons of potential assignments, including how they may affect their career. To help ensure their assignment to a preferred requisition, sailors need to engage with their detailer for the final assignment. CCCs are responsible for ensuring that sailors understand the detailing process as well as the pros and cons of potential assignments. Commands may provide input and rank the sailors who apply for a requisition in their command. Detailers are responsible for making the final matches of sailors to requisitions during each requisition cycle and must balance the inputs of the other key players.

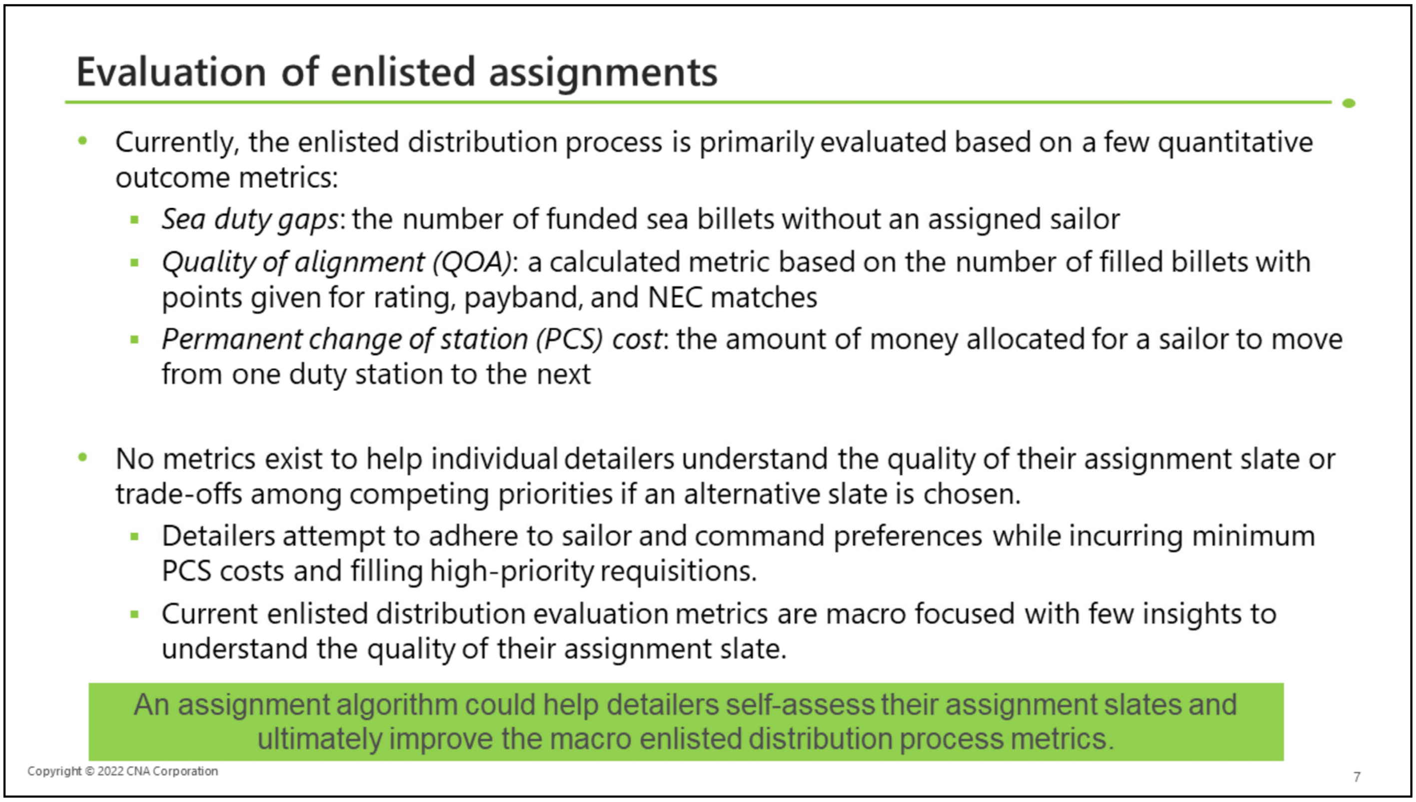
The next slide provides additional detail on how the enlisted distribution process works.



This slide provides an overview of the enlisted distribution process and the roles of each of the key players [2]. Every two months, the Navy completes the cycle to assign enlisted sailors. The process starts with the fleet establishing high-level priorities. USFF and PACFLT both provide guidance on the strategic priorities for the detailing cycle. These priorities guide the MCA in determining which requisitions to prioritize for a given rating and paygrade. The prioritized list is provided to sailors approaching their projected rotation date (PRD). Note that shortages in sailor inventory due to non-deployability, inventory friction, distribution friction, and underfunding of the Individuals Account lead to more requisitions being available than the number of sailors to fill them. Thus, requisitions are categorized as open, view-only, and unadvertised. Currently, sailors can apply to only the open requisitions. The goal of Navy Personnel Command (NPC) is to fill all the open requisitions each detailing cycle.

Once sailors apply for requisitions, the commands have an opportunity to comment and rank the sailors who apply to their requisitions. In this way, the commands communicate to the detailer which sailors they would like assigned to their billets. From our subject matter expert (SME) discussions, we learned that the sailor characteristics that are the most appealing to a command are their experience and Navy Enlisted Classification (NEC) training. Also, when commands are in workup or preparing to deploy, they desire to have sailors arrive as soon as possible. These general preferences guided our decisions on which assignment metrics to include in the algorithm.

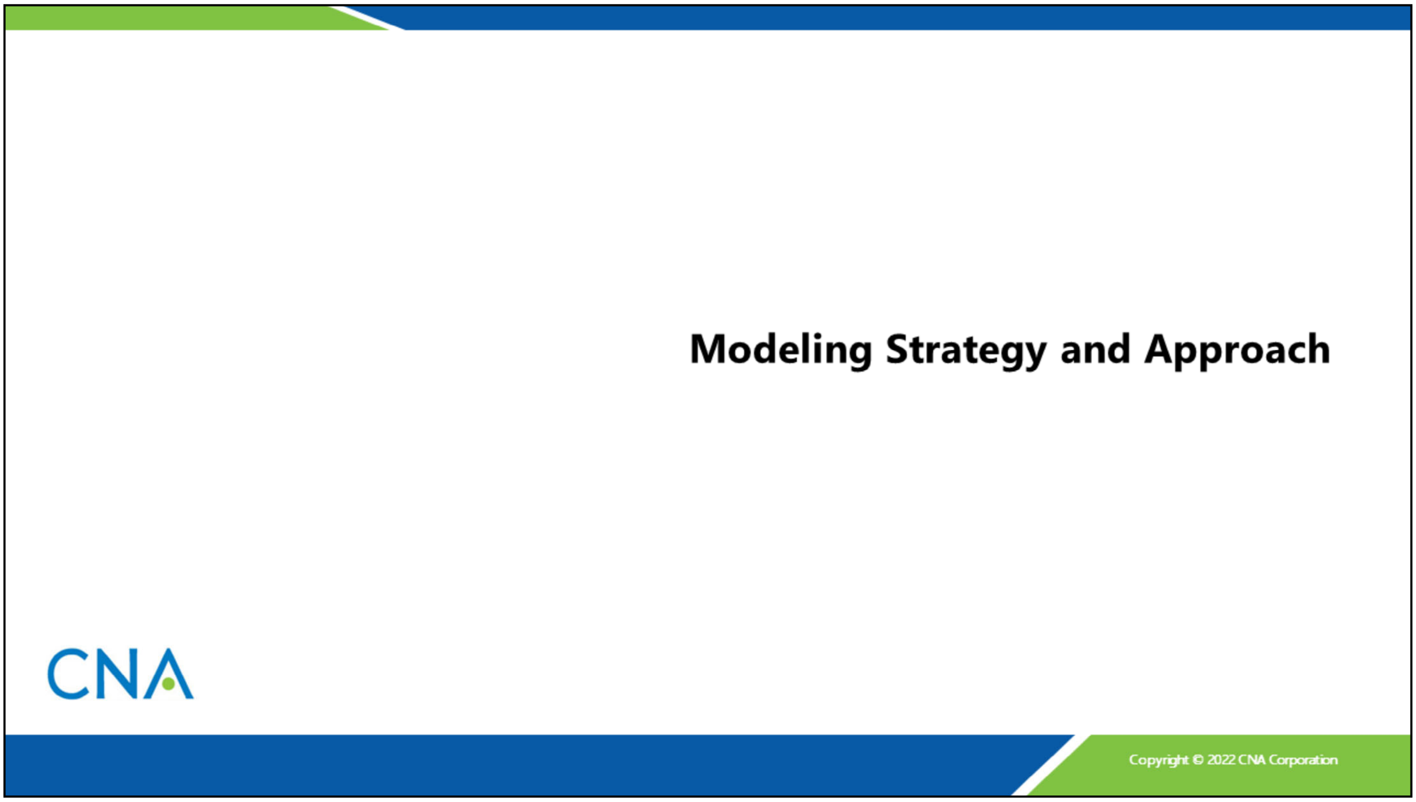
The last step of the process is for the detailer to select an assignment for a sailor and share the determination with the relevant Navy organizations (i.e., Navy Type Commands, Immediate Superior in Charge, and Commands). Currently, detailers determine the best assignments for sailors one at a time. This system creates inefficiencies in the enlisted distribution process because the best assignment for a sailor changes based on the remaining requisitions available to fill. An assignment algorithm will enable detailers to simultaneously consider many possible assignments.



The effectiveness of the enlisted distribution process is often tied to several key assignment metrics, including sea duty gaps, QOA, and PCS costs. However, all of these macro-level metrics are used to better understand fleet-wide issues and trends. Yet, an individual detailer has no concrete way to understand whether they have created the best possible slate of assignments given the set of sailors and requisitions available in a cycle. For example, would it have been better to assign Sailor Jones to Requisition B instead of Requisition D? To answer this question, one must know what makes one assignment better than another.

Without clear quantitative metrics in place, the detailers attempt to make decisions that are the best for the sailor, best for the receiving command, and best for the Navy. This is a delicate balancing act, yet a detailer usually does a good job with a relatively small number of sailors and requisitions for a given distribution cycle. However, as the number of sailors and requisitions grows, it becomes impossible for the detailer to consider every key input or understand the ramifications of choosing one assignment slate over another.

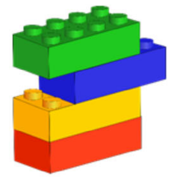
Currently, a detailer makes about 100 assignments each cycle, give or take a few dozen based on the size of the rating group and time of calendar year (e.g., the Navy tends to have more movement in the summer months). Once the Navy fully implements DMAP, that number is expected to grow by 20 to 30 percent. Detailers will clearly need assistance with managing this heavier workload. The use of an assignment algorithm can provide immediate feedback to the detailer on the quality of the assignment slate based on objective metrics and give instantaneous feedback on the trade-offs of making alternative assignments.



In this section, we discuss the modeling strategy and approach starting with an examination of the limitations of the current system to motivate the development of our more flexible proposed approach.

Critical information to assignment algorithm

- The key building blocks of an assignment algorithm are the **availability** and **completeness** of data.
- Demand signal: requisitions
  - Described by rating, paygrade, NECs, location, etc.
  - Expected to be vacated at a particular time
  - Prioritized by the MCA (i.e., open = high priority; unadvertised = lower priority)



- Supply: sailors
  - Described by rating, paygrade, NECs, etc.
  - The relevant group is sailors expected to roll to a new billet at their projected rotation date (PRD) (called “rollers”).
- Preferences: sailors and commands
  - Sailors express preference for a requisition in MyNavy Assignment (MNA) via application (i.e., ~12 months, ~10 months, and ~8 months prior to PRD)
  - Commands respond to applications through rankings and comments.
- Considerations for optimizing requisition and sailor matches:
  - Demand and supply should be aligned on key metrics for a given detailing cycle.
  - Successful assignment should fill fleet priorities and adhere to sailor preferences.
- Way to improve the availability and completeness of data: expand upon expressed preferences with “synthetic preferences”

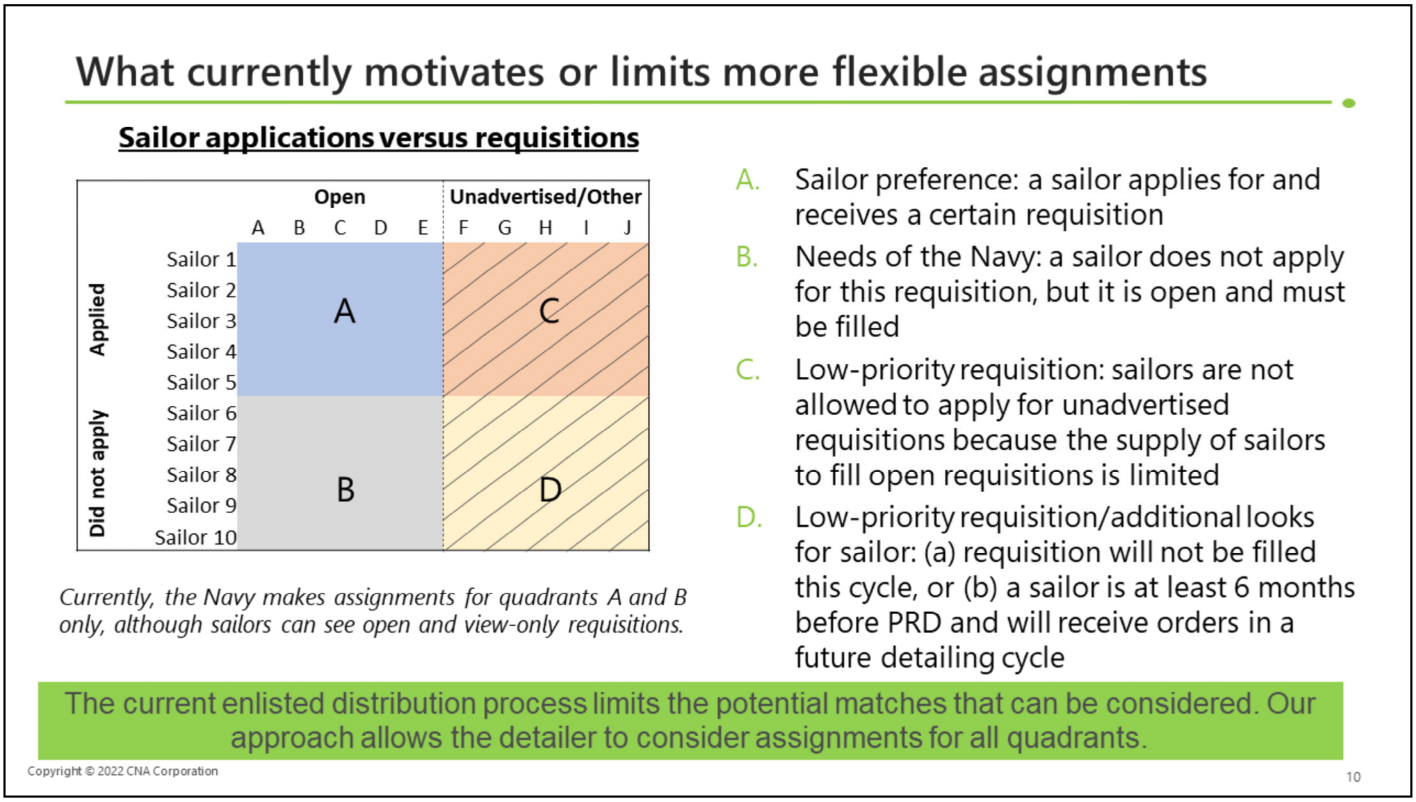
All assignment algorithms start with data. The availability and completeness of the data greatly influences our choice of assignment algorithm. We here note the types of data we require to build an assignment algorithm.

First, the demand signal is given by the number of requisitions to be filled in a cycle. Each requisition represents a demand for a sailor to fill a billet at a unit. The requisitions are described by the rating, paygrade, NECs, and location of the billet. The MCA decides on the priority and status for each requisition. Sailors are able to see requisitions with a status of open and view-only. However, they can apply to only open requisitions.

The supply side of the process is the sailors, each of whom has a rating, paygrade, and NECs. Proximity to their PRD determines whether they can participate in the distribution process. Each sailor will receive at most three opportunities to participate when they are 12 to 11 months, 10 to 9 months, and 8 to 7 months from their PRD. Once they are 6 months from the PRD, they will be assigned based on the needs of the Navy.

Both the sailors and the commands that own the requisitions get an opportunity to express their preferences. In the existing system, the sailors first submit applications to at most their top seven requisitions. The commands then review the applications to their requisitions by ranking and commenting on them.

This system works well for the current process, but the sailors and commands are limited in their ability to provide preferences. For example, they are limited in the amount of time and attention they can give to ranking and applying. Considering even as few as 50 requisitions could be overburdening. In addition, sailors may consider all open requisitions but can rank only their top seven. The commands are even more limited because they can respond only to applicants, and the sailors who apply can vary greatly based on the desirability of a duty station and other factors. Ultimately, an assignment algorithm can consider more options than a human can. As we will show in a later section, the use of synthetic preferences that leverage the existing preference information is beneficial to expand sailor and command preferences.

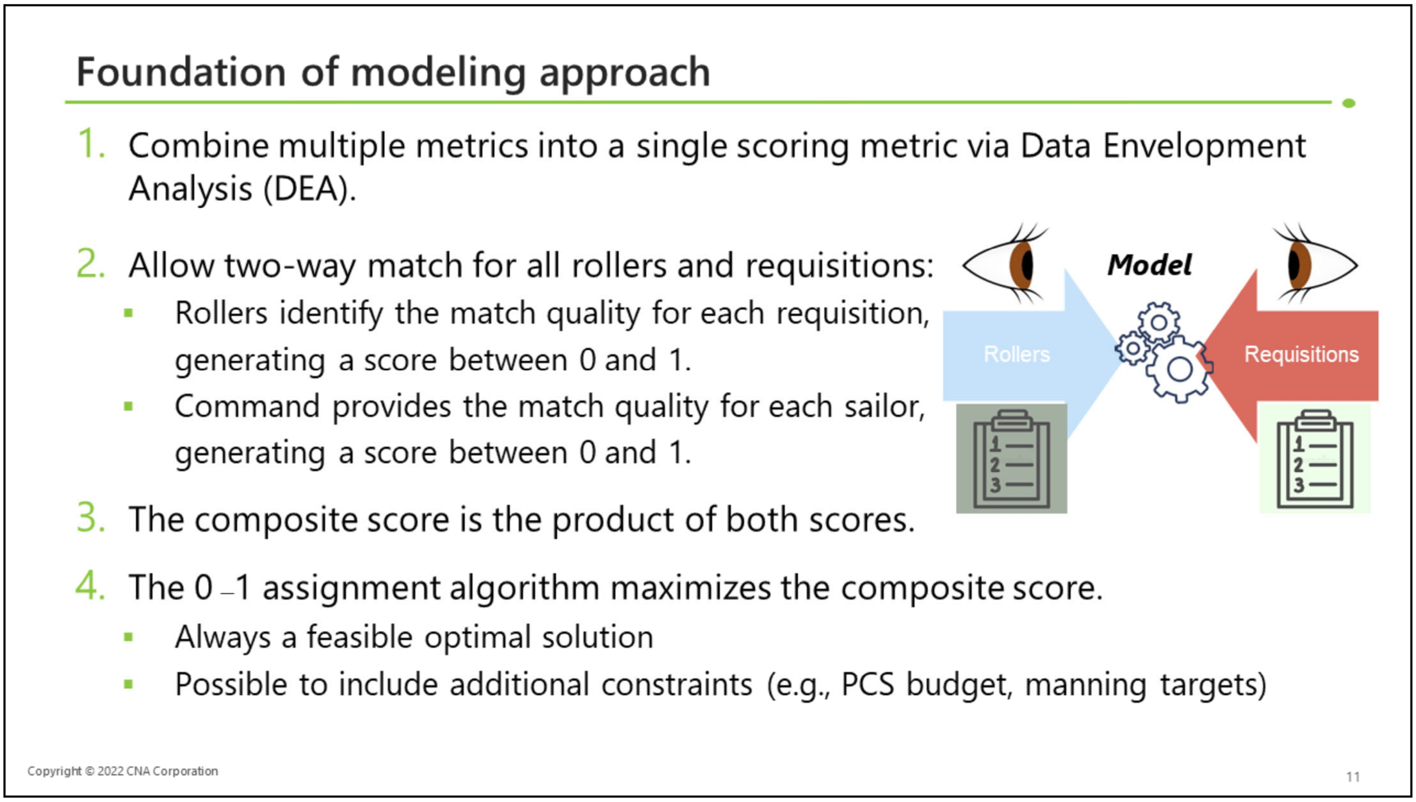


The slide provides a quad chart of sailor application versus requisition status. Note that the symmetry in the size of the quadrants does not imply that equal numbers of sailors or requisitions are in each group. This chart is for illustrative purposes only.

The graph shows that the Navy's current policy allows for assignments to only quadrants A and B—the open requisitions. The number of open requisitions is determined by the number of rollers in a given detailing cycle. Quadrant A represents sailors who receive orders for an open requisition to which they applied (i.e., a requisition of their preference). Quadrant B represents sailors who received orders to an open requisition to which they did not apply. These sailors fall into two groups: those who did not get a requisition that they applied for and those who did not express their preferences and were assigned based solely on the needs of the Navy. Navy policy requires all sailors to participate in the distribution process by submitting an application, so the group of sailors assigned based solely on the needs of the Navy should be relatively small.

The right side of the quad chart represents assignment scenarios that are not currently allowed by Navy policy (quadrant C and D). Sailors are not allowed to express preferences for non-open requisitions (quadrant C) because the supply of sailors available to fill open requisitions is limited. Similarly, sailors who have yet to express preferences are not likely to be assigned to unadvertised/other requisitions. These sailors are typically on their first or second detailing look and will be assigned in a future detailing cycle.

Recognizing that some potential matches are not being considered, the Navy desires to open the aperture to consider potential assignments to unadvertised/other requisitions. Our approach satisfies this requirement by allowing the user to determine any set of sailors and requisitions regardless of application or requisition status.

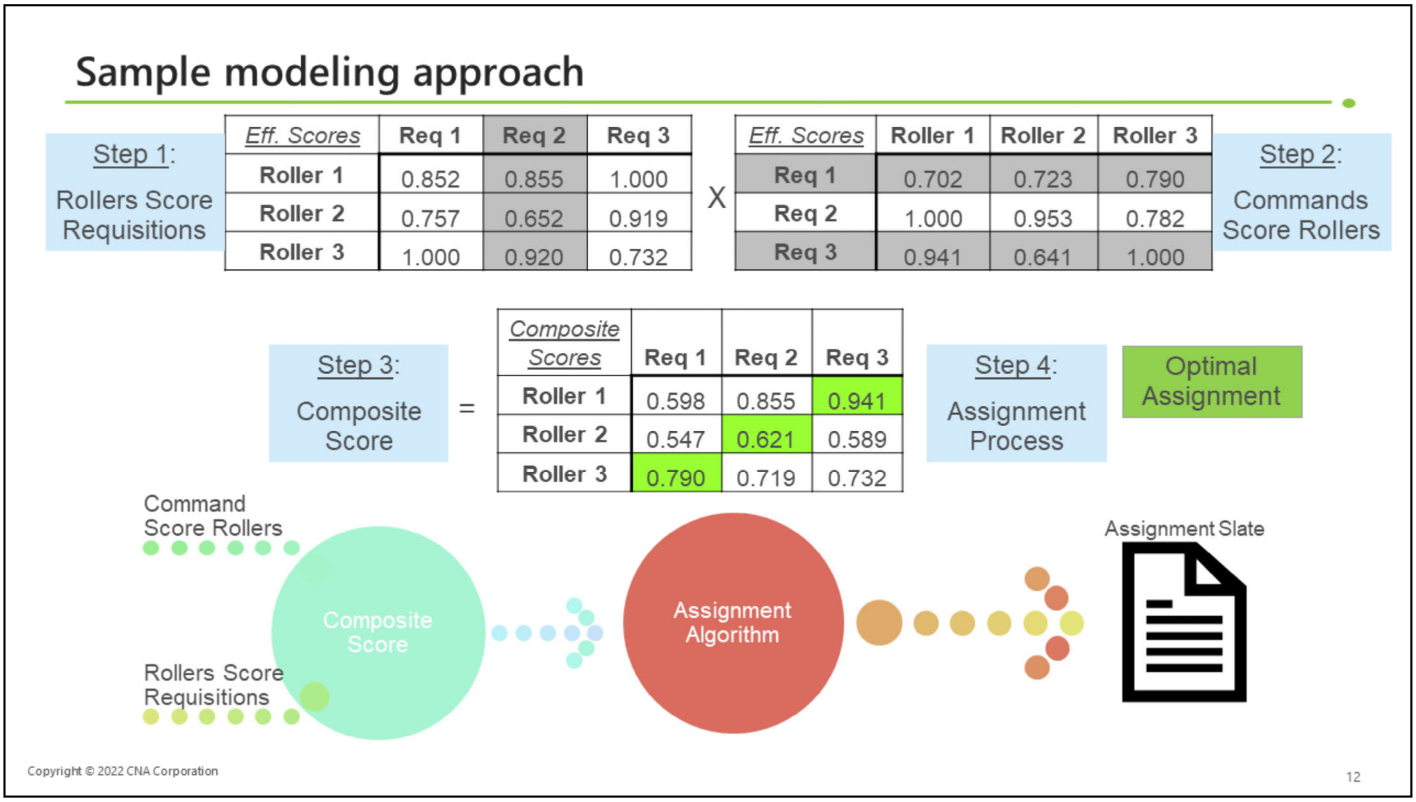


Our approach is grounded in DEA, which is a non-parametric operations research technique that produces a production frontier to measure the relative efficiency of a set of common entities (in our case, potential assignments) [3]. One strength of DEA for this application is the production of a single numeric score based on several metrics of varying dimensions. Also, DEA does not enforce a presupposed set of weights for each metric. The advantages of DEA allow us to set up a two-way matching problem in which the rollers evaluate all the requisitions to determine the best requisition for the roller. Likewise, the command that owns the requisition evaluates all the rollers to determine the best roller for the requisition. Each evaluation results in a generated score between 0 and 1.

By combining the evaluations, we produce a composite score, which is the product of the two matching scores. This composite score represents the value associated with assigning a roller to a particular requisition. The perfect match has a score of 1. Note that DEA produces multiple efficient assignments with a score of 1. Thus, a detailer can select from multiple alternative optimal assignments. (For additional details on the DEA Assignment algorithm, see Chen and Lu, 2007 [4].)

The final step is to select an assignment that maximizes the overall DEA composite score for the entire assignment slate. This final proposed assignment slate is created by solving using a 0–1 assignment algorithm, which is always feasible with our constraint set.

The next slide provides an example of this approach.



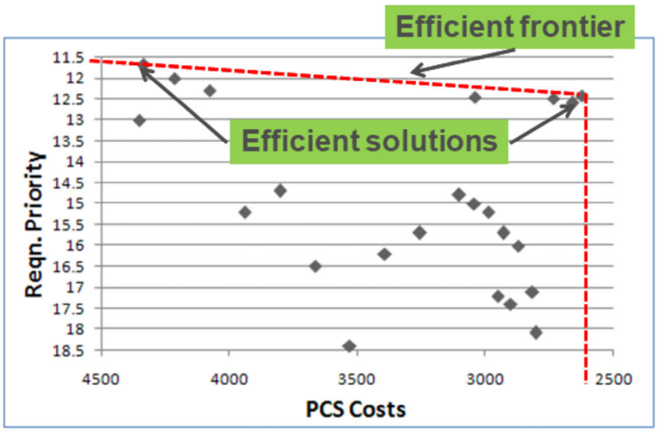
This slide presents a three roller and three req assignment process using the DEA method. In step 1, each roller scores each req relative to one another. In this example, rollers 1 and 3 score req 3 as the highest, and roller 2 scores req 1 the highest. Note that the highest obtainable score is 1. In step 2, the commands score the best roller to fulfill their req. Here, req 1 and 3 score roller 3 as the highest, and req 2 scores roller 1 the highest.

In step 3, the composite scores are generated as the product of the step 1 and step 2 scores for each roller-req pair. Note that step 2 transposes the matrix for easier visual representation. Once the composite scores are generated, step 4 runs an assignment algorithm to produce the optimal assignment slate. In this small example, it is intuitive that roller 1 is assigned to req 3, roller 2 is assigned to req 2, and roller 3 is assigned to req 1. This assignment slate produces the maximum possible aggregate composite score of 2.352.

The next slide digs deeper into the details of the algorithm.

Explanation of efficiency scoring and mathematical formulation

Nominal DEA Model



$$\min z_o(\mu, v) = \sum_{i=1}^{s} v_i x_{io}$$

$s.t.$

$$\sum_{i=1}^{s} v_i x_{ik} - \sum_{j=1}^{t} \mu_j y_{jk} \geq 0 \forall k = 1,2,\ldots,n$$

$$\sum_{j=1}^{t} \mu_j y_{jo} = 1$$

$$\mu_1, \mu_2, \ldots, \mu_t \geq 0$$

$$v_1, v_2, \ldots, v_s \geq 0$$

Variable definitions

x_i is input i

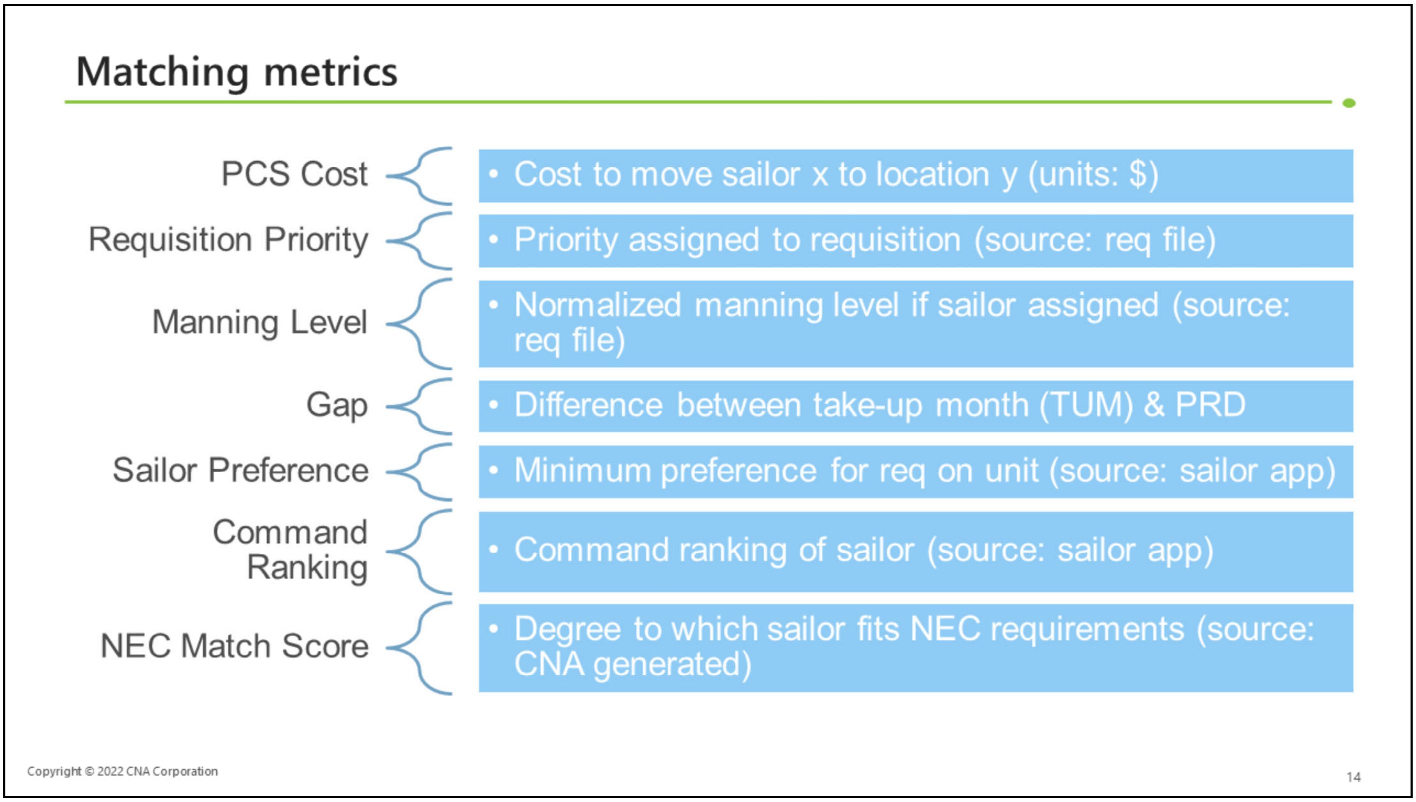
y_j is output j

v_j is the weight of input i

μ_i is the weight of output j

This slide provides the nominal DEA model for an input-oriented model. For ease of understanding, the graphical representation shows a two-dimensional example of DEA. DEA constructs an n-dimensional frontier, where n is based on the number of inputs and outputs. In the graph, we present a simple two-dimensional example with the inverse of PCS costs along the x-axis and the inverse of requisition priority along the y-axis (i.e., the input in our example is the inverse PCS cost, and the output is the inverse requisition priority). The efficient frontier is created by two efficient data points, one at (4300, 11.75) and another at (2650, 12.5). These are the two non-dominated data points, meaning there are no other data points that spend fewer PCS dollars with higher requisition priority. All efficient data points have an efficiency score of 1, and all other data points are given an efficiency relative to the amount they need to reduce their PCS cost (the input) to get the efficient frontier. Note that multiple efficient data points can receive an efficiency score of 1, which will result in alternative optimal assignments in the assignment slate.

The mathematical formulation is a linear program where the objective function is the efficiency score. There is one constraint for decision-making unit (*k*), which is the assignment pairs in our example [3].



The DEA model relies on metrics to evaluate the quality of a potential assignment. This slide presents the metrics we included in our algorithm and the source or units. Recall that DEA does not require the units of the metrics to be the same. Next, we will describe the importance of each metric to the algorithm.

- *PCS cost* is the amount of money given to a servicemember to move from their current location to their next duty station. The PCS budget is fixed, so detailers are encouraged to make as many zero-cost moves as possible.
- *Requisition priority* is the importance of the requisition relative to other requisitions. Given the choice between two requisitions, all else being equal, a detailer should fill the higher priority requisition first. Lower values of requisition priority represent higher priority.
- *Manning level* is the normalized projected manning level 12 months into the future. This manning level comes from the prioritization of the requisitions and is normalized based on where projected manning lies relative to the Navy threshold established in Notice 1000 [6-7].
- *Gap* is a measure of when a sailor will arrive to their next duty station relative to the TUM of the requisition. Ideally, sailors will arrive exactly at the TUM of the requisition.
- *Sailor preference* is a sailor's numerical ranking of the requisitions entered in MNA. When a sailor ranks multiple requisitions at a unit, we use the minimum of the rankings for all requisitions on that unit. Lower values indicate a higher preference.
- *Command ranking* is the ranking that a command gives to the sailors who apply to their requisitions. Higher values are better, and the best ranking is a 5. Note: the commands also provide comments, which are very influential to detailers but are not included in our algorithm.
- *NEC match score* is a CNA-developed measure of how well the sailor meets the NEC requirements of the requisition. The score ranges from 1 to 8 with higher scores indicating a better match.

Results formatting

How to show the effectiveness of the algorithm?

- Use the algorithm to compute various metrics for the optimal assignment slate:
  - Average and total PCS costs
  - Average requisition priority filled/count of unfilled open requisitions
  - Average normalized manning level
  - Average gap
  - Count of sailors receiving one of their top seven choices
  - Average command ranking
  - Average NEC match score/count of matching NECs

The assignment algorithm must collect aggregate metrics to understand the quality of one assignment slate in comparison to another. Collecting aggregate metrics is especially important for our proposed algorithm, which provides many alternatively efficient assignment scores. So, we provide a list of potential aggregate metrics to evaluate the performance of the assignment slate. These metrics enable a detailer to know whether they have created a good assignment slate.

Model Data

In this section, we discuss the model data sources and completeness, which are key for computing metrics for our modeling approach.

Data received summary

- We received MNA data on four core samples comprising historical information on sailors and requisitions.

	Start Date	End Date	Number of Observations
Requisitions	01 NOV 2016	01 AUG 2021	5,375,452
Rollers	SEP 2016	SEP 2021	6,175,021
Applications	01 OCT 2016	01 AUG 2021	2,015,658
Orders[1]	03 OCT 2016	30 AUG 2021	1,869,738

[1] We exclude billets/bodies data here because it is not examined in our core dataset.

[2] The sailor duty preference worksheet (or "dreamsheet") was also provided to represent how data are currently collected.

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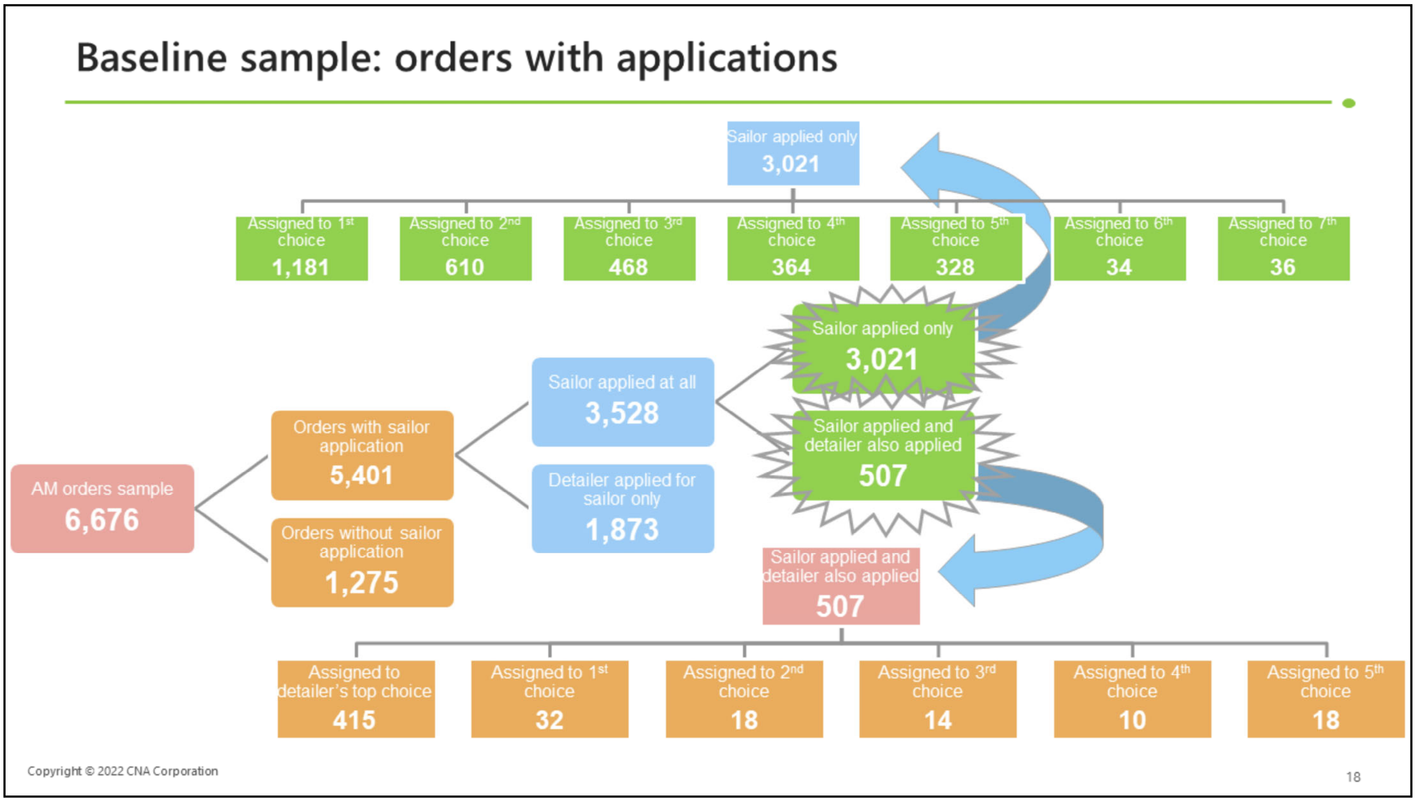
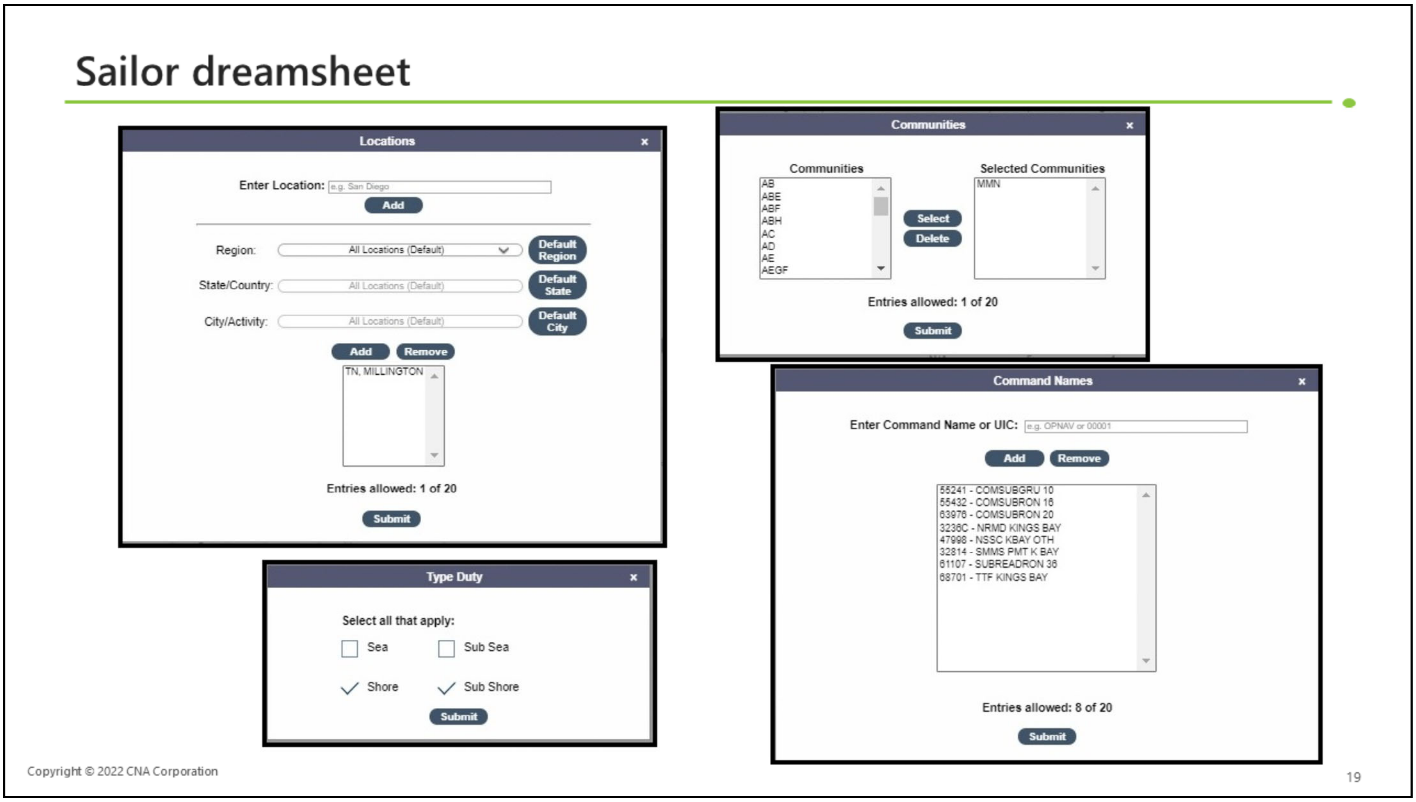
CNA received a variety of MNA data to understand the historical assignment of sailors to requisitions. The table describes the date ranges for each dataset and the number of observations we received. When merged, the separate datasets create an overlapping dataset for November 2016 through August 2021. Although we received data for other ratings, for this study, we restricted our examination to Aviation Structural Mechanics (AM) sailors only. Below we briefly describe each dataset:

- The requisitions is a prioritized list of all the job openings available to sailors. It includes both sea and shore jobs for all paygrades.
- The rollers are all sailors within their detailing window or available to receive orders. Sailors receive three looks (i.e., opportunities) to be given orders. We generated the rollers dataset based on Distribution Guidance Memorandum #4026-1710 [8].
- Applications reflect the preferences of sailors for particular requisitions. We also received the command's comments on those applicants. Each sailor can rank order requisitions 1 through 7. Detailers also submit applications on behalf of sailors, which are recorded with a 0 ranking.
- The orders data include the various orders received by US Navy enlisted personnel. A subset of these orders represent orders for a new assignment in the Navy.

Our goal for merging the datasets is to create a comprehensive picture of what happened in previous detailing cycles. Specifically, we want to understand the requisitions and rollers available, the applications submitted by the rollers to the requisitions, and the orders that resulted from matching rollers and requisitions for the detailing cycles in our date range.



This graphic represents how well we merge the datasets to understand the historical trends. Given that orders are written to the unit and not a billet, we eliminated the merging of the requisition data and the inclusion of Billet Identification Number (BIN) and Billet Sequence Code (BSC). Instead, we merged the orders data directly to the applications data by Unit Identification Code (UIC). By doing so, we matched a much higher percentage of applications to orders (5,401 of 6,676 cases, or 81 percent). Of the applications that match to orders, 3,528 (or 65 percent) include sailor participation. These sample data show that when a detailer is involved in the application process, the sailor is likely to be assigned to the detailer's choice (415 of 507 cases, or 82 percent). Similarly, when a sailor submits preferences without the detailer application, the sailor gets one of their top two choices in 1,791 of 3,021 cases, or 59 percent. These data show that the current detailing system rewards active participation and strongly adheres to sailor preferences.



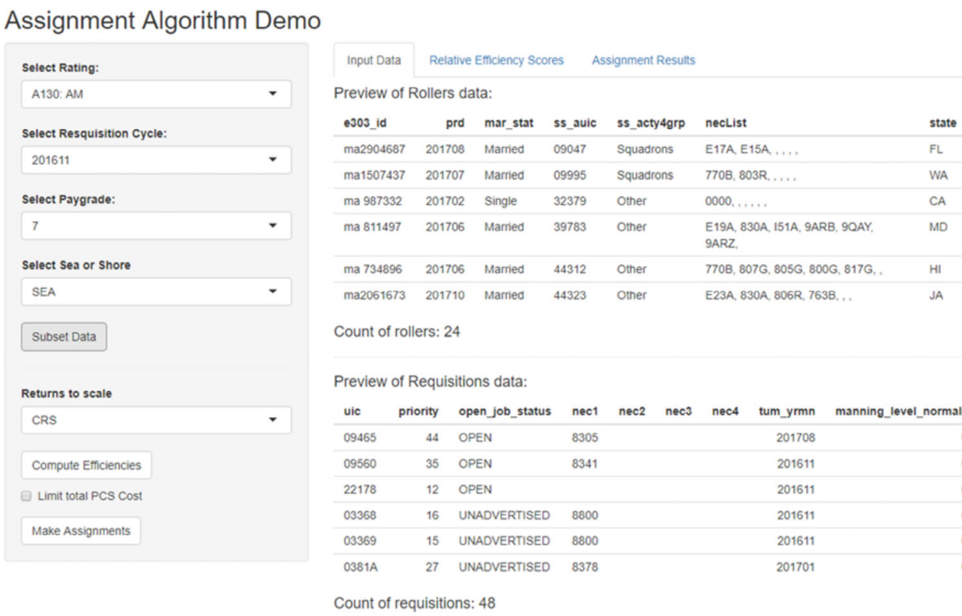
This slide presents screenshots from the sailor dreamsheet, which is a set of information sailors periodically complete to express their general preference for assignments and intentions to stay in the Navy. Although sailors are required to provide this information, it is currently not used in the detailing process. Note that the sailor is free to select any value from the drop-down fields, although they may not always be applicable to their rating or reflect the available opportunities for the sailor.

Sample Results

CNA

In this section, we show some sample results with non-personally identifiable information (PII) fictious data. Our goal is to display the options and selections available for a user in a mock graphical user interface (R-shiny). If the Navy adopts this algorithm, we recommend that they invest in a formal study to evaluate the most useful way to interact with the algorithm to complete Navy business processes.

R-shiny input data screen



Preview of Rollers data:

e303_id	prd	mar_stat	ss_auic	ss_acty4grp	necList	state
ma2904687	201708	Married	09047	Squadrons	E17A, E15A, , , , ,	FL
ma1507437	201707	Married	09995	Squadrons	770B, 803R, , , , ,	WA
ma 987332	201702	Single	32379	Other	0000, , , , , ,	CA
ma 811497	201706	Married	39783	Other	E19A, 830A, I51A, 9ARB, 9QAY, 9ARZ,	MD
ma 734896	201706	Married	44312	Other	770B, 807G, 805G, 800G, 817G, ,	HI
ma2061673	201710	Married	44323	Other	E23A, 830A, 806R, 763B, , ,	JA

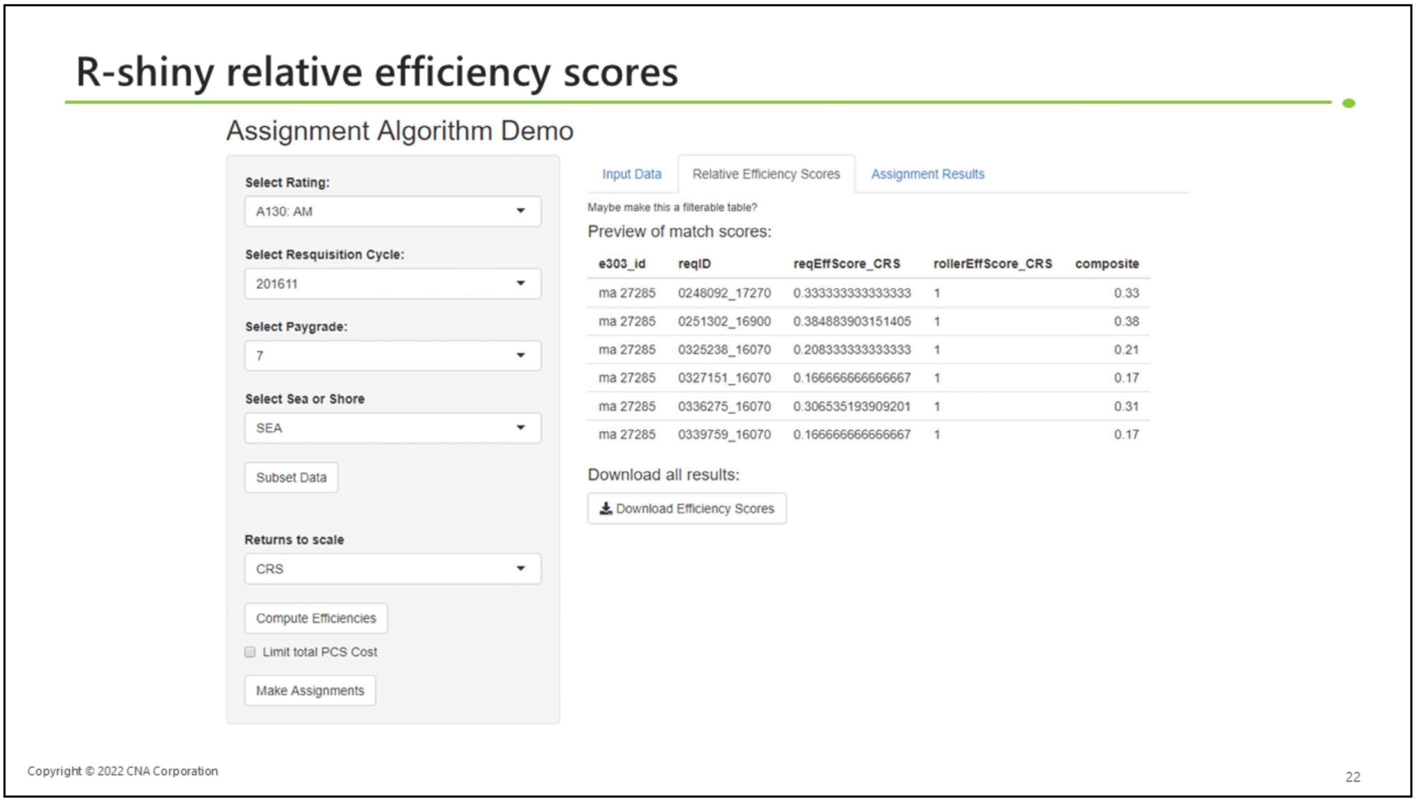
Count of rollers: 24

Preview of Requisitions data:

uic	priority	open_job_status	nec1	nec2	nec3	nec4	tum_yrmn	manning_level_normali
09465	44	OPEN	8305				201708	[illegible]
09560	35	OPEN	8341				201611	[illegible]
22178	12	OPEN					201611	[illegible]
03368	16	UNADVERTISED	8800				201611	[illegible]
03369	15	UNADVERTISED	8800				201611	[illegible]
0381A	27	UNADVERTISED	8378				201701	[illegible]

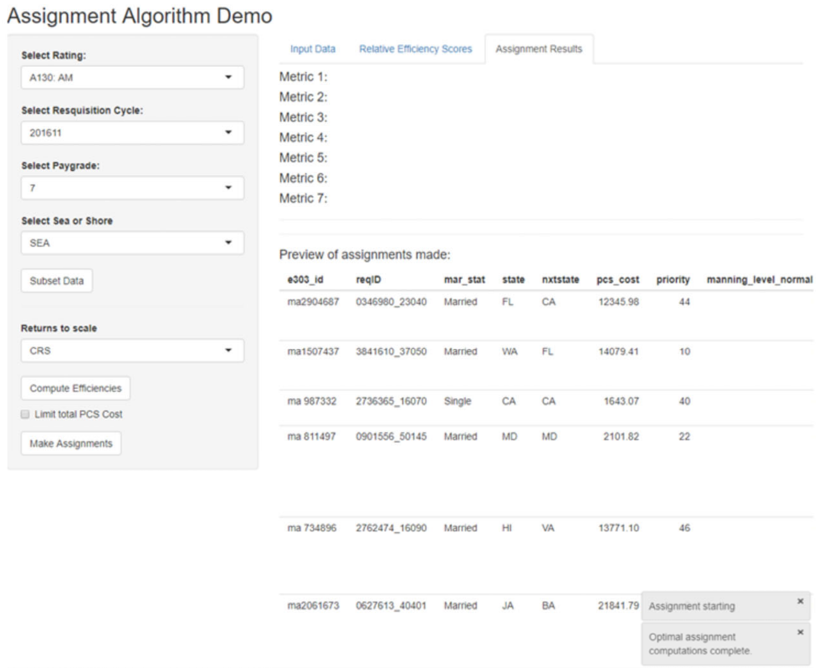
Count of requisitions: 48

This slide presents an example graphical user interface (GUI) with notional data. Our example GUI has three tabs: Input Data, Relative Efficiency Scores, and Assignment Results. This screen shows the Input Data tab that previews the input data for the rollers and requisitions. The count of rollers and requisitions is provided to ensure that all data are loaded into the model. Samples of the data for all the data fields are also displayed for validation purposes.



This screen shows the Relative Efficiency Scores for a sample set of rollers and requisitions. The requisition efficiency scoring of the roller is given in the "reqEffScore_CRS" column, and the opposite is presented in the "rollerEffScore_CRS." The product of these scores is provided in the composite column. A download button is provided to download the full set of results.

R-shiny assignment module



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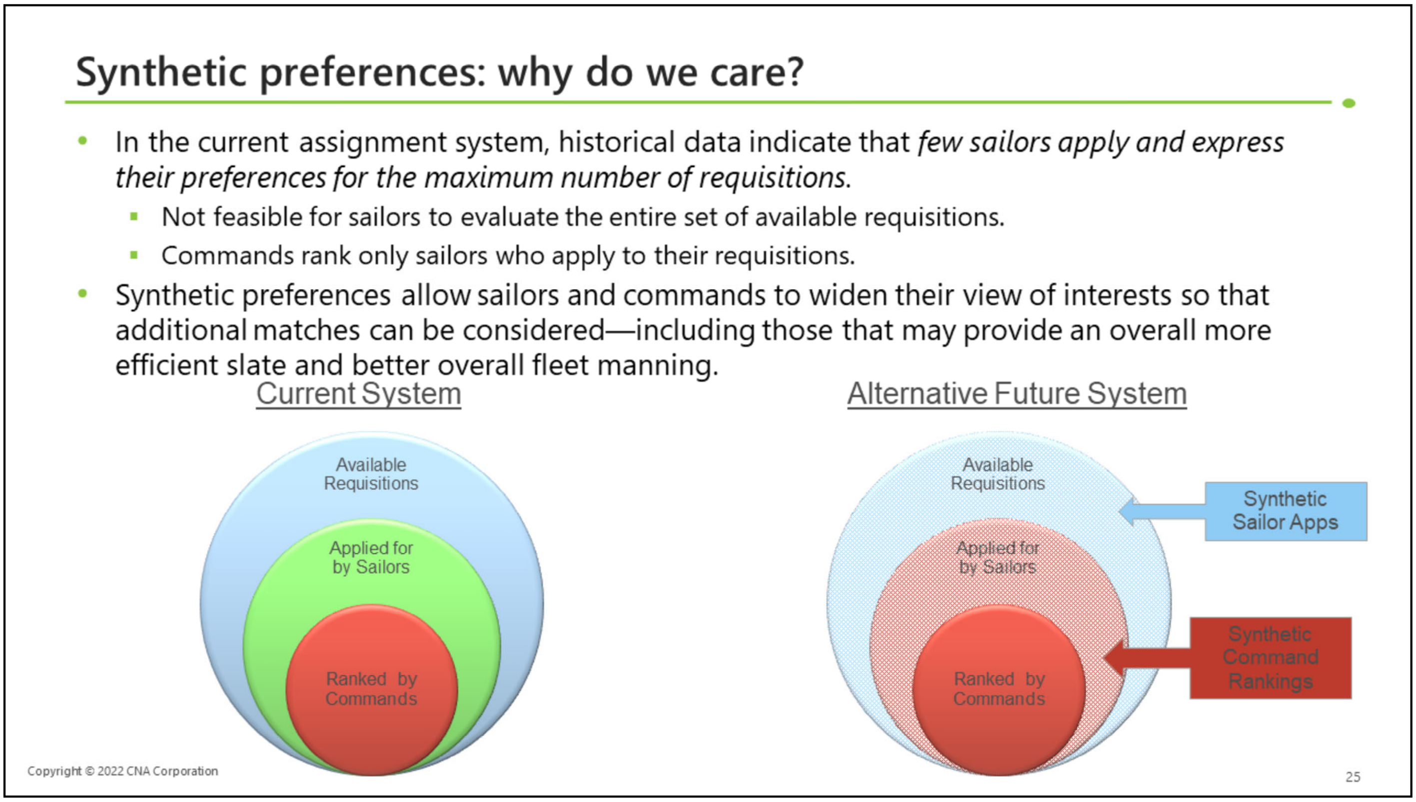
This screen shows the Assignment Results tab, which provides the full assignment slate with the corresponding metrics for each assignment. Future versions of the GUI should include aggregate metrics that are meaningful for detailers and decision-makers.

Alternative Way to Generate Sailor and Command Preferences When They Are Indicated in Application Data

CNA

In this section, we show an alternative way to generate sailor and command preferences based on their identified preference. Our method produces a "similarity score" or synthetic preference, which indicates which requisitions are similar to the ones that a sailor ranked highly. We also supply a "similarity metric" to help commands understand which rollers are similar to those that they rank highly. These similarity metrics are not included in the current algorithm, but they could easily be included in our proposed algorithm or incorporated at some other point in the detailing process to expand the currently limited preference metrics.



The detailing process is initiated with an application from a sailor to a requisition. However, sailors can rank only seven requisitions per cycle. Often, sailors do not take advantage of their ability to rank all seven, leaving the Navy without a full understanding of what requisitions a sailor prefers. Additionally, sailors do not necessarily have the capacity to evaluate the entire set of available requisitions.

Similarly, commands are restricted in their ability to rank sailors. The commands can rank only sailors who have applied to their requisitions. If the ideal sailor does not apply, then the command would lack the opportunity to express their preference for that sailor. Like the sailor, the command also has limited capacity to evaluate all potential rollers without some assistance.

The use of a synthetic preference fills in this gap by using the information provided by the sailors and commands to generate near-peer matches to their expressed preference. In this way, the Navy gets more information on potential good matches without taxing the sailors or commands for additional information.

The main benefits of creating synthetic preferences are as follows:

- Generating synthetic preferences places no additional data collection burden on sailors or commands.
- Using synthetic preferences does not replace expressed preferences; rather, it supplements them with additional information.
- Using synthetic preferences in a matching algorithm expands the possibility of finding good matches for sailors and commands.

Synthetic preferences: background

- **Sailor synthetic preference:**
  - Identify the requisitions that are the *most similar to (or least different from)* the requisition a sailor prefers.
    - Relevant dimensions included:

Dimension	Data Type
Requisition NEC(s)	Non-numeric
Geographic distance (in miles)	Numeric

Mixed-Type Dimensions

- **Command synthetic preference:**
  - Identify the sailors that are the *most similar to (or least different from)* the sailor a command prefers.
    - Relevant dimensions included:

Dimension	Data Type
Sailor NEC(s)	Non-numeric
Gap (in months)	Numeric

Mixed-Type Dimensions

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In this slide, we present an example of how synthetic preferences could be generated for sailors and commands. The goal of synthetic preferences is to determine which requisitions are similar to the requisitions a sailor ranked highly and to identify which sailors are similar to the ones commands ranked highly.

In our example for sailors, we use two dimensions to express the factors that sailors care about when expressing preference for a requisition. In practice, additional dimensions can be selected. We selected the requisition NEC(s) because it represents the skills required of a job and likely represents similar work for alternative jobs. The geographic location dimension measures how close alternative jobs are to those that the sailor has expressed preference for.

Similarly, the commands also generate their synthetic preference based on two dimensions. The sailor's NEC(s) are the skills a sailor would bring to the job. Alternative sailors with the same NEC(s) are likely to be similar in the eyes of the command. Again, additional dimensions can be added to capture nuance. The second metric is the gap measured as the difference (in months) between the requisition TUM and the sailor's PRD. This measure captures how soon a sailor will arrive relative to when they are needed aboard the unit.

Note that both the sailor and command synthetic preference have numeric and non-numeric components. Thus, it is important to use a technique that can handle both types of data.

Gower’s distance (dissimilarity) metric

- The most commonly used metric for *mixed-type dimensions* (both numeric and non-numeric) is **Gower’s distance metric**.
  - For requisition and sailor NECs (non-numeric):
    - Distance is 1 if the dimensions are different and 0 if the dimensions are the same.
  - For geographic distance and gap (numeric):
    - Distance is the absolute value of the difference between the two dimensions divided by the range.
- Range of Gower’s distance metric:

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When the dimensions/variables included in the metric are all numeric or all non-numeric, several distance metrics can be applied. However, when the variables are mixed-type (i.e., both numeric and non-numeric), relatively few options are available. The most popular metric for mixed-type dimensions (like the ones we have) is Gower’s distance metric [9].

Gower’s distance metric applies a different distance metric to each variable/dimension based on the type of data, and it then combines them into a singular value. Items (in our case, sailors or requisitions) that are the most similar (or least dissimilar) receive a score of 0. And conversely, items that are the least similar receive a score of 1.

Non-numeric dimensions receive a 1 if they are different and 0 if they are the same. Numeric dimensions are calculated by the absolute difference divided by the range. Then the final Gower’s distance metric is computed as the average of the scores for all the dimensions.

Gower’s distance metric: sample R output

- Example for requisitions: R computes a matrix of the *pairwise distances (dissimilarities)* between observations (each row is a requisition) in the dataset.
  - Distances closer to 0 are more similar, while those closer to 1 are less similar.

	1	2	3	4	5	6	7	8	9
1	0.00000000	0.37772926	0.522197962	0.36681223	0.68886463	0.33333333	0.05021834	0.01128093	0.67794760
2	0.37772926	0.00000000	0.477802038	0.34425036	0.68886463	0.37772926	0.01637555	0.36644833	0.69978166
3	0.52219796	0.47780204	0.000000000	0.48871907	0.83333333	0.52219796	0.23307860	0.51091703	0.84425036
4	0.36681223	0.34425036	0.488719068	0.00000000	0.34461426	0.36681223	0.00000000	0.35553130	0.68886463
5	0.68886463	0.68886463	0.833333333	0.34461426	0.00000000	0.68886463	0.51692140	0.67758370	0.67758370
6	0.33333333	0.37772926	0.522197962	0.36681223	0.68886463	0.00000000	0.05021834	0.34461426	0.67794760
7	0.05021834	0.01637555	0.233078603	0.00000000	0.51692140	0.05021834	0.00000000	0.03329694	0.53329694
8	0.01128093	0.36644833	0.510917031	0.35553130	0.67758370	0.34461426	0.03329694	0.00000000	0.66666667
9	0.67794760	0.69978166	0.844250364	0.68886463	0.67758370	0.67794760	0.53329694	0.66666667	0.00000000

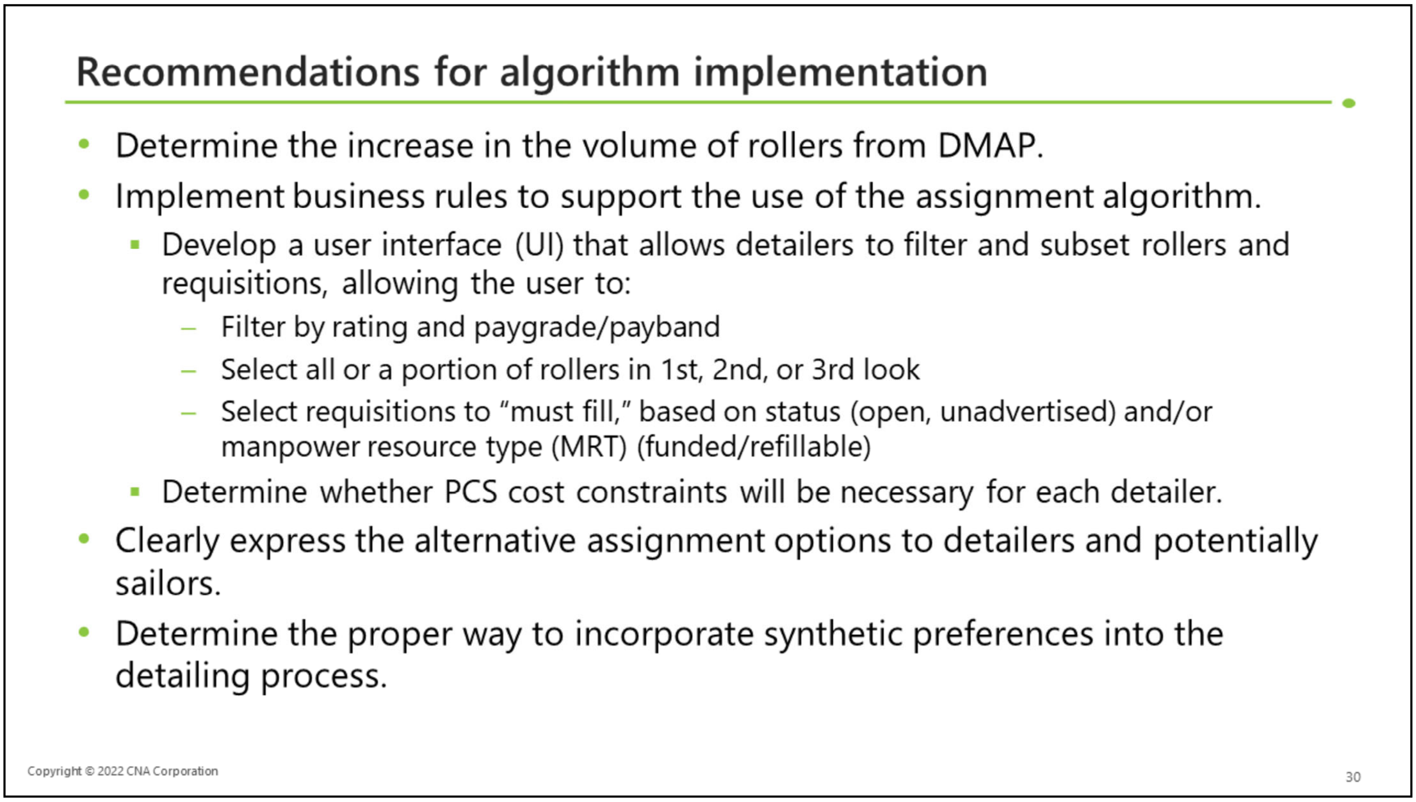
- The same technique can be applied to rollers.

This slide provides an example of the Gower’s distance metric for the requisitions. This example takes the perspective of a sailor who is evaluating requisitions and would like to understand which are similar to their preferred ones. For example, if a sailor has ranked requisition 8 highly, they can tell that requisition 1 is very similar to 8 because of the low Gower score (0.01128093). In contrast, requisition 5 is very dissimilar to requisition 8, with a high Gower score (0.67758370).

This method for identifying similar requisitions also applies to identifying similar rollers. Sailors and commands can use the Gower score as an easy way to identify alternative requisitions and sailors, respectively, or the score can be used directly in the matching algorithm as an additional metric in the DEA score.

Recommendations

The next section provides our recommendations on how to implement this proposed algorithm and enhancement into current data collection procedures to support the future development of assignment algorithms.



In this study, we present an assignment algorithm to assist with the enlisted detailing process. To successfully implement this assignment algorithm, we recommend that the Navy complete the following actions:

- Perform a formal assessment of the increase in demand and workload on the detailers resulting from the implementation of DMAP. This work could begin with the collection of data from the DMAP pilot study and continue for several years to identify emerging trends and any potential capacity issues related to the increased workload on detailers.
- Develop business rules to govern how an assignment algorithm should be used. Currently, our assignment algorithm assumes that every requisition and roller given to it should be assigned. However, a user may desire to assign only a portion of the requisition or rollers based on how many opportunities (or looks) a sailor has received or the status or MRT of a requisition.
- Define how the alternative assignments will be used by the detailer or sailor and how best to present them in a GUI.
- Decide how synthetic preferences are best incorporated into the process, meaning whether they should be used in the assignment algorithm, provided for the commands and sailors prior to assignment, or both).

Recommendations for future data collection: sailors

1. Restrict the sailor **dreamsheet locations to those with billets available**.
   - Currently, sailors can select any location, even if no billets are offered there.
     - Assume the sailor is assigned to a billet within their current rating.
     - Assume a sailor is assigned to a billet within their current rating and set of other ratings to which they could be moved.
2. Add **DMAP survey questions about geographic characteristics** to the sailor dreamsheet.
   - Currently, sailors select their preferred state/country and desirability on the dreamsheet.
   - Question topics to add:
     - Population density (urban vs. rural)?
     - CONUS vs. OCONUS?
     - East Coast vs. West Coast?
   - Retain historical sailor duty preference worksheets.

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Our sponsor asked us to consider alternative ways to collect data to more effectively assign enlisted sailors. We identified two potential sources of improvement for collecting sailor data: revising the sailor dreamsheet and adding questions from the DMAP survey to the sailor dreamsheet.

The sailor dreamsheet allows sailors to select any location, even if no billets are offered or available in that location. A more effective way to collect these data would be to restrict the dreamsheet location preferences to locations with available billets. For example, in our dreamsheet extract, sailors expressed interest in Germany, Brazil, and France, but no billets were currently available in those locations. These observations are based on two underlying assumptions: (1) that the sailor is assigned to a billet within their current rating and (2) that the sailor is assigned to a billet within their current rating and a set of other ratings to which they could be moved.

We also recommend adding questions from the DMAP survey to the sailor dreamsheet. Specifically, adding the questions addressing geographic characteristics would benefit the matching process, since these questions likely influence a sailor's requisition preference. The current version of the sailor dreamsheet asks for preferred state/country and its desirability ranking, so we incorporated the preferred state/country in our model. However, the Navy may benefit from incorporating information on more broad geographic characteristics, such as population density, CONUS vs. OCONUS, or East Coast vs. West Coast.

Finally, we recommend that the Navy retain and archive historical sailor duty preference worksheets to fully understand historical matching metrics.

Recommendations for future data collection: commands

1. Proactively **survey commands about their ideal applicant**.
   - Currently, commands reactively rank only sailors who apply to their requisitions.
   - Question topics to include:
     - Relevant experience (platform, billet, or duty type)?
     - PFA and PRT evaluations?
     - Relative importance of NEC match, gap, and PCS costs?

2. Identify the **specific requisitions that are filled** with the generated orders.
   - Currently, detailers generate orders at the individual command level.
     - But there are multiple requisitions for one UIC in each requisition cycle.
   - Otherwise, the Navy (and the CNA algorithm) requires a simplifying assumption that the highest priority requisition was filled.

We also identified two potential areas for improvement regarding data collection from the commands. One limitation of the current assignment system is that commands rank only sailors who apply to their requisitions, meaning that they provide only reactive comments. It would be helpful if we could provide commands with a short questionnaire/survey about their ideal applicant to fill the requisition. The types of questions might cover relevant experience (platform, billet, or shore/sea duty), physical fitness assessment (PFA) and physical readiness test (PRT) results, and the relative importance of NEC match, gap, and PCS costs. Collecting these data from commands would enable us to refine the similarity metric calculations by including the most important dimensions from the command's point of view, which in turn would improve the assignment model overall.

In the current assignment system, orders are generated at the individual unit/command level (represented by the UIC), but requisitions are generated at the billet level. Thus, there is no clean way to match requisitions to orders (not a 1-1 mapping) because there are multiple requisitions to one UIC within each requisition cycle. We therefore had to make a simplifying assumption about the requisition that was actually filled, which we chose as the highest priority requisition.

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