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MONTEREY, CALIFORNIA

THESIS

OPTIMIZING NAVY RECRUITER ALLOCATION

by

Joshua P. Murrell

June 2023

Thesis Advisor:
Second Reader:

Javier Salmeron-Medrano
Samuel E. Buttrey

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OPTIMIZING NAVY RECRUITER ALLOCATION

Joshua P. Murrell
Ensign, United States Navy
BS, United States Naval Academy, 2022

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Approved by: Javier Salmeron-Medrano
Advisor

Samuel E. Buttrey
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

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ABSTRACT

Navy Recruiting Command (NRC) assigns recruiters to recruiting stations across the country. A station's demographics, historical data, and number of recruiters assigned are important considerations that affect the number of recruits signed. Naturally, some stations are more suitable for signing recruits than others. The current allocation process used by NRC is guided primarily by previous market share from each station. This process fails to consider unique characteristics about a station and the number of recruiters invested in order to achieve the result. Consequently, some stations might be underperforming relative to their potential while others might be able to perform at nearly the same level with fewer recruiters. This thesis proposes a model that estimates the number of recruits signed by a station as a function of the number of recruiters assigned with parameters that capture the unique characteristics of each station. The estimates from this model inform a mathematical optimization model whose objective maximizes expected recruits signed. The results of the optimization give a solution for recruiter allocation. We identify an allocation solution that results in more expected recruits signed than the current number of recruits signed.

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LIST OF ACRONYMS AND ABBREVIATIONS

AFQT	Armed Forces Qualification Test
GNC	Gross New Contracts
JAMRS	Joint Advertising Market Research and Studies Group
NRC	Navy Recruiting Command
NRPOM	Navy Recruiter Prediction and Optimization Model
NTAG	Navy Talent Acquisition Group
QMA	Qualified Military Available
RAF	Recruiter Allocation Factor
RAM	Recruiter Allocation Model
REM	Recruit Estimation Model
RSID	Recruiting Station Identification Code

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EXECUTIVE SUMMARY

People are at the center of how the U.S. Navy operates. Supporting people begins before sailors have signed a contract; supporting sailors begins with recruitment. U.S. Navy Recruiting Command (NRC) is the agency in charge of allocating recruiters to recruiting stations across the U.S. With a limited number of recruiters at NRC's disposal, recruiting effectively is vital in order to support required manning within the fleet. Effective recruiting begins with allocating recruiters in a manner that maximizes the number of recruits signed. The better the recruiting process is, the more capable the U.S. Navy will be. This thesis presents a methodology for optimizing recruiter allocation in order to maximize the expected number of recruits signed.

The current situation at NRC with regard to recruiter allocation is one of a market-share based approach. That is, the number of recruiters recommended to be assigned to a particular station is directly proportional to the percentage of recruits signed by that particular station with respect to the rest of its Navy Talent Acquisition Group (NTAG, a regional collection of recruiting stations). This process fails to consider the impact of the people involved in recruiting. Previous literature and data indicate that the number of recruits signed by a station can be influenced by the number of recruiters assigned to the station.

Our thesis presents an alternative for market-share recruiter allocation that places the people involved at the heart of our algorithm. First, we develop our recruit estimation model (REM) that estimates the expected number of recruits signed as a function of the number of recruiters assigned to stations. Operations research literature on military recruiting processes suggest that there are diminishing returns from the addition of recruiters to stations. That is, with the addition of each recruiter, we expect an increase in the total number of recruits signed, but a decrease in the marginal difference. This idea is at the heart of REM, which we derive for each station from demographics, historical data of monthly recruiters, and signed contracts.

For any given station, there will be a number of youths in the area of responsibility for any station that will sign a contract regardless of the number of recruiters at the station. We refer to these youths as predisposed recruits. There were around 100 stations which, for at least one month in the data, had zero recruiters assigned. For each of these “zero-recruiter” stations, we determine the average number of recruits signed during that time period, and assign them to be the predisposed recruits for their respective station. For each of the remaining 700 “positive-recruiter” stations, we assign the estimation for predisposed recruits from its “most similar” zero-recruiter station, using Gower distance as the metric. We then proceed with the calculation of diminishing return rate in order to complete REM for each station, and validate its suitability using the adjusted R-square (approximately 80% for most recent years).

The REM estimates inform a formal mathematical optimization model whose objective is to maximize the expected number of recruits signed. Our recruiter allocation model (RAM) provides a solution for the optimal allocation of recruiters to stations.

Using the same number of recruiters and permitted number of closed stations that NRC used in year 2021, RAM provides a solution for recruiter allocation that results in 6,000 more expected recruits signed (a 16% increase) than what was actually achieved in 2021. In addition, station-level comparisons highlight specific stations which we believe to be currently undermanned or overmanned. For example, we find 280 stations where RAM suggests an increase of at least two recruiters, and 233 stations where it suggests at least two fewer recruiters. Lastly, sensitivity analysis shows that the marginal gain in expected recruits beyond allowing more than 20 closed recruiting stations is very small. This raises the question to decision makers if closing additional stations, and consequentially reallocating recruiters elsewhere, is worth only three or four additional expected recruits signed.

The results from this thesis hold applicable and relevant near-term applications for NRC. In the words of the commander of NRC, the approach and results from this research are “expected to serve as the basis for NRC recruiter allocation decisions” (Walker 2023). This is especially important when considering that NRC is currently facing what the commander categorizes as “the most difficult environment for recruiting since the

inception of the all-volunteer force.” Through an optimal approach for recruiter allocation, we can best address the difficulties faced in the current recruiting environment by placing recruiters and recruits at the heart of how allocation decisions are made.

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I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

In his most recent strategic guidance, The Honorable Carlos Del Toro, Secretary of the Navy, lists “Empowering our People” as one of his three main enduring priorities (Del Toro 2021). People are at the center of how the U.S. Navy operates. The process of empowering people begins before sailors have signed a contract or taken an oath. The process begins with recruitment. In the same strategic guidance, Del Toro states that the mission of the Department of the Navy is to “recruit, train, equip, and organize combat-ready naval forces.” The importance of recruitment is not only recognized by senior leaders; it is identified as a primary mission for supporting the Navy’s strategic posture and as the first step in ensuring combat-ready naval forces.

The U.S. Navy Recruiting Command (NRC) is the agency in charge of allocating recruiters to recruiting stations across the U.S. With a limited number of recruiters at NRC’s disposal, recruiting effectively is vital in order to support required manning within the fleet. From a recruiter’s perspective, there are both doctrinal and qualification barriers to effective recruiting. A doctrinal barrier is the fact that since 1973, the U.S. military has strictly been a volunteer-based force. As a result, recruiters must present a career path to prospective recruits that is more enticing than other post-high school options such as university, apprenticeships, or workplace experience. The imperative to recruit effectively is further heightened when considering that only 23% of American youths are eligible for military service without a waiver (Office of People Analytics 2022). Possible disqualifying characteristics include obesity, mental health considerations, criminal history, or prior drug use. There are also environmental conditions that make recruiting more difficult such as economic climate, job market, and political landscape. Better recruiting begins with allocating recruiters in a manner that maximizes the number of recruits signed. The better the U.S. Navy can recruit, the more capable the U.S. will be at winning wars, deterring aggression, and maintaining freedom of the seas.

B. CURRENT APPROACHES FOR NAVY RECRUITING

The process for recruiter allocation currently used by NRC is primarily conducted at the Navy Talent Acquisition Group (NTAG) level. There are 26 NTAGs across the country and each NTAG has a specific allotment of recruiters available. The chief recruiters and senior leadership of each NTAG assign recruiters to stations in the NTAG's jurisdiction. This process is aided by a metric called the Recruiter Allocation Factor (RAF). The RAF is equal to the number of gross new contracts (GNC) signed at a station divided by the total number of GNC signed across the NTAG. This is referred to as market share. For example, if there are 115 recruiters allotted to an NTAG, and a station within that NTAG accounts for 5% of the GNCs signed in that NTAG, the RAF would recommend that 5.75 recruiters be assigned to that station. The chief recruiters and senior leadership at the NTAG would then use the RAF output to inform their allocation decision.

There are benefits and shortcomings associated with using the RAF. The benefits are associated with accessibility and interpretability of the RAF outputs. Chief recruiters and analysts are able to interface with the RAF via a program called WebSTEAM. Analysts at NRC headquarters, Millington, Tennessee, showed the author how WebSTEAM and the RAF are used by chief recruiters (VanMeter 2023). This program shows subset populations based on demographics, Armed Forces Qualification Test (AFQT) category, or other specifications. Different populations can also be assigned varying weights. This allows chief recruiters and analysts to tailor their recruiter allocations for more specific missions (e.g., nuclear, special warfare, medical, etc.). This aligns with the primary benefit of the RAF: an easily interpretable output for chief recruiters and senior leadership that can be explained and justified in an allocation process. Further, the RAF output compels chief recruiters and analysts to consider allocation options. Because the process is rather easily understandable, it serves as a check to these decision makers for the allocation suggested by the RAF.

The chief recruiters have vast knowledge of both the experience necessary to recruit in certain areas and the abilities of the recruiters assigned to their area. The current allocation process allows leaders to synthesize their knowledge of the area, the ability of

their recruiters, and the guidance suggested by the RAF when making decisions. For example, suppose that leadership knows that a particular recruiter performs at a very high level (e.g., frequently visiting high schools, community engagements) and is consistently overachieving quotas. Subsequently, the RAF would suggest more recruiters being sent to that area. However, the market-share for that station is perhaps misrepresented by such an exceptional recruiter. Chief recruiters can intervene and use their expertise to adjust the solution offered by the RAF (instead of trusting such solution without any questions).

While the primary benefits to RAF are accessibility and interpretability, the main issue inherent with the RAF is that it has the potential to perpetuate a recruiting “chicken-and-egg” dilemma. That is, high-performing stations will continually be recommended to have more recruiters assigned because there is neither consideration given to the underlying demographics of a given station nor the population of youths predisposed¹ to enlist without recruiter effort.

With the RAF, we cannot mathematically consider whether a station consistently performs at a given level because of the population covered, or rather if the performance is on account of the number of recruiters assigned to the station. Considerations for propensity of youths and underlying recruiter performance are left to the best judgement of decision makers. We maintain that an improved metric should account for these considerations in the output. If the model we propose is to be effective, it should not only be as user-friendly and interpretable as the RAF outputs, but also address the propensity of youths to enlist and station population characteristics.

C. ORGANIZATION

In Chapter II, we provide a literature review and discuss assumptions drawn and findings from relevant works in operations research. In Chapter III, we present our Recruiter Estimation Model (REM). This is a diminishing returns model that estimates the expected number of recruits signed by a station given a certain allocation of recruiters. The

¹ Throughout this paper, we use “predisposed” or “predisposed recruits” to describe recruits who we estimate would have signed a contract at a station regardless of whether or not a recruiter was assigned to the station. It is worth emphasizing that with this definition, predisposed is in units of recruits.

model accounts for unique station characteristics such as predisposed recruits and a diminishing rate of return from additional recruiters for each station. In Chapter IV, we present the Recruiter Allocation Model (RAM), a formal mathematical optimization model whose objective maximizes the expected number of recruits signed across all stations for a year. In Chapter V, we discuss the results of RAM and how it could be relevant for the type of analysis conducted by NRC. In Chapter VI, we conclude with a summary of the thesis and potential lines for future work.

II. REVIEW OF RECRUITING LITERATURE IN OPERATIONS RESEARCH

One of the primary assumptions made in this thesis is that the relationship between the number of recruiters assigned to a station and the number of recruits signed is one of diminishing returns. That is, the addition of a recruiter to a given station will result in slightly fewer recruits signed than the previous recruiter addition. Past work simulates the effect of changing the number of recruiters at stations as part of a report on analyzing performance measurement in Army recruiting (Dertouzos and Garber 2008). The report was sponsored by the Commanding General, U.S. Army Training and Doctrine Command and was conducted in the Manpower and Training Program of the RAND Corporation Arroyo Center. Dertouzos and Garber find that “there are diminishing returns to adding recruiters, and these declines are similar across AFQT [Armed Forces Qualification Test] categories and gender” (2008, p. 55). The fact that the declines are similar across subsets of recruits is reassurance that the diminishing returns assumption can be applied to all types of recruits equally. We need not alter model assumptions based on the type of recruits in question.

The estimated elasticity shown in this study is about 0.5. That means about one additional contract for every two recruiters added. This falls in line with many other studies conducted. Table 1 shows estimated elasticities of high-quality contracts for a handful of studies. They each suggest an elasticity that implies a diminishing returns relationship between recruits and recruiters.

Table 1. Recruiter Elasticities in Literature

Research Source	Estimated Elasticity
Asch and Heaton (2010)	0.57-0.63
Knapp et al. (2018)	0.15-0.60
Warner and Simon (2007)	0.47-0.62
Warner and Simon (2004)	0.53

Adapted from Asch (2019).

The work of Dertouzos and Garber, among others, provides a key assumption for developing our model. In a Naval Research Studies Program project at the Naval Postgraduate School, Salmeron and Buttrey present a simple formula to describe the diminishing rate of expected recruit return as a function of the number of recruiters (Salmeron and Buttrey 2018). The function takes the form:

$$R(r) = A(1 - e^{-Br}), \quad (1)$$

where $R(r)$ is the expected number of recruits signed as a function of r (the number of recruiters assigned to the given station). A describes the maximum number of recruits available for a station and B describes the decreasing rate of recruit return as more recruiters are added to a station. Both A and B vary by station, so this allows $R(r)$ to represent how difficult it is to recruit at a particular station. Another key feature of this model is that it is logically structured to assume that zero recruiters assigned to the station results in zero recruits signed.

Salmeron and Buttrey use a piecewise linear approximation of Equation (1) to guide what they call the “Navy Recruiter Prediction and Optimization Model” (NRPOM). The objective of NRPOM is to maximize the expected number of recruits signed. NRPOM seeks to optimally determine the stations to open, the Zip codes to assign to the area covered by each open station, and how many recruiters should be assigned to each station. Constraints in NRPOM include limits on the number of stations that can be opened,

recruiter capacity limits, that Zip codes are assigned only to open stations, and limits on the amount of recruiter effort permitted in each station and Zip,

Salmeron and Buttrey assume that recruiter effort is a function of the distance between the location of the station and the Zip code centroid. As a result, effort can be split among station sections and Zip codes and is dependent upon proximity between stations and Zip code centroids. For example, a recruiter might be assigned to split his or her time between two or more nearby stations. The modified production rate, $prod_{szk}$, of a segment k if Zip code z is assigned to station s is taken to be:

$$prod_{szk} = r_{zk} \left(1 - \frac{d_{sz}}{dmax} \right) (1 - wdmeps)^{\frac{dmeps_s}{dmax}}, \quad (2)$$

where: r_{zk} is the nominal production rate of segment k ; d_{sz} is the distance from station s to Zip code centroid z ; $dmax$ is the maximum desired distance between any station and Zip codes assigned to the station; $wdmeps$ is a penalty weight for distances to a military entrance processing station; and $dmeps_s$ is the distance from station s to the closest one. Should the distance between a station and a Zip code exceed the specified maximum distance, the production rate of the given segment will be negative. This indicates that a recruiter would be expending effort in an area that would be put to better use elsewhere. NRPOM will allocate Zip codes and recruiters to stations in a manner that maximizes the aggregate product of the production rate and recruiter effort in a given Zip code.

While we present a different objective (maximizing expected number of recruits as a function of number of recruiters), the NRPOM objective shares similarities in that the objective drives the optimal allocation of recruiters. The main difference with our methodology is that NRPOM also considers the reallocation of Zip codes whereas we do not. Zip codes not covered by a station in our model will contribute the estimated predisposed recruits.

Jarosz and Stephens (1999) examine the effects of metropolitan recruiter allocation and recruiting stations on Navy enlistment supply. Their model specifically seeks to maximize high quality recruits, which are defined as recruits that score in categories I, II, or IIIA on the AFQT. Inputs to Jarosz and Stephens' model include the number of Navy

recruiters and stations, the number of Army recruiters and stations, collated stations, population, unemployment rates, per capita income, travel distance, seasonal time trends, and fiscal year dummy variables. Each of the inputs is unique to the respective geographical area. Notable in the list of inputs is the consideration for the number of Army recruiters and stations in the local area.

The hypothesis presented is that an increase in the number of Army recruiters will either increase or decrease the number of Navy enlistments. This depends on whether recruiting is complementary or competitive, respectively, in the area. But Jarosz and Stephens find that the effect of having Army recruiting stations in the same area of a Navy station ranges from a small positive effect to no effect at all. This suggests that the presence of recruiters from other military branches does not hinder the mission of Navy recruiters. In fact, their presence might slightly help the Navy mission. Warner (1990) comes to a similar conclusion and suggests that the presence of a military recruiter from any branch might stimulate youths' interest in military service, even if it is not for the branch of the recruiter.

The findings of Jarosz and Stephens, and of Warner, are contradicted by the position held by analysts at NRC. Recruiting analysts consider the presence of other military branches to be at odds with the Navy mission (Powell 2023). That is, the success of Army recruiters in a given area is likely at the detriment of the Navy recruiters. While this research does not consider the impact of other branches on the Navy's ability to recruit, the implications raise an important consideration with regard to presence of recruiters. Specifically, is assigning recruiters in an area that would yield fewer recruits (for the sake of maintaining a community presence) worth not signing as many recruits? The posture and presence of recruiters might provide some citizens the only interaction they will ever have with military members. Asch (2019) notes the generally shallow knowledge of what military service entails for most civilians. Joint Advertising Market Research and Studies (JAMRS) suggest that a majority of young Americans believe that the military does not consist of "people like them" (Office of the Undersecretary of Defense for Personnel and Readiness 2016). Given how they interact with the community, recruiters serve not only as source for securing the future sailors, but also as a source for helping bridge the gap of

understanding between American youths and the military – even if many of those youths do not end up joining the military. While the value of informing youths cannot be easily measured by a metric like a signed contract, it is an essential part of a recruiter’s job and one that should not be overlooked. It is also a decision that an analyst or chief recruiter might have to consider when determining recruiter allocations.

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III. RECRUIT ESTIMATION MODEL

A. REM OVERVIEW

We take inspiration from the model proposed by Salmeron and Buttrey in Equation (1) to model the expected number of recruits signed from a given station. Their model captures the diminishing rate of return from adding additional recruiters to a station, but is intentionally designed such that if zero recruiters are assigned to a station, there will be no recruits signed from that area. Recruiting data received from NRC shows that there are youths predisposed to join the Navy regardless of recruiter effort. Thus, we need an updated model that reflects not only a diminishing rate of return character, but also reflects predisposed recruits for a given station.

The updated model we propose, REM, is displayed in Equation (3). REM is very similar in structure to NRPOM, but has the key addition of the term A_0 :

$$R(r) = A_0 + (A - A_0)(1 - e^{-Br}), \quad (3)$$

where $R(r)$, A , B , and r describe the same characteristics they did in Equation (1). A_0 describes the number of predisposed recruits in the jurisdiction of a station (notice that if $r = 0$, $R(0) = A_0$). Note: $R(r)$, A_0 , A , and B are specific to each station, s , but we drop the index s , for brevity. For some basic intuition for the shape of this function, consider Figure 1, a randomly selected station from our data and the expected number of contracts signed as a function of the number of recruiters assigned to the station. Notice that we would expect about four contracts signed ($R(r)$) when there are zero recruiters assigned ($r = 0$). This is the A_0 value for this particular station. We also can clearly observe that as the number of recruiters assigned to the station increases, the expected number of contracts signed increases, but at a diminishing rate. The red dashed line indicates A , the maximum qualified military available (QMA) youths in the area of the station. As we increase the number of recruiters, the expected number of recruits signed approaches A .

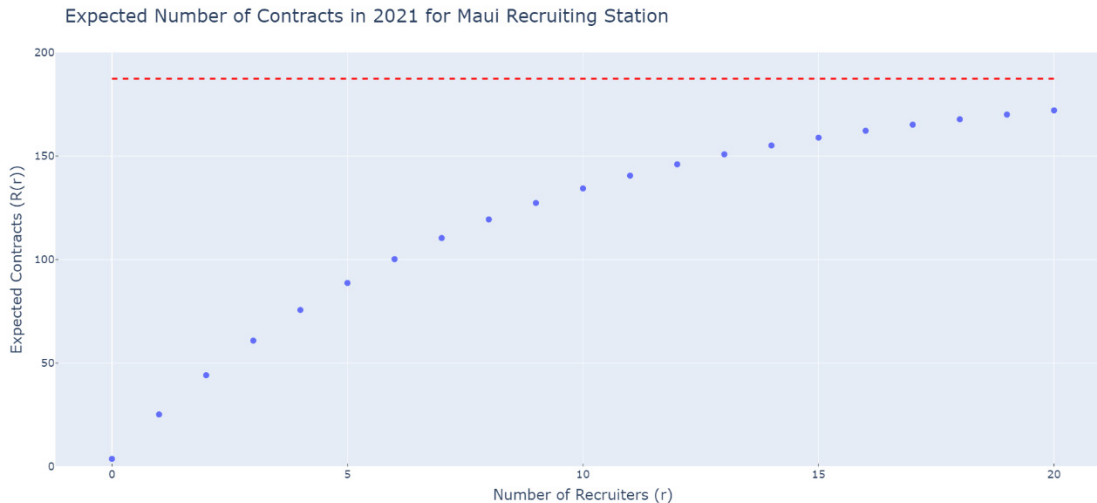


Figure 1. Expected Contracts Signed from Increasing the Number of Recruiters

B. DATA ORGANIZATION AND DISCUSSION

The data sets provided from NRC include:

- (1) NTAG data: This data file represents a snapshot of the stations that were open on 01 August 2022. At any time, stations may be opened or closed, or Zip Codes may be realigned to a different NRS. It is managed by N5 and updated on a monthly basis.
- (2) NRS latitude and longitude: NRC N5 filters and geocodes the addresses to obtain the latitude and longitude coordinates for each facility. Like the NTAG data, this data represents a snapshot in time of the locations of recruiting facilities.
- (3) GNC data: This data represents the monthly number of contracts signed by stations from fiscal year 2018 through 01 August 2022. The data is retrieved by NRC N2 from the Personalized Recruiting for Immediate and Delayed Enlistment Modernization II System.
- (4) Station recruiter data: This data represents the number of recruiters assigned to stations by month. NRC N2 collates the data from the NRC Personnel Status Report system, which is managed by the NRC N1.
- (5) QMA data: This estimates the number of the 17-to-24-year-old citizens within the area of responsibility for each station who are qualified to enlist in the military without a waiver. QMA estimations are commissioned by JAMRS.

Most of the data organization hinges on the recruiting station identification number (RSID), a unique indicator for each station. The first three digits of the RSID indicate the Navy recruiting district (NRD) to which the station belongs. Between 2017 and 2021, the configuration of many stations, and their assignment, to their respective NTAGs and NRDs changed. As a result, the first three digits of the RSIDs changed as well. NRC provided a mapping of the old NRDs to the new NRDs. Some of the RSIDs had already been updated, though. To maintain continuity and accurately track the performance of each station, the RSIDs in all of the data frames were first reverted to their original NRD. Then, all of the RSIDs were updated to accurately reflect the NRD to which they belonged after the NTAG realignment.

With standardized RSIDs in place, the data can begin to be compiled into data frames that are easier for manipulation and calculating statistics. The QMA data frame provided by NRC offers information regarding the expected number of qualified recruits by AFQT score. “High-quality” recruits are defined as having an AFQT score of I, II, or IIIA. Other recruits have a score of IIIB, IV, or V. Using this definition, three separate data frames are compiled: high-quality QMA, low-quality QMA, and total QMA data frames, each indexed by RSID. Based on conversations with NRC analysts, approximately 59% of those qualified for military service are currently available (i.e., not in college or career) (Powell 2022). Additionally, only about 10% of youth consider the military as a career option. The analysts at NRC advise that a QMA that more accurately reflects the ceiling of prospective recruits would be:

$$\text{adjusted QMA} := A = 0.59 \times 0.1 \times H,$$

where H represents the number of high-quality QMA. The adjusted QMA (which we also denote as A as it relates to Equation (3), and for the remainder of the paper) is important for expressing the nature of diminishing returns for recruits signed when adding recruiters to a station. It establishes an upper bound for the number of recruits that could potentially be signed in a station area of responsibility.

The recruiter and GNC data represent monthly snapshots of the number of recruiters assigned and the number of contracts signed at each station. The data is indexed

by RSID. Another data frame is created by grouping the RSIDs and months which offers a better view of the performance at each station.

Lastly, data frames are created by month and year. These data frames merge all of the other data frames using the RSID value as the merge value. The resulting data frame encapsulates all the data regarding number of recruiters, contracts signed, and adjusted QMA for each station by month or year. This allows for performing easy calculations. For replication purposes, the data is not manipulated in the text files. Rather, we use Python (van Rossum 2022) to read, manipulate, and export the data.

C. ESTIMATING PREDISPOSED RECRUITS AND RATE OF DIMINISHING RETURNS

Using historical data provided by NRC, we can estimate the values of A_0 and B to derive $R(r)$. We set $R(r)$ equivalent to the number of GNCs in a given month. A is estimated to be the adjusted QMA, as discussed in the previous section. However, we do not have data for A_0 or B . We must estimate these values from the historical data.

1. Estimating Predisposed Recruits

While we have data for the QMA for the area serviced by each station, there is not a previously existing data set for the expected number of recruits without any recruiter effort. However, there are instances within the historical data where the number of recruiters assigned to a station for a month is equal to zero. Specifically, there are 101 stations which for at least one month in our historical data (January 2019 to July 2022) have zero recruiters assigned. Of those, 94 stations have recruits that signed at some point when there are no recruiters assigned. It is worth clarifying that the GNC statistic is associated with the home of record for a recruit – not the station they use to sign. This is why the data reflects stations with zero recruiters signing recruits. We assign A_0 to be the average of the GNC signed across the months when there are zero recruiters assigned to the station.

Having assigned A_0 for observed cases of zero recruiters assigned to a station, we must deal with the stations that always had a positive number of recruiters assigned. To

approximate the predisposed recruits in these cases, we use the Gower distance in order to determine the zero-recruiter station most similar to the positive-recruiter station. The Gower distance is a multivariate similarity metric that can handle both categorical and numerical values (Gower 1971). We use the scaled values of adjusted QMA, GNC, and recruiters as the variables for calculating the Gower distance. Having estimated A_0 for stations that at some point had zero recruiters, we now calculate the Gower distance between those and the set of stations which always had a positive number of recruiters. Note: a Gower distance of zero indicates that the two stations being compared are identical; a Gower distance of one indicates maximum dissimilarity. Finally, we assign A_0 from the most similar zero-recruiter station to the positive-recruiter station.

When calculating the Gower distance, we consider the statistics from the zero-recruiter stations for the months when those stations in fact had a positive number of recruiters assigned. For example, a station might have had zero recruiters assigned in April, May, and June, but had three, two, and four recruiters assigned in July, August, and September, respectively. To calculate A_0 , we use the statistics from April, May, and June. In performing the Gower distance calculation, we will use the given zero-recruiter station's statistics from July, August, and September since there were a positive number of recruiters at the station during those months.

Using the *gower_matrix* function from the *gower* library in Python, we find the minimum Gower distance value for each observation to determine the station in the set of zero-recruiter stations most similar to each positive-recruiter station. There are 693 stations in the positive-recruiter set. For the set of minimum Gower distances, the mean Gower distance is 0.039 and the median is 0.029. The 25th and 75th percentiles are 0.018 and 0.050, respectively. The maximum of the minimum Gower distances is 0.408. Only five of the minimum Gower distances are greater than 0.25. Figure 2 displays the boxplot of the minimum Gower distances. The summary statistics and the boxplot suggest that almost always, we find a similar zero-recruiter station to use as a proxy for an A_0 estimate of a positive-recruiter station.

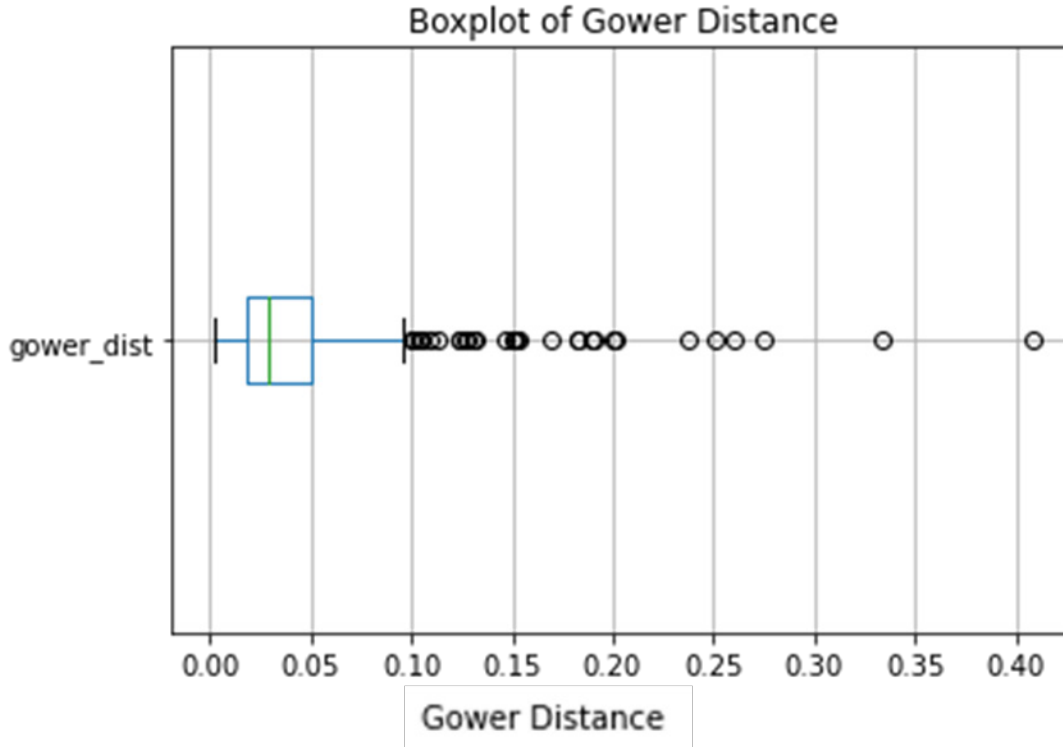


Figure 2. Minimum Gower Distance from Positive-Recruiter Stations to Zero-Recruiter Stations

2. Estimating Diminishing Return Rate

Having estimated the predisposed recruits for each station, we must now estimate the rate of diminishing returns for the stations, B . We once again turn to the observed values of r and $R(r)$ provided by NRC, and our estimates of A and A_0 . We use Equation (4) to derive B as follows:

$$B = \frac{-\ln\left(1 - \frac{R(r) - A_0}{A - A_0}\right)}{r}. \quad (4)$$

Specifically, we calculate B for each station in each month between January 2019 to July 2022. We then average the monthly values to estimate B for each station. Months where there are zero recruiters assigned to the station are ignored in the calculation of B .

D. REM PERFORMANCE

We calculate the adjusted R-squared and the sum of squared error (SSE) values by year to measure REM performance. In Table 2, SSE, average error per station, R-squared, and adjusted R-squared values are displayed. The performance statistics are based on what REM projects the number of recruits signed would be provided the average number of recruiters assigned to a given station over the course of a year. The projection value is then compared to the actual number of recruits signed at the station over the course of the year.

We observe that the performance of REM is worse for year 2019 than for the other three years analyzed. We hypothesize that the reason could be the COVID-19 pandemic or the conclusion of the NRC RSID realignment. For years 2020, 2021, and 2022, the adjusted R-squared values indicate that about 80% of the error in REM is explained by the model considering the number of predictors used. This is indication that REM performs decently well. If the R-squared value were lower, we would become concerned with the ability to project. Considering how low the R-squared value is for 2019, we will only analyze results from 2020, 2021, or 2022.

Table 2. REM Performance by Year

Year	SSE ($\times 10^4$)	Average Error/Station	R-Squared	Adjusted R-Squared
2019	34.44	20.912	0.509	0.508
2020	8.43	10.348	0.820	0.819
2021	9.93	11.234	0.778	0.777
2022	8.30	10.269	0.775	0.775

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IV. RECRUITER ALLOCATION MODEL

A. OVERVIEW

With REM estimating the expected number of recruits signed as function of the number of recruiters assigned to a given station, we must determine how to allocate recruiters such that we maximize the total expected recruits across all stations. We develop a mixed-integer linear program, RAM, whose output gives the optimal allocation of recruiters. REM estimates of $R(r)$ serve as input data. We note the RAM may recommend closing some stations that were previously open, and reallocating the recruiters that would have been assigned to that station elsewhere. As previously discussed, if a station has zero recruiters assigned, it still contributes the predisposed recruits (A_0) to the objective.

B. ASSUMPTIONS

The main assumption for RAM is that the estimates from REM for a given number of recruiters are in fact representative of the number of recruits signed. We also assume that: recruiter effort is spent exclusively in their assigned station area of responsibility; recruiting effort is independent between stations; and, all recruiters are identical in their recruiting expertise.

C. MATHEMATICAL MODEL

1. Indices and Index Sets

There are two sets used in our formulation: S and R_s . S represents the set of recruiting stations. Each $s \in S$ is the unique RSID value associated with the station. R_s is the set of the potential number of recruiters that could be assigned to station s . $R_s \in \{0, 2, \dots, m_s\}$, where m_s is the maximum number of recruiters that could be assigned to station s based on capacity constraints. Notice the exclusion of single recruiter from R_s . As a force protection consideration, the number of recruiters assigned to a station must be at least two (if the station is to be manned). Excluding one recruiter from the set of the number of potential recruiters assigned implicitly enforces the constraint of requiring at least two recruiters at opened

recruiting stations. Of course, other values could be excluded for any given station at the discretion of the analysts.

2. Input Data and Parameters

We use $g_{r,s}$ to indicate the expected number of recruits signed at station s if r recruiters are assigned. The values of $g_{r,s}$ are the estimates calculated using Equation (3). That is, $g_{r,s} = R(r)$ for stations s . We use p to indicate the total number of recruiters available for assignment, c to indicate the maximum number of closed stations (i.e., 0 recruiters assigned), and m_s to indicate the maximum number of recruiters permitted at station s .

3. Decision Variables

Our binary decision variables are denoted $z_{r,s}$. The logic of $z_{r,s}$ is displayed below:

$$z_{r,s} = \begin{cases} 1, & \text{if } r \text{ recruiters are assigned to station } s \\ 0, & \text{otherwise} \end{cases}.$$

4. Formulation

The mathematical formulation for RAM is displayed below. The objective, Equation (5), is to maximize the expected number of recruits signed. The first constraint, Equation (6), ensures that each station is assigned a specific number of recruiters. Equation (7) ensures that the total number of recruiters does not exceed p , the number of recruiters available for assignment. Equation (8) ensures that the number of unopened stations is not greater than c . Equation (9) establishes the integrality for the decision variables.

$$\text{(RAM): } \max_z \sum_{s \in S} \sum_{r \in R_s} g_{r,s} z_{r,s} \quad (5)$$

$$\text{subject to } \sum_{r \in R_s} z_{r,s} = 1, \quad \forall s \in S; \quad (6)$$

$$\sum_{r \in R_s} \sum_{s \in S} r z_{r,s} \leq p; \quad (7)$$

$$\sum_{s \in S} z_{0,s} \leq c; \quad (8)$$

$$z_{r,s} \in \{0,1\}, \quad \forall s \in S, \forall r \in R_s. \quad (9)$$

D. MODEL DISCUSSION

The results of RAM give three important statistics:

- (1) The number of recruiters to assign to each station. This is expressed by the binary decision variables. For each station s , a choice of $\hat{r}$ recruiters is represented by the variable $z_{\hat{r},s} = 1$.
- (2) The recruiting stations to open. This is also expressed through the decision variables. RAM recommends not opening a station s for which $z_{0,s} = 1$.
- (3) The total expected number of recruits signed for the optimal solution and the expected number of recruits signed by station.

Each of these statistics is useful for analysis and comparison among alternative solutions. Comparisons between RAM recommendations and the NRC implementation in past years offer insight into where improvement could be made.

All scenario excursions have been solved with the *glpk* (Makhorin 2023) solver in Python Pyomo (Hart et al. 2011). RAM creates 12,592 binary decision variables and 1,576 constraints. The average solve time is 0.6 seconds and uses 9.9 Mb of memory. The processor used is an Intel® Core™ i7-8650U CPU @ 1.90GHz-2.11GHz. Because the solve time is short, RAM is flexible to include additional constraints if so desired at a later time. More constraints are not included in RAM in its current form due to lack of data and agreement with NRC analysts that additional constraints are not necessary. In the future work section, we present constraints that we anticipate could be requested and their respective mathematical formulations.

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V. RESULTS

As a preface to our results, it is worth reiterating that NRC data is a monthly snapshot of recruiting station statistics. Thus, there might be variations from month to month in the number of recruiters assigned. These variations may be due to recruiters being transferred to their next duty station, or recruiters taking leave or temporary duties elsewhere. Thus, a monthly level of granularity presents potential for a high degree of volatility in the RAM solution. To capture the average performance of a station, RAM does not intend to prescribe a monthly allocation for recruiters, but rather, a yearly one. For excursions, we explore the following assumptions:

- Baseline: RAM assumes the statistics for the average number of recruiters available ($p = 3,656$), and the maximum number of closed stations ($c = 26$), in any given month during year 2021.
- Any station closed: Same as Baseline, but allowing any number of stations to close ($c = 787$, the cardinality of S).
- All stations open: Same as Baseline, but enforcing all stations open ($c = 0$).

A. BASELINE RAM RESULTS UNDER YEAR 2021 CONDITIONS

The assumptions for solving RAM under the average 2021 conditions are 3,656 recruiters available and a maximum of 26 closed stations. Running RAM under these conditions will help facilitate comparisons between the RAM optimal solution and the actual solution implemented by NRC in 2021 (referred to as the “NRC solution” for the remainder of this section).

The number of recruits signed with the NRC solution was 36,250. Under the above conditions, RAM finds an optimal solution with 42,015 expected recruits signed. We visualize RAM outputs using a *Folium* map created through the *Leaflet* library (Graul 2016). *Folium* maps are interactive maps that give the ability to zoom and embed information within plotted location markers. Consider Figure 3, which shows the solution

for this scenario. The red circles indicate stations that should be closed. Green circles represent open stations. Since the map is interactive, clicking on a station reveals the station name and the optimal number of recruiters to assign to the station. (In Figure 3, we show the solution for NRS Millington. RAM allots five recruiters to this particular station.)

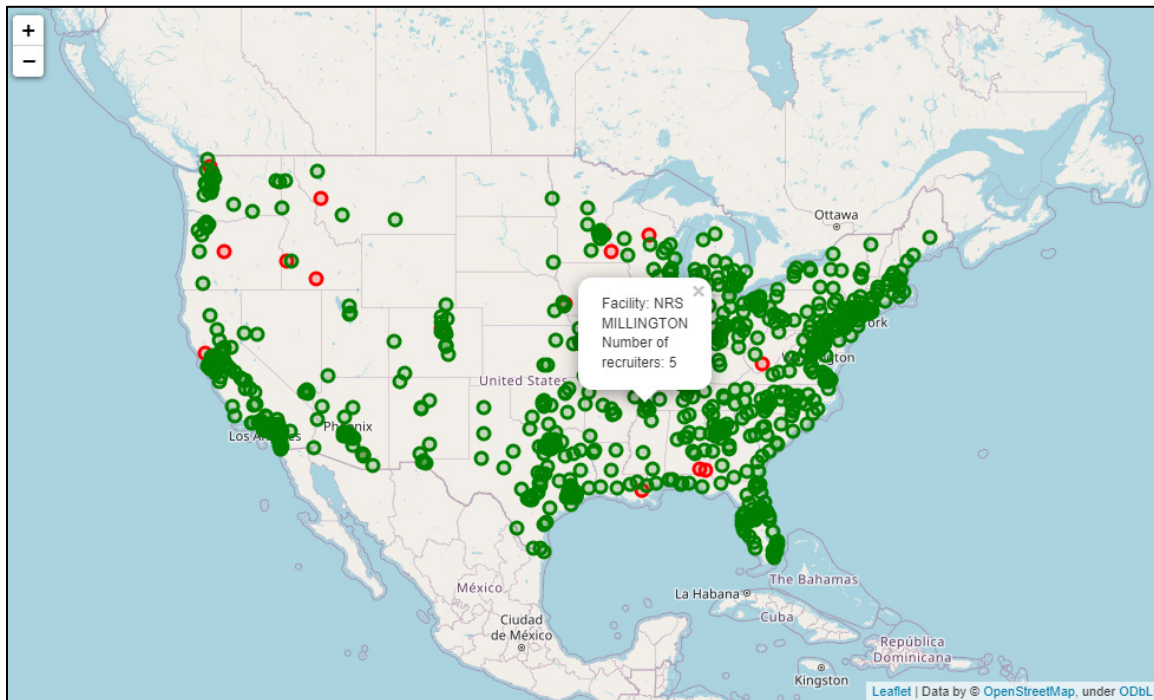


Figure 3. Optimal Recruiter Allocation Under Initial Conditions

An intriguing observation gathered from the results is that the stations closest to prominent U.S. Navy installations are allotted fewer recruiters than surrounding stations. For example, in Hawaii, the station closest to Pearl Harbor has the smallest number of recruiters (two) assigned out of the five stations spread across the Hawaiian islands. In fact, the recommended number of recruiters assigned to the other stations on the islands is between four and eight. In Norfolk, the recommended number of recruiters assigned to the Newport News and Norfolk recruiting stations is five for each station. The number of recruiters assigned to the Virginia Beach, Chesapeake, and Lynnhaven stations (suburbs of Norfolk and Newport News) are eight, eight, and nine, respectively.

We believe that this is indication for the predisposed recruits consideration at work. The areas immediately around the Navy installation naturally have a larger proportion of their population that is familiar with the Navy and will have a higher propensity to enlist without much recruiter effort. On the periphery of the Navy installation, populations might be aware of the Navy's presence, but not as familiar with the process for joining. Thus, the recruiter effort is more effective in these areas than in areas in close proximity to Navy installations.

B. COMPARISON TO 2021 NRC SOLUTION

We observe differences and similarities between the number of recruiters RAM suggests to assign to stations and the NRC solution. There are 280 stations where RAM suggests at least two more recruiters, and 233 stations where it suggests at least two fewer recruiters, than what was actually implemented. There are 274 stations whose average 2021 recruiter allotment was within two recruiters of what RAM suggests.

In Figure 4, we display a comparison between the RAM recruiter allocation results and the NRC solution for stations in the San Francisco Bay Area. Notice that each icon has a plus or minus sign. A plus sign represents that RAM suggests more recruiters be assigned to the station than the NRC solution. In addition to having a decent number of stations in a relatively close geographic area, we see a diverse spread of comparisons between the RAM solution and the NRC solution. Green stations represent stations whose RAM allocation does not differ by more than two recruiters from the NRC solution. Yellow stations represent stations whose RAM allocation of recruiters differs from the 2021 solution by more than two, but fewer than six, recruiters. Red stations indicate stations whose RAM recruiter allocation differs from the NRC solution by more than six recruiters. In Figure 4, we have selected the station in Stockton, California. The station icon is colored yellow with a plus sign to indicate that RAM suggests an additional four recruiters should be added. The recommended number of recruiters assigned to the station is also included in the information that appears upon clicking on an icon. RAM recommends 11 recruiters should be assigned to the Stockton station.

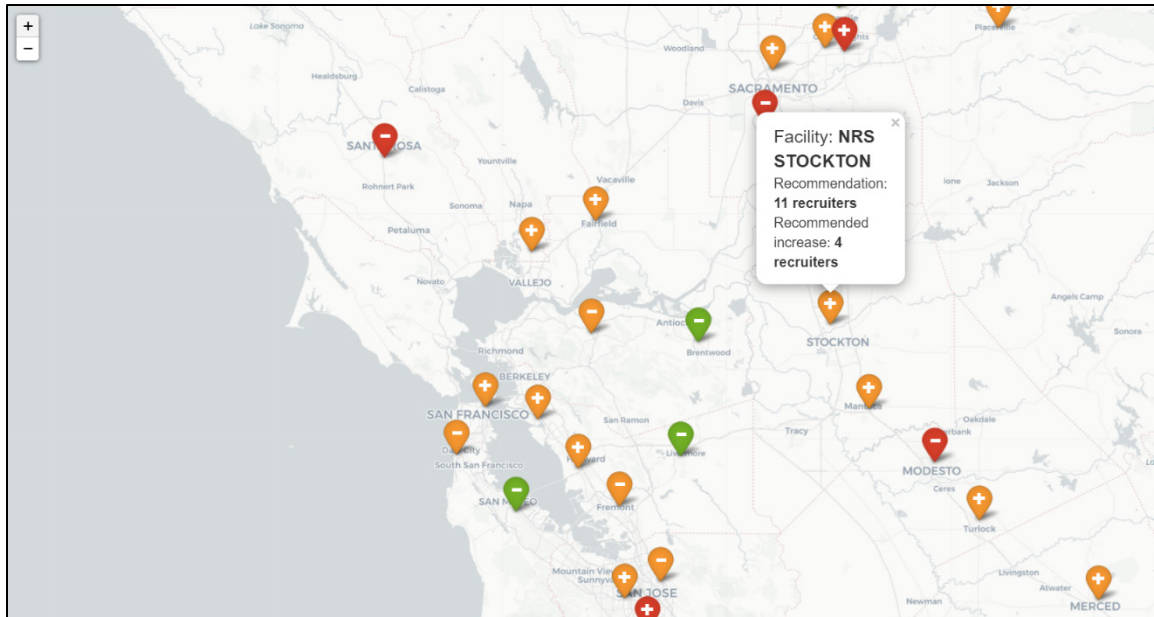


Figure 4. Comparison of RAM Results to 2021 Solution in San Francisco Bay Area

The largest difference in the number of recruiters between the RAM solution and the NRC solution is at NRS Sparks which is located near Reno, Nevada. In 2021, there was an average of 14.75 recruiters at this station. RAM suggests only two recruiters should be assigned to the station. This is a decrease of 12.75 recruiters. The greatest increase in number of recruiters between the RAM solution and the 2021 implementation is at NRS Raleigh in Raleigh, North Carolina. In 2021, there was an average of 5.58 recruiters at this station. RAM suggests that 13 recruiters should be assigned to this station.

We find there are 23 stations with an average of more than two recruiters assigned in 2021 that RAM suggests should have zero recruiters assigned. These are stations that were open in 2021 that RAM suggests should be closed. Conversely, we find 20 stations that had an average at or below one recruiter assigned in 2021 that RAM suggests should have at least two recruiters assigned. These are stations that, on average, were closed in 2021, which RAM suggests should be opened.

C. NO CLOSED STATION LIMIT

Here, we remove the constraint for the maximum number of closed stations by setting $c = 787$, the total number of stations. In practice, RAM will not close all p stations because then only the predisposed recruits would sign. Setting $c = 787$ is a known upper bound for the number of stations that could be closed. We hold all other considerations and constraints unchanged as in the Baseline scenario. The solution from this excursion finds that 238 stations should be closed to achieve an expected number of recruits signed of 42,689. This is about 650 expected recruits more than the solution provided in the Baseline excursion which limited to a maximum of 26 stations to be closed. In Figure 5, we see the impact of relaxing the closed stations constraint.

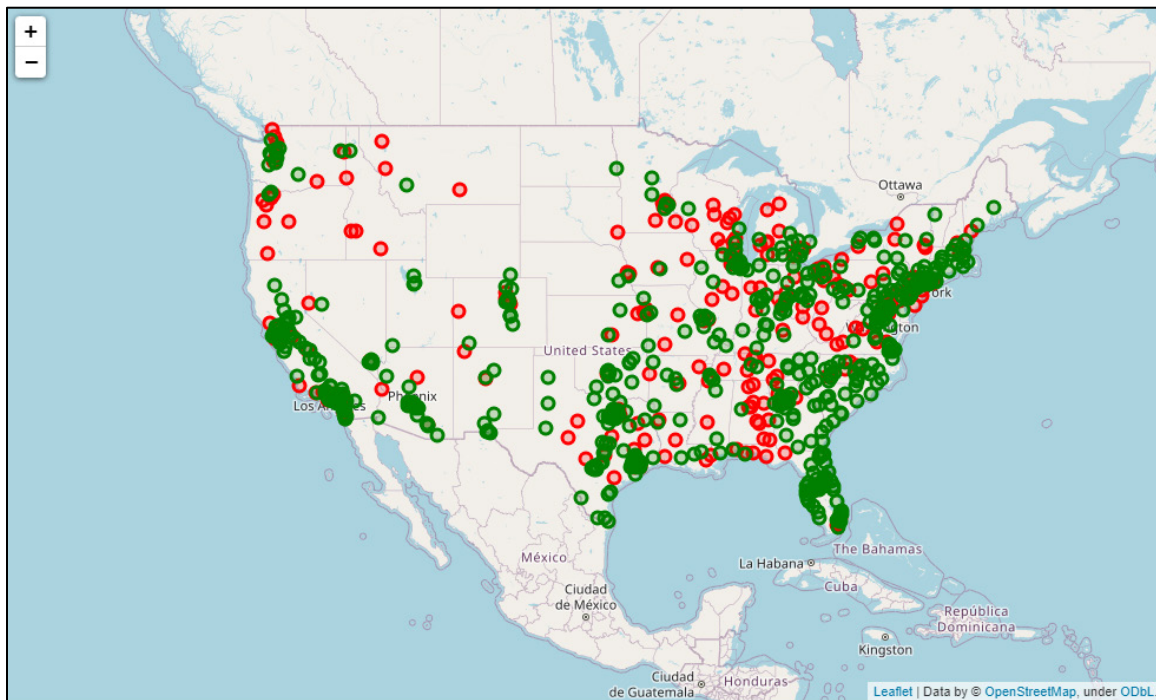


Figure 5. Recruiter Allocation Map with No Closed Station Limit

It is important to discuss the consequences of adopting this result for implementation carefully. As acknowledged in the literature review, the mere presence of recruiters in towns may be vital to ensuring long-term recruit return. If analysts and chief recruiters were to follow the solution offered by omitting a constraint on the maximum

number of closed stations, the number of recruits signed might exceed the previous mark in the short-term. However, from a strategic perspective, the absence of recruiters in a large number of closed stations would likely become counterproductive over time and result in a decrease in the number of recruits signed.

Relaxing the constraint on the number of closed stations also reveals that the difference in the expected number of recruits signed between this excursion and the Baseline conditions is comparatively small. Indeed, we would expect to gain about 650 more recruits from closing over 200 more stations. This result might seem non-intuitive at first because it indicates an increase in recruit production despite closing stations. It is worth emphasizing that by closing stations, recruiters can be reallocated to stations where they are expected to produce more recruits, which is why we observe an increase in total recruit production for the first 238 station closures.

We iteratively run RAM and increase the number of closed stations by one with each iteration. In Figure 6, we observe the marginal return resulting from the closure of an additional station. For approximately the first 20 stations closed, there is a sharp decrease in the additional recruits signed with the closure of each subsequent station. Then, the rate of decrease becomes less severe. In fact, the behavior of the decrease is rather linear at a rate of approximately -1 additional recruits for every 25 stations closed between 20 and 238 closed stations. At 238 closed stations, there is no improvement in the expected number of recruits signed from closing an additional station.

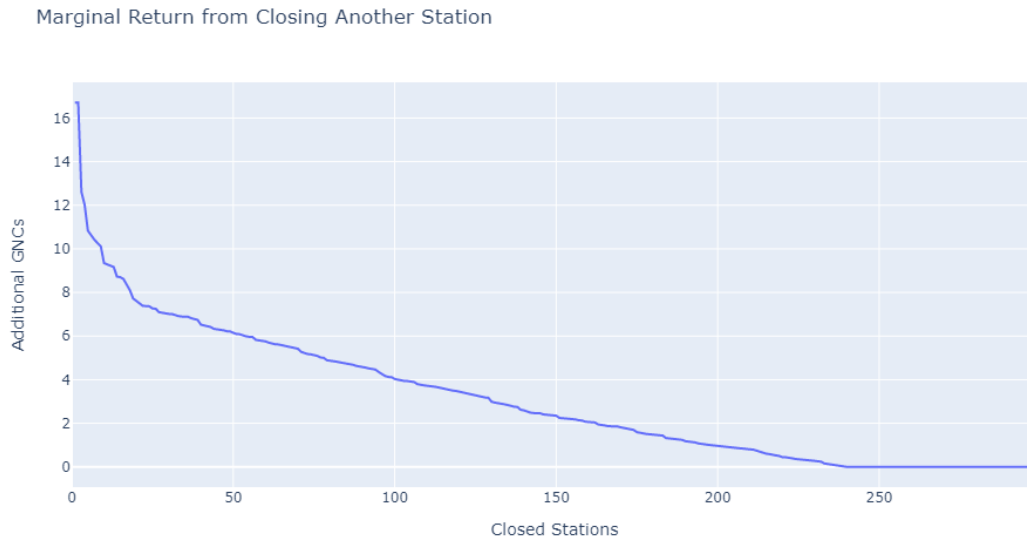


Figure 6. Marginal Return of Recruits from Station Closures

D. ALL STATIONS OPENED

The other extreme with regard to closing stations is mandating that every station be open. We do this by setting $c = 0$ in RAM. This establishes a worst-case scenario because it is the most restrictive. Forcing every station to be open obliges that at least two recruiters are present at every station. In Figure 7, the difference between the expected number of recruiters when $c = 0$ and when $c = 238$ is less than 1,000 expected recruits. Even though requiring all stations be open results in the smallest number of expected recruits with RAM, this solution results in over 5,000 more expected recruits the number of recruits signed under the NRC solution (the red point in Figure 7). This is indication that even under extreme constraints, RAM offers a solution for recruiter allocation that would be an improvement from the actual results, assuming the assumptions of the model hold.

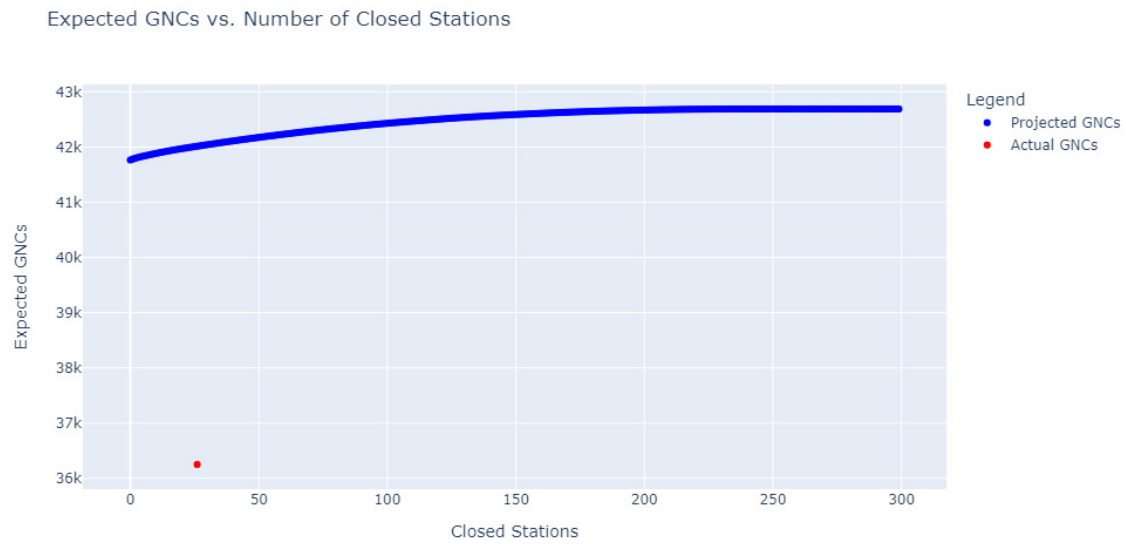


Figure 7. Expected Contracts from Increasing the Number of Closed Stations

VI. FUTURE WORK AND CONCLUSIONS

A. FUTURE WORK

Through the author's email conversations and an in-person presentation at NRC in Millington, Tennessee, analysts in the N2 and N5 departments have expressed that this thesis can set the foundation for a new approach to recruiter allocation. In fact, the Commander, Navy Recruiting Command, in a statement of support for the MORS Tisdale Award said that our algorithm is "expected to serve as the basis for decisions on the placement of recruiters as NRC navigates the most difficult recruiting environment since the inception of the All-Volunteer Force" (Walker 2023). This is encouraging feedback and affirms that the work we have done in this thesis carries relevant applications to support recruiting efforts.

The author's visit to Millington also helped guide and inform what future work still remains for this project. The greatest work will be the development of a user-friendly interface for inputs and outputs. In its current state, the model requires installation of Python, optimization solvers, and a slight working knowledge of Python code. This is fine when answers regarding recruiter allocation occur infrequently (once or twice a year, perhaps). An analyst can run the model once, obtain a solution and implement it. But recruiter allocation is a dynamic process and is often conducted by non-analysts who likely do not have access to or familiarity with Python. For this work to be fully embraced by NRC and become part of how they make allocation decisions, it must be conveyed over a medium with which the non-analyst can operate.

As mentioned in Chapter IV, because the run-time of RAM is not of great concern, additional specifications can be added. During the author's visit to NRC, he discussed with analysts whether additional constraints ought to be added to RAM. Analysts and chief recruiters agreed that the constraints currently in place for RAM suffice to capture the considerations required when allocating recruiters. Although there are not additional constraints requested currently, we offer a handful of potential features that we anticipate might be eventually added to RAM.

First, we consider the case where a specific station $\hat{s}$ is required to have a specific number of recruiters, $\hat{r}$. The mathematical formulation would simply restrict $R_{\hat{s}} = \{\hat{r}\}$. A similar specification might seek to ensure that at least a specified number of recruiters, $\tilde{r}$, are assigned to a particular station $\hat{s}$.

A constraint with respect to NTAG manning requirements would require creating new sets and indices to indicate the stations that belong to NTAGs. For this notation, let N represent the set of NTAGs, S_n represent the set of stations that belong to NTAG n , and m_n represent the minimum number of recruiters required to be assigned to NTAG n . The mathematical formulation would be as follows:

$$\sum_{s \in S_n} \sum_{r \in R_s} r z_{r,s} \geq m_n, \quad \forall n \in N. \quad (10)$$

For this constraint, the analysts must be careful that the sum of the number of recruiters they desire to be assigned to each NTAG be less than the number of recruiters available.

Otherwise, the problem would become infeasible. That is, $\sum_{n \in N} r_n \leq p$, where p , as it is in

RAM, represents the total number of recruiters. This could easily be checked by the user's interface in the data preprocessing.

The constraints listed offer only a sampling of the potential considerations that can be addressed by RAM. There are many more potential constraints that could be added to RAM, and they will vary based on the questions being asked. Alterations to RAM beyond constraints could include penalty functions in the objective for an unequal spread of recruiters assigned across stations. Though NRC has not requested specific excursions or scenarios thus far, it is worth reemphasizing that due to the structure of RAM, and its comparatively low run-time, constraints and alterations can be made quite easily.

B. CONCLUSIONS

The intent of this thesis has been to offer a formal approach for Navy recruiter allocation. At each step in our methodology, we focused on considering the people involved in the recruiting process: recruiters and recruits. Through our mathematical models, we have demonstrated an approach for recruiter allocation that maximizes the

number of expected recruits signed. This process supports the recruiters and the recruits because it places recruiters in locations that offer the best opportunity of signing recruits and provides prospective recruits a proper exposure to the opportunities available to them in the U.S. Navy. In this work, we have shown that optimal recruiter allocation increases the expected number of contracts signed.

Referencing operations research literature on military recruiting, it is clear that a model for estimating the number of recruits signed as a function of the number recruiters assigned to a station should have an element of diminishing returns. We have developed a recruit estimation model, REM, with this consideration in mind. We have used historical data from NRC to determine the unique rate of diminishing returns from adding recruiters for each station. It is also apparent from our data the need to estimate the number of predisposed recruits for each station. Incorporating a term for the number of predisposed recruits signed allows for some expected contracts signed despite no recruiters being assigned to a station. This is particularly important when inputting REM results as parameters for our recruiter allocation model, RAM.

RAM is a formal optimization program whose objective maximizes the expected number of contracts signed through optimal recruiter allocation. RAM ensures that each station is assigned a specific number of recruiters and is constrained by the number of recruiters available and the permitted number of closed stations. We have found that when running RAM under the same conditions observed in year 2021, RAM outperforms 2021 results by 6,000 expected recruits. Just through the redistribution of recruiters, we expect a 16% increase in recruit production. We also have compared the number of recruiters assigned to each station between the RAM solution and the 2021 NRC solution. This has allowed us to identify stations which RAM suggests are overmanned or undermanned.

This research has shown that by placing recruiters in the correct places, the recruiting process can be more effective, which in turn means more recruits being signed and supporting our Navy as the next generation of sailors.

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