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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MEPS WORKLOAD BALANCE AND CAPACITY RATIONALIZATION

by
Chad W. Seagren and Kenneth H. Doerr

10 May 2022

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Chad W. Seagren	*(831) 656-7902*

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NAVAL POSTGRADUATE SCHOOL
Monterey, California 93943-5000

Ann E. Rondeau
President

Scott S. Gartner
Provost

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This report was prepared by:

Chad W. Seagren

Kenneth H. Doerr

Reviewed by:

Raymond D. Jones, Chairman
Defense Management

Released by:

Kevin B. Smith
Dean of Research

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Abstract

The U.S. Military Entrance Processing Command (USMEPCOM) is charged with screening all applicants for enlistment into the U.S. Armed Forces according to the qualification standards of each of the four services. These applicants are screened and processed at one of 65 Military Entrance Processing Stations (MEPS) distributed throughout the United States, to include Alaska, Hawaii, and Puerto Rico. Archived data exists that describes the daily work each site has experienced in the broad categories such of medical, testing, and processing. The workload between stations can vary widely, as certain sites serve areas with denser populations of applicants. The workload at each station also tends to vary according to time of year, as well as time of month. This workload variability at and between MEPS presents unique challenges for deciding on optimal capacity levels. We develop a short list of candidate locations that exhibit particularly high congestion relative to other MEPS and regions. Namely, 7th Battalion in California and 10th Battalion in Florida each contain several MEPS that rank highly with respect to relative congestion. Another regional area with substantial relative congestion includes MEPS from 4th and 12 Battalions. Finally, individual MEPS such an Minneapolis and Columbus exhibit consistent high relative congestion in the medical technician workflow, while Denver and Montgomery exhibit high congestion in the human resources workflow.

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CHAPTER 1: MEPCOM and over-utilization

The U.S. Military Entrance Processing Command (USMEPCOM) is charged with screening all applicants for enlistment into the U.S. Armed Forces according to the qualification standards of each of the four services. USMEPCOM screens over 300,000 applicants each year to determine who is physically, medically, mentally, and intellectually qualified to serve. Among those screened, fewer than 200,000 are ultimately inducted into the military.

These applicants are screened and processed at one of 67 Military Entrance Processing Stations (MEPS) distributed throughout the United States, to include Alaska, Hawaii, and Puerto Rico. Archived data exists that describes the daily work each site has experienced in the broad categories of medical, testing, and processing. The workload between stations can vary widely, as certain sites serve areas with denser populations of applicants. Several MEPS are known as Mega-MEPS due to the particularly large numbers of applicants they are able to support. The workload at each station also tends to vary according to time of year, as well as time of month. This workload variability at and between MEPS presents unique challenges for deciding on optimal capacity levels.

Like any organization, USMEPCOM's ability to devote resources to its mission is limited. It may be possible to improve the manner in which the current constellation of resources is employed to meet demand. While taking the current state as a point of departure, we identify the most over-utilized MEPS. MEPS with capacity that is insufficient to keep up with demand experience congestion and backlogs. As congestion grows, throughput slows and the services are less able to process as many applicants as they would like, which puts their ability to accomplish their accession missions at risk. The analysis also identifies the most under-utilized MEPS. MEPS that are under-utilized might possess resources better employed elsewhere or it might make sense to redirect demand there under certain circumstances.

MEPCOM may consider three general ways to mitigate the problem of over-utilization at the MEPS we identify. The first is to add capacity at the affected MEPS. The second is to add capacity in the general vicinity such as a Remote Processing Unit (RPU). The third is to move an existing MEPS from one location to another. Our analysis identifies the centers most in need of mitigation. Due to the unique circumstances at each MEPS, sponsor input is necessary to determine which types of mitigation to be considered at each location, as well as the relevant details. For example, adding capacity of a certain type might be unfeasible at a particular MEPS due to building constraints at that location, while RPUs might be limited to a particular size in certain cities due to factors like costs.

The purpose of this study is to achieve the following objectives:

1. Document the demand for services by geographic area for each MEPS.

2. Identify where standing up a new or satellite MEPS/RPU might be useful, among a short list of candidate locations.

3. Identify where moving a MEPS from one location to another might be more useful, among a short list of candidate locations.

We develop a short list of candidate locations that exhibit particularly high congestion relative to other MEPS and regions. Namely, 7th Battalion in California and 10th Battalion in Florida each contain several MEPS that rank highly with respect to relative congestion in both workflows. Another regional area with substantial relative congestion includes MEPS from 4th and 12 Battalions. Finally, individual MEPS such an Minneapolis and Columbus exhibit consistent high relative congestion in the medical technician workflow, while Denver and Montgomery exhibit high congestion in the human resources workflow.

CHAPTER 2: Background and Data

MEPCOM is divided into two sectors, the Western Sector and the Eastern Sector. Each sector is comprised of six battalions. The battalions correspond to geographic areas that contain from one to six states. There resides five or six MEPS in each battalion. Figure 2.1 shows the geographical distribution of the MEPS, as well as the battalion and sector organization structure. While the primary consideration to locate a MEPS in a particular area is proximity to sufficiently dense populations of likely applicants, other considerations of a political nature sometimes prevail.

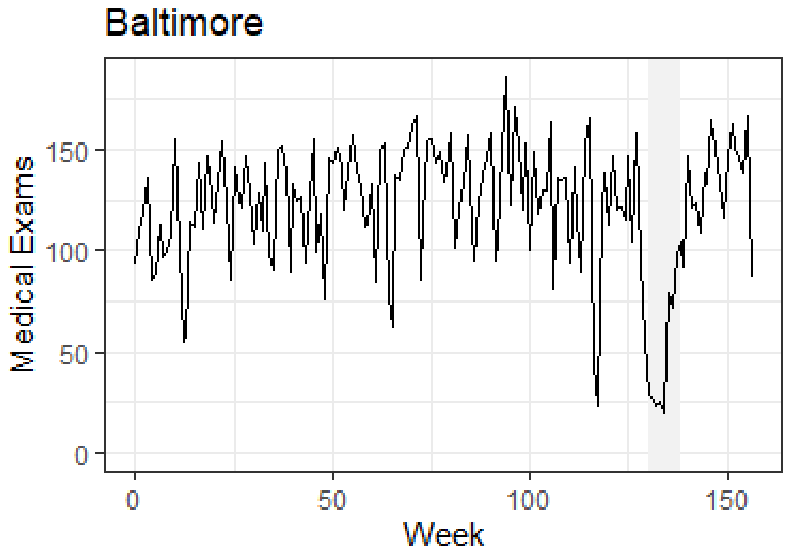
Figure 2.1. MEPCOM Sector, Battalion, and Station Locations

Our conceptual model of each MEPS has two workflows, one for conducting medical examinations and the other for processing contracts. We examine each independently. The medical examinations workflow is primarily served by medical technicians. We refer to this workflow as the medical exam workflow or the medical technician workflow. The contract processing workflow is supported by HRA technicians. We refer to this workflow as the contract workflow or the HR workflow.

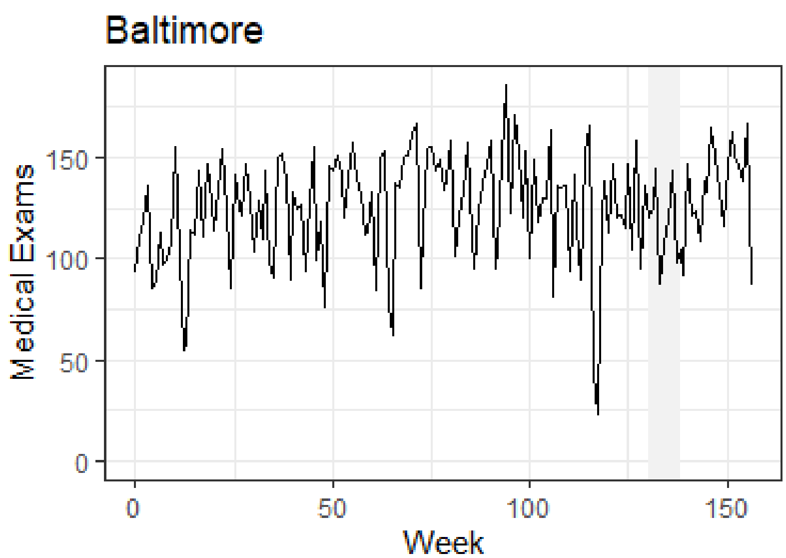
2.1 The Data

The original dataset contains 10,519 observations. These are weekly observations for each of the 67 MEPS from FY2018 to FY2020. We drop all observations from the Riverside and the Las Vegas MEPS for most of the analysis because both of those MEPS are fraught with missing values due to the fact they do not appear to have been in operation for all three years. The final requirement for cleansing is an adjustment for the period of time in 2020 in which most MEPS experienced vastly fewer arrivals due to the onset of the COVID-19 pandemic in 2020.

In order to correct for the effects of the COVID pandemic, we take all pre-covid obvserations for a given MEPS (129 observations each) and fit the most appropriate Seasonal ARIMA model to them. We use the Seasonal ARIMA model to forecast the next 8 observations with which we replace the 8 weeks of pandemic-affected observations. Panel (a) of Figure 2.2 shows the number of weekly medical exams for the Baltimore MEPS. The grey shaded region corresponds to the first eight weeks of the onset of the pandemic and exhibits a precipitous drop in applicants during this time. Panel (b) of the same figure shows the observations for those eight weeks replaced with the forecast from the seasonal ARIMA model. We perform this adjustment for contracts as well.



(a) Medical Exams at Baltimore MEPS



(b) Medical Exams at Baltimore MEPS adjusted for COVID.

Figure 2.2. Example of adjusting time-series for COVID.

The primary variables we use in our analysis are shown in Table 2.1. The Medical Maximum Daily Capacity/Allocation (MDCA) describes the maximum number of medical applicants a MEPS can accommodate in a given week, based on the fact each Medical Technician may process five applicants per day. Similarly, the Process MDCA describes the maximum number of contracts a MEPS can accommodate in a given week, based on a capacity of five contracts per HRA per day. Fee-Based Providers (FBP) are contracted to augment the capacity of the medical workflow. This variable describes the number of FBP hours contracted at the given MEPS each week. Next, Medical Exams, is the number of medical exams completed at a given MEPS each week. This is the primary variable that describes the demand for services in the medical workflow. Similarly, the count of Accessions and DEPS processed at a given MEPS during a week are the primary variables that describe demand for the HR workflow. We use the term contracts to refer to the sum of Accessions and DEPs.

Table 2.1. Summary Statistics

Variable	**FY**	**N**	**Mean**	**Std. Dev.**	**Min**	**Pctl. 25**	**Pctl. 75**	**Max**
Medical MDCA	2018	3380	188.3	63.60	60	140	225	375
Medical MDCA	2019	3445	200.7	72.90	60	150	250	425
Medical MDCA	2020	3380	202.4	76.59	60	150	240	425
Process MDCA	2018	3380	194.9	86.13	40	125	250	500
Process MDCA	2019	3445	200.9	83.86	60	140	250	500
Process MDCA	2020	3380	202.1	83.59	45	140	250	500
FBP Hours	2018	3153	64.6	43.61	1.5	31.75	89.5	280.75
FBP Hours	2019	3254	75.0	48.77	2.5	37.25	103	332.5
FBP Hours	2020	3037	70.1	49.00	1.5	32.5	98.75	309
Medical Exams	2018	3380	89.0	52.68	1	47	122	288
Medical Exams	2019	3445	94.5	55.59	2	50	129	309
Medical Exams	2020	3380	81.3	51.15	1	42	112	312
Shippers	2018	3357	52.6	39.74	1	22	73	250
Shippers	2019	3438	52.1	40.00	1	22	72	239
Shippers	2020	3275	56.8	44.09	1	23	80	264
Accessions	2018	3380	67.7	41.51	1	35	91.25	264
Accessions	2019	3445	70.3	43.94	3	36	94	265
Accessions	2020	3380	63.8	44.24	1	30	88	254
DEPS	2018	3380	54.5	37.38	1	26	75	215
DEPS	2019	3445	57.0	39.29	1	26	79	220
DEPS	2020	3380	47.9	34.82	1	21	67	234

It is important to note that most of the MEPS exhibit a relatively high degree of variance in the Medical Exams and Contracts data. In general, the last week of the month tends to see a higher number of applicants than the other weeks of the months, though this does not always hold. (See Figure 2.2.) In addition, the periods of highest demand a MEPS experiences during a given year tends to vary across years at the same MEPS and tends to vary between MEPS. This variability presents a unique challenge to forecasting future behavior.

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CHAPTER 3: Analytical Approach

3.1 Queueing Theory

We employ Queueing Theory to derive a number of our measures of congestion. Each of the workflows have the same basic structure that we illustrate in Figure 3.1. Namely, applicants arrive in the system and begin waiting in a single queue for one of S servers to become available. In our case, the technicians (i.e. Medical Technicians or Human Resource Associates) perfrom the role of the severs. Once a server becomes available, they draw an applicant from the queue and process the applicant. Upon completion of that stage of processing, the applicant is released.

Shortle, et al (2018, p. 4) identify six characteristics of queueing systems. We address each in turn as they concern the present analysis:

1. *Arrival pattern of customers* – Of all the elements of the MEPS process we may observe, the most thorough data we possess is on the arrival patterns of customers. We have weekly observations of arrivals at every MEPS over a period of three years.

2. *Service pattern of servers* – We possess no empirical data on the service patterns of servers. Ideally, we would know how long it took each technician to process each applicant. Alternatively, an aggregate measure such as mean processing time at a given MEPS for a particular workflow could suffice. The best we can do in this case is to make use of the MDCA for each workflow, that states each technician has a maximum capacity of five applicants per day.

3. *Number of servers and service channels* – Our data includes the number of technicians (servers) authorized at each MEPS for each workflow. It is important to note that the number of servers actually present at the MEPS during the given week can deviate from this number and in a manner that might last a few days or even months. For example, a MEPS might be authorized five Medical Technicians and they might have five Medical Technicians on the payroll. However, on any given day or week, one or more of those technicians might be executing annual leave or they might be out sick, etc. Alternatively, that MEPS might only have four technicians on the payroll and are trying to hire an additional technician. The hiring process may take weeks or months, in which case that MEPS' capacity is less than our data show.

4. *System queue space* – In this context, queue space is the amount of "room" at each MEPS to accommodate all the applicants who are awaiting service. While each MEPS certainly has a finite space, we neglect this aspect and assume the process by which applicants are scheduled to arrive at the MEPS does not typically result in applicants, say, being turned away due to insufficient waiting room in the lobby.

5. *Queue discipline* –Queue discipline is typically assumed to be First In First Out (FIFO) in queuing models, and our model follows this assumption as well. This does not exactly hold true in our setting, however, since for the most part inductees arrive in batches at the beginning of the day. But we do not use our queuing models to make precise estimates of inductee wait time, rather, we use the models to compare facilities in terms of the degree of congestion they are likely to experience. Since we make this assumption for all facilities, our rank-comparisons should be valid.

6. *Number of service stages* – We assume both workflows adhere to the process outlined in Figure 3.1. That is, we assume one stage in the service workflow.

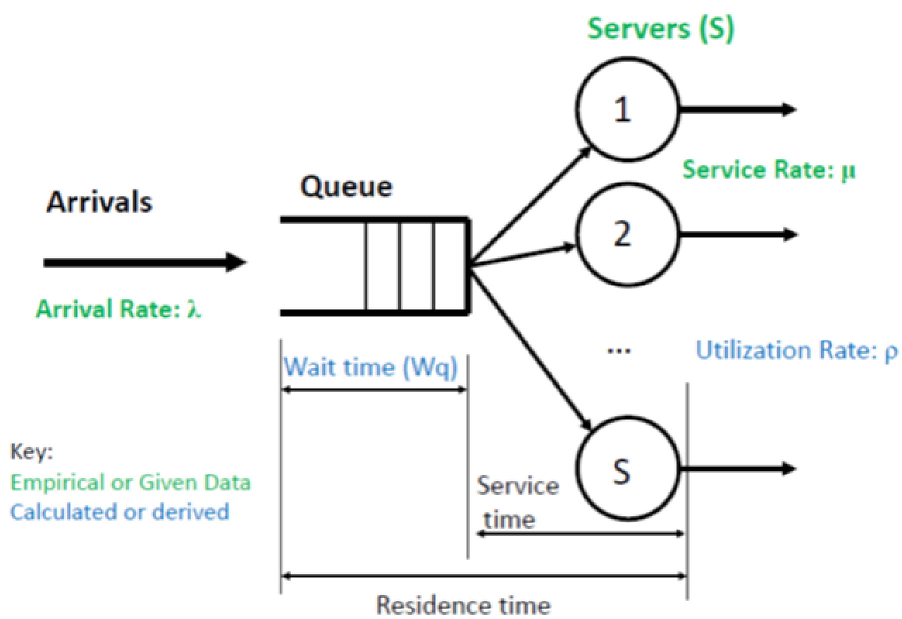


Figure 3.1. Elements of Queueing Theory

The parts of Figure 3.1 that are labeled in green are parameters we can estimate due to empirical data or assumptions we base on planning factors. The elements in blue indicate measures that we calculate or derive. Thus, we estimate a wait time (Wq) and a Utilization Rate (ρ) for each MEPS over a given duration of time.

3.2 Measures of congestion

Queueing theory allows us to calculate several useful measures of congestion. For textbook treatments of queueing theory, see Anupindi et al. (2011) and Hopp and Spearman (2008). See Andrews and Parsons (1989) for an example from industry.

3.2.1 Mean Utilization Rate

As we calculate it, the utilization rate is an estimate of the proportion of time that the workers (medical technicians for the medical exam workflow; HRA technicians for the contract processing workflow) are busy with their primary task. We leverage queueing theory to fill in the gaps of our understanding. For example, in order to calculate this measure, one needs an estimate of the number of arrivals over a particular period of time; we need to know the number of workers; and we need to know how many applicants each server processes. In our case, we have good empirical data on arrivals and numbers of workers, but we rely on the assumption that each worker is able to process an average of five applicants per day.

In general, mean utilization rate is given by:

$$\rho \equiv \frac{\lambda}{c\mu} \tag{3.1}$$

where λ is the average arrival rate, c is the number of servers, and μ is the average service rate (Shortle et al. 2018, p. 20).

We actually calculate the mean utilization rate for each MEPS for each year, so a more accurate description of this calculation is given by:

$$\bar{\rho}_t \equiv \frac{\bar{\lambda}_t}{\bar{c}_t \bar{\mu}_t} \tag{3.2}$$

where $\bar{\lambda}_t$ is the mean weekly arrival rate for year t for that MEPS, $\bar{c}_t$ is the mean number of servers available each week during year t for that MEPS, and $\bar{\mu}_t$ is the average service rate each week. Table 5 shows some details of the distributions of this measure.

	Mean Utilization MT			Mean Utilization HR		
	2018	**2019**	**2020**	**2018**	**2019**	**2020**
Top Third	0.519	0.505	0.464	0.664	0.681	0.640
Median	0.459	0.462	0.439	0.596	0.604	0.574
Mean	0.444	0.442	0.413	0.595	0.594	0.559
Bottom Third	0.354	0.415	0.365	0.529	0.501	0.509

Figure 3.2. Distribution of utilization rates

We see that in order to rank in the top third relative to other MEPS in terms of this metric for the MT workflow during these years, a MEPS's Mean Utilization must exceed a level of 0.464 to 0.519 depending on the year. It appears the mean utilization rates on the HR workflow tend to be substantially higher. For example, to qualify as top third in 2020, a MEPS's Mean Utilization rate must exceed 0.640, while even the upper limit for bottom third was 0.509.

It is important to acknowledge that given our gaps in the data, it is impossible for us to determine whether a MEPS is over-utilized or congested in an absolute sense. Ideally, we'd like to be able to say that any MEPS whose mean utilization exceeds a particular level is genuinely congested. However, the best we can do is identify those MEPS who are relatively more congested than others.

3.2.2 Expected Wait Time

We leverage queueing theory again to derive an estimate of the mean wait time experienced by applicants. Theoretically, this measure is a function of the utilization rate (above), as well as the number of workers, the variance of inter-arrival times, and the variance of service times. We have a firm empirical basis from which to estimate the variance of inter-arrival times, but we must use the planning factor of five applicants per worker in order to derive the variance of service times, since we lack any empirical data on that aspect.

In general, the expected time spent waiting in queue is given by:

$$W_q = \frac{\rho^{\sqrt{2(c+1)}}}{1-\rho} \cdot \frac{C_i^2 + C_p^2}{2} \cdot \frac{1}{\lambda} \tag{3.3}$$

where ρ is the utilization rate, c is the number of servers, C_i is the coefficient of variation of inter-arrivals, C_p is the coefficient of variation of service time, and λ is the average arrival rate. As with the utilization rate, when we calculate expected wait time for a given MEPS during a particular year, we estimate the parameters from that year.

The most important take-away from this criterion is that the actual estimate is probably not actionable since we lack actual data on service times. However, we are confident we can reliably compare this measure across MEPS. In other words, if the estimated wait time for a given MEPS for a particular year is higher than that for a different MEPS, then we may reliably infer that congestion in terms of wait time at the former MEPS is higher. See Figure 3.3 for the distributions of this criteria for each of the years.

	Expected Wait Time MT			Expected Wait Time HR		
	2018	2019	2020	2018	2019	2020
Top Third	0.3	0.2	0.2	1.5	1.2	1.3
Median	0.0	0.0	0.0	0.0	0.0	0.0
Mean	1.9	0.3	0.2	2.4	9.2	1.8
Bottom Third	-0.2	-0.2	-0.3	-2.1	-1.3	-0.7

Figure 3.3. Distribution of estimated wait times

We convert each MEPS's estimated wait time to an index number that is the distance from the median for that year. Thus, in order to qualify for the top third of this criterion for the HR workflow in 2020, a MEPS's estimated wait time must exceed the median by 1.3 minutes. For that same year and workflow, those MEPS with expected wait times of 0.7 minutes below the mean are considered to be in the bottom third.

3.2.3 Forecasted Peak Applicants per Worker

Recall that each record in our dataset is a MEPS-week. For each week, we easily calculate the observed number of applicants per worker for each workflow. For the present criterion, we develop a univariate time-series model that describes the weekly applicants per worker for a given workflow. We use all three years of data and select the best seasonal ARIMA model. We then use that model to create a forecast for 2021. Next, we find the maximum value of that forecast, we adjust the variance to account for daily instead of weekly arrivals, and craft a 95% prediction interval. Our Forecasted Peak Applicants per Worker criterion is the upper bound on the peak forecasted day for 2021. Figure 3.4 shows the distribution of this criteria for each year.

	Peak Arrivals per Worker MT	Peak Arrivals per Worker HR
	2021	**2021**
Top Third	5.2	7.3
Median	4.7	6.8
Mean	4.7	6.8
Bottom Third	4.2	5.9

Figure 3.4. Distribution of forecasted peak arrivals per worker

The MEPCOM planning factor is 5 applicants per worker each day. A good number of MEPS on the MT side have a peak that are still well below. For example, the median for that workflow is 4.7, however, those in the top third can expect to have days for which this measure exceeds 5. In contrast, this criterion suggests that a solid majority of MEPS can expect days in 2021 in which the number of applicants per worker will exceed 5.

3.3 Assumptions about both workflows check out

The data we were given have several limitations, and we are not able to capture better-fidelity data via direct observation at a MEPS, as one would typically do in a capacity analysis.

In the introduction, we discuss six characteristics of queueing systems. We assume three of these (queue space, queue discipline and number of service stages) are constant across MEPS. We have good data on the number of servers, but the number varies from week to week, so we choose to do our analysis on a per-server basis. For the other factors, we make key assumptions about: (1) the arrival pattern: average demand and standard deviation, and (2) the service pattern: average work rate and standard deviation.

We have average demand for the two primary flows for both server categories such as physical exams performed by med techs. But, the demand being tracked is not the entire workload, and we are unable to determine a satisfactory way to account for the fact that the servers have other things to do. Since capacity is stated as a number of, for example, physical exams that a server could perform in a day, we assume that the capacity numbers had been adjusted satisfactorily to leave sufficient time for that other work. In other words, we assume that other work never causes congestion. We have week-to-week variance in demand, but of course, congestion happens within a day and not between weeks. We translate the units from weeks to days (dividing the weekly variance into the number of days and taking the square root) but this of understates the day-to-day variance and further understates the hour-to-hour variance that can create problematic congestion within a day.

As is standard in queuing models, we assume servers process applicants at the rate given by capacity (e.g., 5 per day) when they work. But we have no data on how the workload varies between servers, so we assume it is divided equally. Also, we have to ignore the (intermittent) workload given to contract workers. These assumptions understate the variance in average workload per server. We have no data at all on within-server processing time variance. We make the standard assumption that the variability in processing time follows an exponential distribution. Unfortunately, this almost certainly overstates the amount of variability in that task, since the coefficient of variation (standard deviation divided by the mean) of the exponential distribution is 1.0, and the standard deviation in the time required for manual tasks is substantially less than the mean, for most well-organized tasks (Doerr and Arreola-Risa 2000).

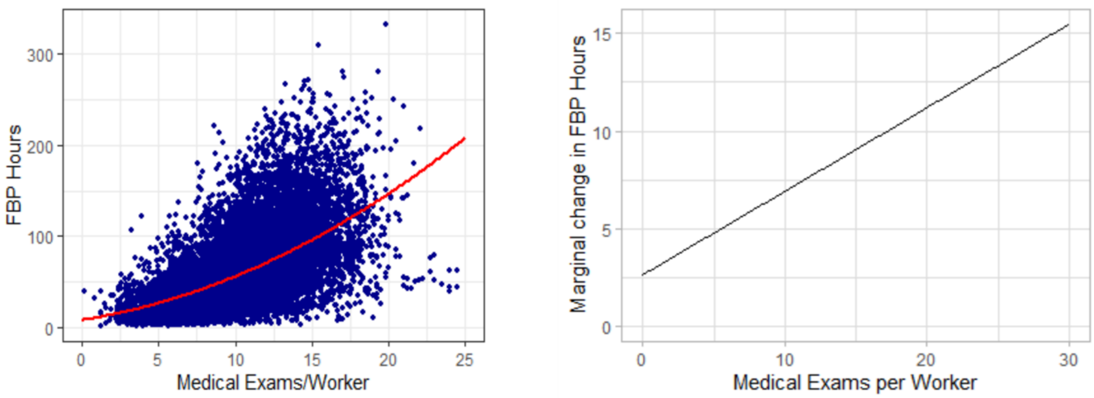
The only way we have to assess the validity of these assumptions is the graph in Figure 3.5, which shows how 'outside labor' is called out to help as the demand rate increases. The x-axis on that graph shows the data that forms the basis of our workload assumptions. If those data can be used to capture congestion, 'outside labor' should grow in a non-linear way as demand increases up to and beyond the capacity of regular staff. The non-linear pattern shown provides some limited support that the data we were given can be used to estimate congestion.

Finally, note that we make all assumptions across all MEPS. As the outcome of our analysis is a ranking of MEPS in terms of model predictions, the question is not really whether these assumptions are entirely accurate, but whether they are biased in some way that would reverse ranks between MEPS sites. We have no reason to suspect that sort of bias exists.

As we state above, to get a sense of the "outside labor" associated with the MT workflow, we examine FBP Hours. MEPS tend to contract FBP Hours when demand for Medical Technician services exceed capacity. We use the pooled dataset to fit a univariate regression model where y is FBP hours and x is the Medical Exams per Worker for week w at MEPS i. Equation 3.4 shows the formulation of this model.

$$\sqrt{\hat{y_{iw}}} = \hat{b}_0 + \hat{b}_1 \cdot x_{iw} \tag{3.4}$$

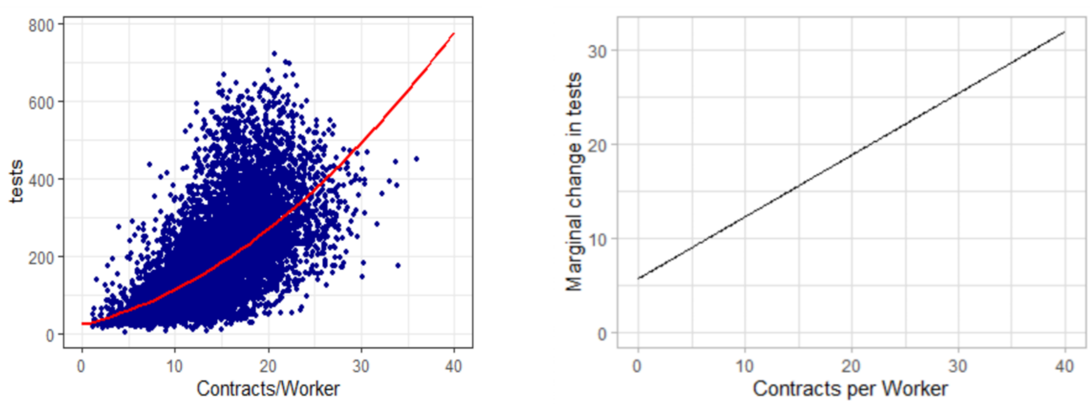
The model is well behaved in that the residuals appear normally distributed and exhibit constant variance. Panel (a) of Figure 3.5 is a scatterplot of FBP Hours and Medical Exams per Worker, with the regression line, while the Panel (b) shows the interpretation of the coefficient. In a typical linear regression without a transformation, the interpretation of the coefficient is constant. However, since our model transforms the dependent variable, the interpretation of the coefficient changes as we vary the value of the independent variable. For example, at approximately 5 medical exams per worker, adding another medical exam per worker results in an expected increase of approximately 5 FBP Hours. At 20 medical exams per worker, adding another medical exam per worker results in expected increase of approximately 11 FBP Hours. However, the most important conclusion to draw is to recognize the non-linear way in which FBP Hours increase as demand increases.



(a) Regression line (b) Interpretation of regression coefficient

Figure 3.5. Regression of Square Root of FBP Hours on Medical Exams per Worker

In similar fashion, the number of tests given is a measure of work that is outside the capacity of the HRAs. We employ the same form as Equation 3.4, but in this case y is the total number of tests for a given week and x is the number of contracts per worker that week at the particular MEPS. As above, we fit this model on the pooled dataset.



(a) Regression line (b) Interpretation of regression coefficient

Figure 3.6. Regression of Square Root of Tests on Contracts per Worker

Panel (a) of Figure 3.6 shows the scatterplot with the regression line and panel (b) shows the graphical interpretation of the coefficient. At a level of 10 contracts per worker, an additional contract per worker results in an expected increase of approximately 12 tests. At 30 contracts per worker, adding one contract per worker results in an expected increase of 25 tests. As above, the model is well behaved and has residuals that are normally distributed and exhibit constant variance. Again, the most important take-away is the non-linear relationship between the variables. Both Figures 3.5 and 3.6 provide support for our claim that our data may be used to estimate relative congestion at MEPSs.

3.4 Limitations

We must acknowledge two significant, and related, limitations to this work. First and most important, we can really only quantify "congestion" at a MEPS relative to other MEPS. In other words, our criteria allow us to identify which MEPS experience the most congestion, but we have no way of telling which, if any, MEPS experience too much congestion. We should point out that at this point, we really can't tell what the best mitigation would be. For example, in some MEPS – even those seemingly beset with consistent congestion, merely hiring more people might resolve the apparent congestion. Second, and relatedly, our first two criteria would be greatly improved if we had more information regarding the performance of workers, either individually or collectively.

Along those lines, we use the weekly MCDA at a particular MEPS to infer the number of technicians that service a given workflow. This MCDA is based on the number of technicians a MEPS is authorized to employ, rather than the actual number of technicians on-hand that week. We were unable to acquire daily or weekly on-hand data for technicans. So, another limitation of our analysis is that small MEPs in areas that are difficult to attract workers might be optimistically biased. That is, those MEPS might appear to be less congested than they really are. However, the good news is that to the extent that applies to a given MEPS, the solution to the problem is to solve the staffing problem.

Finally, in this chapter we outline three measures of congestion that we might use to compare performance at various MEPS. They each have strengths and weaknesses with respect to helping us identify which MEPS are most in need of increased capacity in some form. However, taking each into account in a manner that appropriately aggregates the information contained in each is a practical and philosophical challenge typical of all multi-criteria decision problems. In other words, our ability to compare these measures across MEPS is limited.

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CHAPTER 4:
Analysis

4.1 Congestion Analysis

We examine each workflow at each MEPS according to three utilization-related criteria for the Fiscal Year (FY) 2020. Namely, we calculate mean utilization rate, expected wait time, and peak arrivals per worker for both workflows. For each of the six criteria, we rank the MEPS and award a MEPS one point each time they appear in the top (worse) third of a given criteria. We repeat the analysis using 2018 and 2019 data as well. However, we only present the 2020 data in this report for three reasons: to help ensure clarity; it is the latest year and therefore should be weighted slightly more; and the other years can be found in the Excel workbook if the reader is interested.

We consider any MEPS with a score of 2 or 3 to exhibit a “high” level of congestion for that workflow. That is, we declare a MEPS that finds itself in the top third of all MEPS with respect to, say, MT Mean Utilization Rate and MT Expected Wait Time, to have high congestion in the MT workflow. A MEPS with “Moderate” congestion is in the top third of only one of the three criteria, while a MEPS with a score of 0 for a workflow exhibits an “Acceptable” level of congestion for that given workflow.

We first look at the MEPS scores for both workflows simultaneously. Our thinking is that a MEPS that experiences relatively higher congestion in both workflows is, all else equal, likely to be a better candidate for significant mitigation measures, like creating a satellite MEPS, than a MEPS that only experiences congestion in one workflow. Figure 4.1 is a list of those MEPS for 2020 we find high congestion in both workflows. For example, Harrisburg and San Jose MEPS are in the top third of every measure of congestion for both workflows (3,3).

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
2	BALTIMORE	3	2
5	NEW YORK	2	2
6	HARRISBURG	3	3
31	RALEIGH	2	3
32	FORT LEE	3	2
48	SAN ANTONIO	2	2
54	CHICAGO	2	2
57	COLUMBUS	3	2
72	SACRAMENTO	3	2
75	SAN JOSE	3	3

Figure 4.1. MEPS with high congestion in both workflows for 2020

Since there are three categories (Acceptable, Moderate, High) for each of two workflows, we assign each MEPS to a cell in a 3x3 matrix as shown in Figure 4.2. The ten MEPS in the lower right of this matrix are the same ten MEPS listed in Table 1. Notice there are 18 MEPS that experience acceptable congestion in both workflows (upper left).

Totals		MT Workflow		
		Acceptable	Moderate	High
HR Workflow	Acceptable	18	7	5
	Moderate	4	6	4
	High	4	7	10

Figure 4.2. Summary of workflow congestion for 2020

The MEPS that experience high congestion in just one workflow also warrant additional scrutiny. Figure 4.2 shows that a total of 19 MEPS exhibit high congestion in the MT workflow (right column) and 21 MEPS exhibit high congestion in the HR workflow (bottom row). Figure 4.3 shows the other nine MEPS with high congestion in the MT workflow. For example, both New Orleans and Minneapolis exhibit acceptable congestion in the HR workflow, but are in the top third of all three congestion measures with respect to the MT workflow.

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
13	SPRINGFIELD	2	1
21	BECKLEY	2	1
36	ALBUQUERQUE	2	1
74	LOS ANGELES	2	1
22	CHARLOTTE	2	0
46	NEW ORLEANS	3	0
47	OKLAHOMA CITY	2	0
62	MILWAUKEE	2	0
63	MINNEAPOLIS	3	0

Figure 4.3. Additional MEPS with high MT congestion

Figure 4.4 shows the other eleven MEPS that exhibit High congestion in the HR workflow. One note is the prevalence of MEPS from Florida and the southeast, namely Tampa, Atlanta, Jacksonville, and Miami.

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
17	TAMPA	1	3
20	ATLANTA	1	2
25	JACKSONVILLE	1	3
28	MONTGOMERY	1	3
39	DENVER	1	3
67	SAN DIEGO	1	3
76	PHOENIX	1	3
4	BUFFALO	0	2
23	MIAMI	0	3
41	HOUSTON	0	2
43	KANSAS CITY	0	2

Figure 4.4. Additional MEPS with high HR congestion

There are at least three clusters of MEPS that appear to exhibit relatively high degrees of congestion and warrant additional scrutiny.

1. California/7th Battalion –Sacramento and San Jose exhibit relatively high levels of congestion in both workflows. In addition, San Diego and Phoenix make the list for the HR workflow, while Los Angeles makes the list for the high congestion in the MT workflow.

Each of these MEPS, with the exception of Los Angeles, are similarly congested according to 2018 and 2019 data.

2. Florida/10th Battalion – Atlanta, Jacksonville, Miami, and Tampa all rank in the high congestion category for the HR workflow in 2020. We find that Atlanta, Jacksonville, and Tampa tend to exhibit relatively high levels of congestion in both workflows according previous years as well.

3. Mid-Atlantic/Southeast – Baltimore, Fort Lee, Harrisburg, and Raleigh exhibit relatively high levels of congestion in both workflows and Beckley makes the list for congestion in the MT workflow. However, of these five MEPS, only Fort Lee is reliably congested in both if we look to previous years, and only Raleigh is consistently high in the HR workflow. These MEPS span 4th and 12 Battalions, which presents unique opportunities and challenges in resourcing a solution.

Geographic regions with multiple congested MEPS present a particular sort of challenge in terms of mitigation efforts. In addition, single MEPS that regularly experience particularly high congestion should also be considered. For example, Minneapolis and Columbus are both consistently highly ranked in terms of congestion in the MT workflow, while Denver and Montgomery are consistently highly ranked in the HR workflow.

Finally, we present the 18 MEPS that exhibit "acceptable" congestion in Figure 4.5.

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
11	PITTSBURGH	0	0
12	PORTLAND (MAINE)	0	0
40	EL PASO	0	0
42	JACKSON	0	0
44	LITTLE ROCK	0	0
45	MEMPHIS	0	0
49	SHREVEPORT	0	0
50	LANSING	0	0
60	FARGO	0	0
61	INDIANAPOLIS	0	0
64	OMAHA	0	0
65	SIOUX FALLS	0	0
66	ST LOUIS	0	0
71	BUTTE	0	0
77	PORTLAND (OREGON	0	0
78	SALT LAKE CITY	0	0
80	SPOKANE	0	0
81	ANCHORAGE	0	0

Figure 4.5. MEPS with acceptable congestion

A course of action USMEPCOM may consider is to shift resources from these lesser used MEPS to others that are more congested, if possible.

4.2 Marginal Analysis

From a managerial perspective, it is not entirely clear what the next step should be for any MEPS we identify as "congested." Possible courses of action for any given MEPS include establishing a new facility in the area; adding space to existing facilities; hiring more technicians; or maintaining the status quo. In this section we gain insight into the extent to which the congestion we identify may be mitigated through hiring additional workers.

Essentially, we replicate the congestion analysis above, but for each MEPS we "add" a technician to each workflow and change the MCDA accordingly. We recalculate each of the measures (Mean Utilization Rate, Expected Wait Time, and Forecasted Peak Applicants per Worker) with the new MCDA for that MEPS. However, we compare these measures to the original, unchanged values for all of the other MEPS. This allows us to answer the question: Would we have still concluded a particular MEPS was congested if they would have had an additional technician on staff for that workflow for the period of observation?

MEPS	MT	HR
SACRAMENTO	Drops Out	Drops Out
SAN JOSE	Stays In	Stays In
LOS ANGELES	Stays In	
PHOENIX		Drops Out
SAN DIEGO		Stays In
ATLANTA		Drops Out
JACKSONVILLE		Stays In
MIAMI		Stays In
TAMPA		Stays in
BALTIMORE	Stays In	Drops Out
FORT LEE	Drops Out	Drops Out
HARRISBURG	Drops Out	Drops Out
RALEIGH	Drops Out	Stays In
BECKLEY	Drops Out	
COLUMBUS	Stays In	
MINNEAPOLIS	Drops Out	
DENVER		Stays In
MONTGOMERY		Stays In

Figure 4.6. Marginal Analysis

Table 4.6 shows the results of the marginal analysis. The 18 MEPS we identify in the previous section each have a row in the table. The MEPS are primarily grouped according to battalion or region. Recall that we identify a MEPS as congested if they are in the top third for at least two of the three measures of congestion for a given workflow. The table shows that, for example, if Sacramento had an additional medical technician on staff, they would have dropped out of our definition of congestion for that workflow. In fact, the same is true for Sacramento and the HR workflow, as well. However, even if San Jose had authorized an additional technician for each workflow they would have still met our definition of congested for both workflows.

There are two primary take-aways from this analysis. First, for those MEPS that maintain their classification as congested, this is additional evidence of the persistence and reliability of the existence of congestion at that MEPS. Resolving the congestion at these MEPS is likely to require more ambitious measures than simply hiring more technicians. Second, the fact that a MEPS's congestion problem appears to be mitigated by adding a technician does not, in and of itself, solve the problem at that MEPS. There could be organizational or capacity barriers that prevent that MEPS from hiring any more technicians. Which would mean that these MEPS would also require more substantial action to mitigate the congestion issues.

4.3 The impact of Riverside was minimal

In response to congestion that is concentrated at MEPSs in the same geographical area, MEPCOM may consider establishing a new MEPS to offer relief. Before concluding that the benefits of doing so would exceed the cost, it is important to be able to forecast the effects that opening another MEPS has on neighboring MEPS. In our dataset, MEPS Riverside was open and accepting applicants for the last 17 weeks of 2020. In this section, we assess the impact this had on the other MEPS in 7th Battalion.

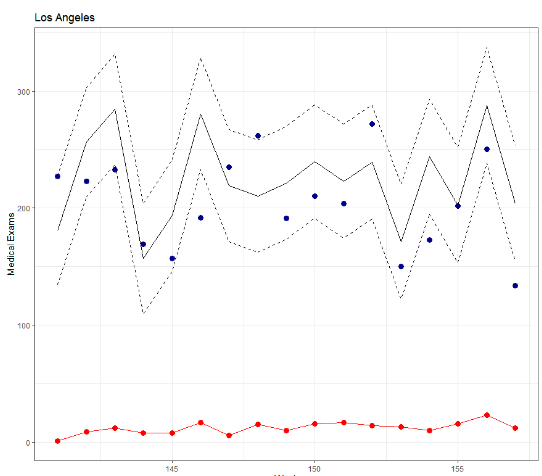
First, we might expect that the additional capacity that Riverside MEPS provides 7th Battalion would likely benefit those MEPS closest to it the most. Figure 4.7 gives the approximate distance of Riverside to the closest MEPS.[1]

[1]The MEPS facility in Las Vegas is approximately 240 miles from Riverside, but we exclude Las Vegas from this section due to insufficient data for that MEPS.

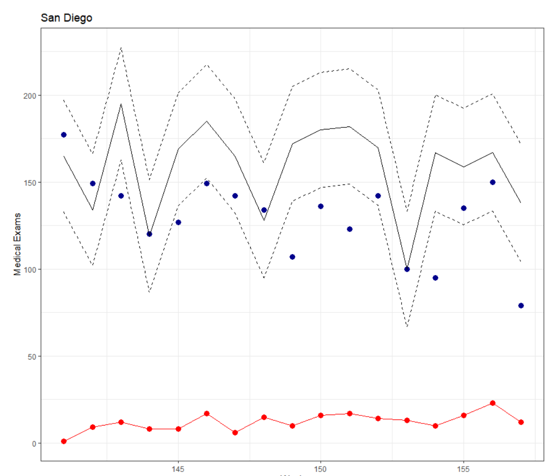
MEPS	Approximate Distance (miles)
Los Angeles	68
San Diego	90
Phoenix	320
San Jose	417
Sacramento	437

Figure 4.7. Approximate distances from Riverside

For each of these five MEPS, we use their first 140 observations of weekly medical exams to train an ARIMA model that forecasts the final 17 weeks of medical exams for 2020. The idea is that if the actual observations at a particular MEPS are systematically lower than the forecast, we might be able to attribute that reduction to Riverside. We replicate that process for the HR workflow as well. Figure 4.8 shows this comparison for the MEPS at Los Angeles and San Diego, the two MEPS that are closest to Riverside.[2]



(a) Forecast of MT activity at Los Angeles MEPS



(b) Forecast of MT activity at San Diego MEPS

Figure 4.8. MT activity at Riverside and closest MEPS

For each panel of Figure 4.8, the solid black line is the forecast of weekly medical examinations for that MEPS during the period in which Riverside is operational. The dotted lines depict an 80% Prediction Interval. The blue dots are the actual observations while the red line is the activity at Riverside.

[2]The corresponding graphs for the other MEPS under consideration can be found in the Appendix.

Perhaps the most important aspect to notice in Figure 4.8 is that Riverside's activity is tiny compared to these MEPS, and the other MEPS in the area. During this time, Riverside performed approximately 12 exams per week while the other MEPS each saw several hundred. It is worth mentioning, however, that both MEPS in the figure exhibit inordinately high numbers of observations that are below the forecast. In fact, this phenomenon occurs in MEPS not shown, as well. To the extent the actual observations are below even the lower bound, we might say that those observations are significantly lower from a practical perspective. That said, this widespread occurrence is unlikely due to Riverside since Riverside's activity level is such a small proportion of the overall activity of these MEPS.

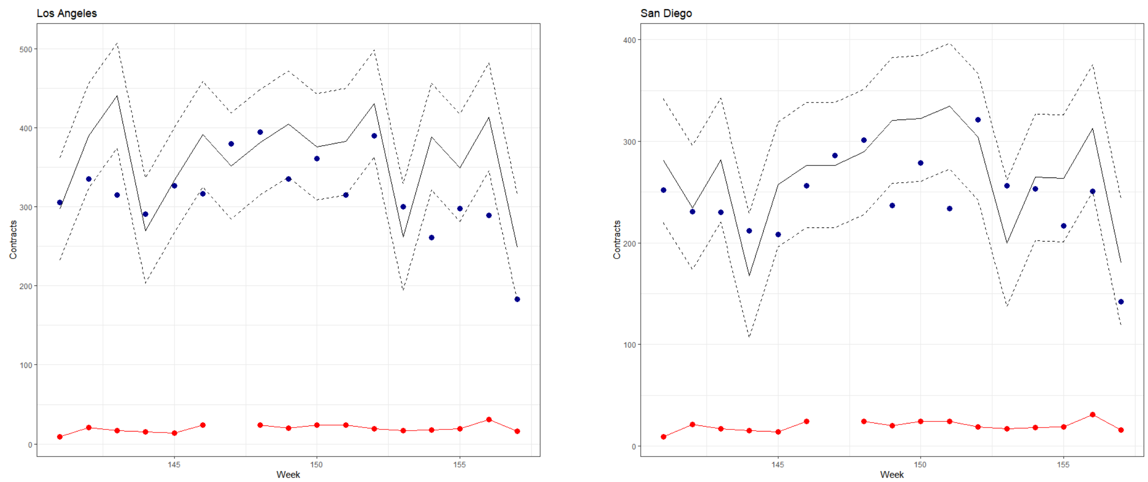
In order to better assess and operationalize the forecasts for each MEPS, we calculate Mean Utilization Rate (Ro) and Expected Wait Time (Wq) using the forecast, the actual data, and the lower bound of the prediction interval. The results are shown in Figure 4.9. Every MEPS experienced an actual value below the forecast value. For Phoenix, their actual measures are below the lower bound, so we can say that Phoenix experienced substantially lower demand than forecasted.

MT Workflow

	SAN DIEGO	SACRAMENTO	LOS ANGELES	SAN JOSE	PHOENIX
Forecast Ro	0.475	0.525	0.555	0.579	0.538
Actual Ro	0.384	0.478	0.501	0.575	0.435
Forecast Lower Bound	0.376	0.371	0.435	0.427	0.442
Forecast Wq	0.24	0.97	0.35	2.49	0.70
Actual Wq	0.08	0.62	0.18	2.41	0.24
Forecast Lower Bound	0.07	0.20	0.08	0.68	0.26

Figure 4.9. MT Summary of Riverside Impact

We replicate this process for the HR workflow. Figure 4.10 shows the forecasts of contracts for Los Angeles and San Diego for the relevant period. As above, the solid black line is the forecast and the dotted lines are the 80% Prediction Interval. The blue dots are the actual observations and the red line is the activity at Riverside. Again, Riverside accounts for only a tiny proportion of the activity of the other MEPS. Namely, during this time Riverside processed approximately 20 contracts per day.



(a) Forecast of HR activity at Los Angeles MEPS (b) Forecast of HR activity at San Diego MEPS

Figure 4.10. MT activity at Riverside and closest MEPS

We also notice that the actual observations for each of these MEPS are routinely below the forecasted values. For each MEPS, we calculate Mean Utilization Rate (Ro) and Expected Wait Time (Wq) using the forecast, the actual data, and the lower bound of the prediction interval and we show the results in Figure 4.11.

	HR Workflow				
	SAN DIEGO	SACRAMENTO	LOS ANGELES	SAN JOSE	PHOENIX
Forecast Ro	0.861	0.820	0.750	0.752	0.884
Actual Ro	0.783	0.762	0.657	0.762	0.726
Forecast Lower Bound	0.660	0.656	0.609	0.606	0.733
Forecast Wq	14.20	11.05	2.01	6.88	23.73
Actual Wq	6.04	6.24	0.71	7.48	4.66
Forecast Lower Bound	1.85	2.39	0.41	1.94	4.93

Figure 4.11. HR Summary of Riverside Impact

As with the MT workflow, all MEPS experience lower utlization rates and wait times than expected. Again, Phoenix exhibits substantially lower demand than expected, though there is insufficient evidence to attribute this to Riverside's existence.

In this section we examine the behavior of those MEPS closest to Riverside in order to get a sense of how opening a new facility affects neighboring MEPS. While all the MEPS in the area experienced lower than expected demand, there is very little practical or statistical evidence to attribute it to Riverside. However, this was only the first 17 weeks of Riverside's operations. As more data are collected, we will be better able to assess the extent to which opening the facility at Riverside helps to reduce congestion at neighboring MEPS.

CHAPTER 5: Discussion

We encourage the reader to consider four insights from the analysis we present. First, the data with respect to applicant demand in both workflows are highly variable. This variability is sufficiently large to be transmitted throughout the relative ranking process. Thus, MEPS that exhibit high relative congestion in one or both workflows one year may not exhibit high congestion in other years. However, as more data are collected over the years MEPCOM stands a better chance of boosting the signal to noise ratio.

Second, some of the relative congestion, especially among MEPS that generally process fewer applicants could be due to differences between authorized numbers of servers (i.e. medical technicians or human resource agents) and actual employed numbers of servers. In other words, some MEPS in our dataset may have been working short-handed with fewer employees than they are authorized. However, if we identify a MEPS as congested and it is known to MEPCOM as understaffed, then the problem at that MEPS is likely even worse than we estimate - because our analysis must assume each MEPS is fully staffed according to their MCDA.

Third, the marginal analysis further refines the list of congested MEPS and helps to identify those MEPS with the most robust levels of congestion. Such MEPS are likely better candidates for more ambitious means of increasing capacity either at those locations or in the same geographic region. In addition, it helps to identify those MEPS whose congestion could be mitigated by hiring additional technicians.

Finally, the data's inability to support an absolute determination of congestion at each MEPS is certainly a limitation of this analysis and it does complicate the managerial process of deciding where to devote additional resources. In short, it prevents a determination of whether the benefits of expanding capacity in some way, such as establishing a Remote Processing Unit, are worth the costs. However, if the decision has already been made to devote resources to expanding capacity where needed, then this relative analysis can still be helpful in directing resources to where they could be most useful.

We recommend that our analytical process be validated with newly available 2021 data. Doing so will give another indication as to the extent of the year-to-year variability in congestion and it will provide a benchmark for the forecasting process. Furthermore, we recommend that MEPCOM closely examine the battalions and MEPS we highlight as exhibiting high congestion. Given the data, each are likely good candidates to devote resources in an effort to reduce congestion and improve efficiency. MEPCOM should continue collecting this data and comparing MEPS across the criteria we outline above. The measures could be easily modified as changes to parameters such as MDCA evolve. Lastly, MEPCOM should strongly consider collecting data on service times or other measures of server performance, since doing so would fill the largest gap in MEPCOM's ability to analyze congestion at the MEPS.

APPENDIX: Previous Years

In this appendix, we provide congestion rankings for previous years.

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
17	TAMPA	2	3
20	ATLANTA	3	3
24	FORT JACKSON	2	2
25	JACKSONVILLE	2	3
32	FORT LEE	3	3
39	DENVER	2	3
47	OKLAHOMA CITY	2	2
30	SAN JUAN	2	1
36	ALBUQUERQUE	2	1
41	HOUSTON	3	1
43	KANSAS CITY	2	1
46	NEW ORLEANS	3	1
48	SAN ANTONIO	3	1
72	SACRAMENTO	3	1
76	PHOENIX	2	1
2	BALTIMORE	2	0
6	HARRISBURG	3	0
42	JACKSON	2	0
57	COLUMBUS	3	0
63	MINNEAPOLIS	3	0

Figure A.1. MEPS with high MT congestion, 2019

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
17	TAMPA	2	3
20	ATLANTA	3	3
24	FORT JACKSON	2	2
25	JACKSONVILLE	2	3
32	FORT LEE	3	3
39	DENVER	2	3
47	OKLAHOMA CITY	2	2
5	NEW YORK	1	2
28	MONTGOMERY	1	2
67	SAN DIEGO	1	3
75	SAN JOSE	1	2
78	SALT LAKE CITY	1	3
10	FORT DIX	0	3
13	SPRINGFIELD	0	3
27	LOUISVILLE	0	3
31	RALEIGH	0	3
49	SHREVEPORT	0	2
50	LANSING	0	2
73	HONOLULU	0	2

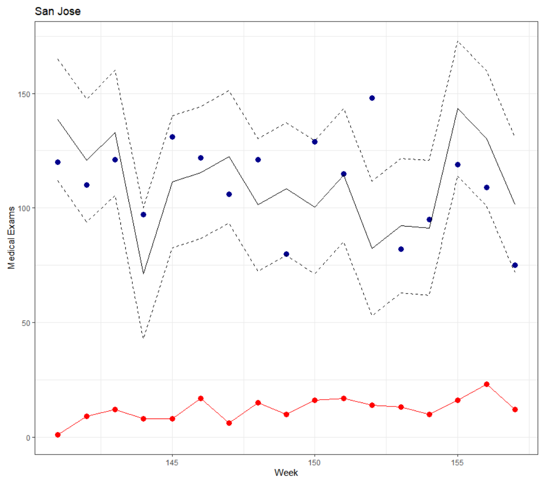
Figure A.2. MEPS with high HR congestion, 2019

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
5	NEW YORK	2	2
23	MIAMI	3	3
25	JACKSONVILLE	3	2
30	SAN JUAN	2	2
39	DENVER	2	3
41	HOUSTON	3	2
46	NEW ORLEANS	3	2
48	SAN ANTONIO	3	2
67	SAN DIEGO	3	3
75	SAN JOSE	2	3
76	PHOENIX	3	3
20	ATLANTA	2	1
32	FORT LEE	2	1
57	COLUMBUS	3	1
72	SACRAMENTO	2	1
24	FORT JACKSON	3	0
56	CLEVELAND	2	0
61	INDIANAPOLIS	2	0
63	MINNEAPOLIS	3	0
74	LOS ANGELES	2	0
77	PORTLAND (OR	2	0

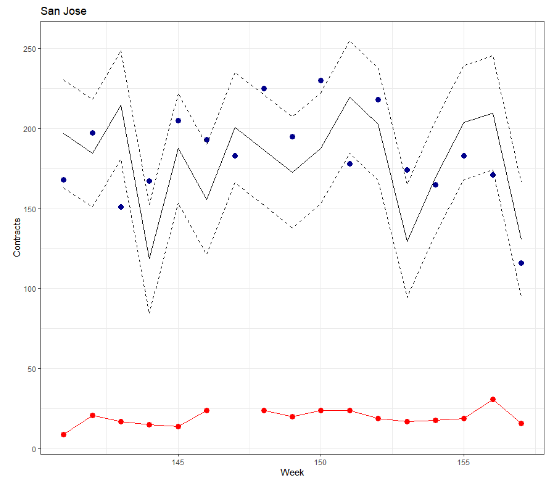
Figure A.3. MEPS with high MT congestion, 2018

MEPS_ID	MEPS_NAME	MT_Sum	HR_Sum
5	NEW YORK	2	2
23	MIAMI	3	3
25	JACKSONVILLE	3	2
30	SAN JUAN	2	2
39	DENVER	2	3
41	HOUSTON	3	2
46	NEW ORLEANS	3	2
48	SAN ANTONIO	3	2
67	SAN DIEGO	3	3
75	SAN JOSE	2	3
76	PHOENIX	3	3
4	BUFFALO	1	2
6	HARRISBURG	1	3
17	TAMPA	1	3
31	RALEIGH	1	2
78	SALT LAKE CITY	1	2
2	BALTIMORE	0	2
13	SPRINGFIELD	0	3
28	MONTGOMERY	0	3
66	ST LOUIS	0	2
79	SEATTLE	0	3

Figure A.4. MEPS with high HR congestion, 2018

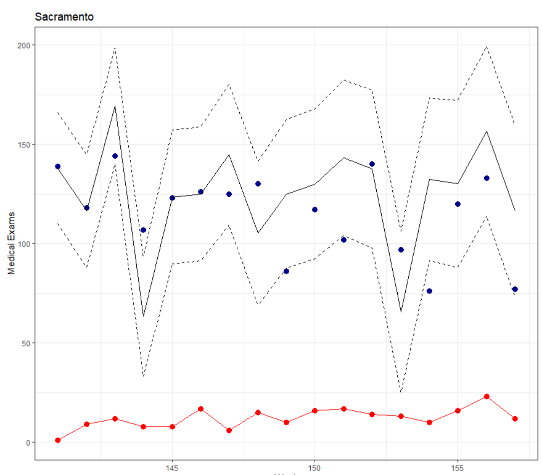


(a) Forecast of MT activity at San Jose MEPS

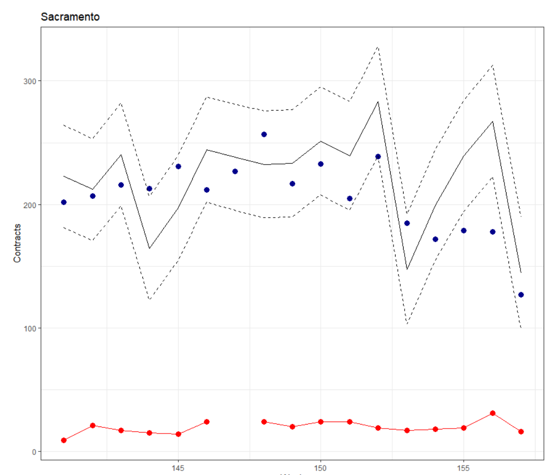


(b) Forecast of HR activity at San Jose MEPS

Figure A.5. Activity at San Jose MEPS while Riverside operational

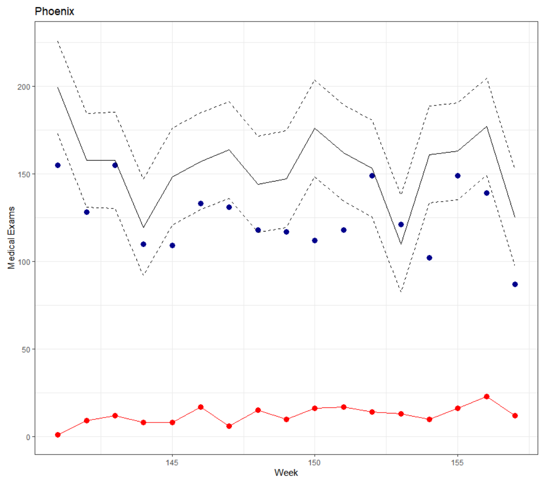


(a) Forecast of MT activity at Sacramento MEPS

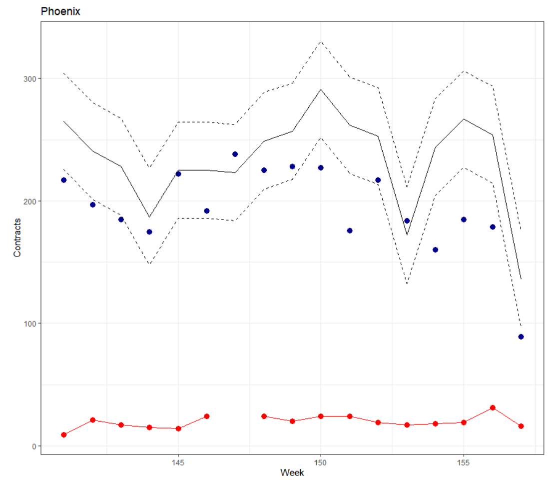


(b) Forecast of HR activity at Sacramento MEPS

Figure A.6. Activity at Sacramento MEPS while Riverside operational



(a) Forecast of MT activity at Phoenix MEPS



(b) Forecast of HR activity at Phoenix MEPS

Figure A.7. Activity at Phoenix MEPS while Riverside operational

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