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Reducing Military Personnel Flight Wait Times Using a Simulation

THESIS

Matthew D. Cornman, Capt, USAF AFIT-ENS-MS-21-M-148

# DEPARTMENT OF THE AIR FORCE AIR UNIVERSITY

# AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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# REDUCING MILITARY PERSONNEL FLIGHT WAIT TIMES USING A SIMULATION

## THESIS

Presented to the Faculty Department of Operational Sciences Graduate School of Engineering and Management Air Force Institute of Technology Air University Air Education and Training Command in Partial Fulfillment of the Requirements for the Degree of Master of Operations Research

> Matthew D. Cornman, BS Capt, USAF

> > March 26, 2021

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# REDUCING MILITARY PERSONNEL FLIGHT WAIT TIMES USING A SIMULATION

# THESIS

Matthew D. Cornman, BS Capt, USAF

Committee Membership:

Dr. Raymond R. Hill, PhD Chair

Dr. Lance E. Champagne, PhD Member

### Abstract

A shortage of resources and system failures strains Military Personnel Flights' (MPFs) ability to service their customers in a timely manner. Prolonged customer wait times are becoming a common problem in most MPFs creating friction between customers and leadership. This research uses historical data of an MPF to develop a simulation model of daily operations in an MPF. Subject matter expertise of current MPF operations and resource levels were used to provide a baseline model of the MPF queuing system. The analysis examines the effects of number of Defense Enrollment Eligibility Reporting System (DEERS) terminals, the number of personnel and their work efficiency rating on average customer wait times. The goal is to produce a simulation model that an MPF can utilize. The simulation model will provide insights to improve the current operations of the MPF to reduce customer wait times. The results recommend MPFs have 5 terminals with 6 or more personnel with an efficiency rate of 0.95 or less to significantly reduce the customer wait times and manage the resources' utilization rates.

# Acknowledgements

I would like to give all praise to God for giving me the wisdom and endurance to complete this rigorous degree plan. I would like to give my gratitude to my thesis advisor, Dr. Hill. With your continuing guidance and reinforcement of my abilities to do this, I was able to graduate. I would also like to thank Dr. Champagne for always being available when I needed the help! I am excited to utilize my new operational research abilities to help my career field.

Matthew D. Cornman

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# REDUCING MILITARY PERSONNEL FLIGHT WAIT TIMES USING A SIMULATION

## I. Introduction

#### 1.1 Motivation and Background

Military Personnel Flights (MPFs) are responsible for managing the personal information of all base personnel. The customer support section is responsible for servicing the majority of the customers by producing deliverables; i.e. Common Access Cards (CACs), dependent identification (ID) cards, or retiree ID cards. MPFs service multiple types of customers such as military personnel, dependents, retirees, and civilian government employees. Certain bases service larger populations than others.

The customer support section has airmen or civilian personnel servicing the customers in terminals. The systems used in the terminals are crucial in servicing customers. The terminals provide a multitude of services, but can not be used without personnel from the MPF. The Air Force has recently started moving some services online to allow customers more access to their personal information. This lessens the workload on customer support sections, allowing MPFs to manage operations with unreliable systems and low resources.

MPFs are criticized for poor management because of the long customer wait times, and MPF leadership is the first to try to fix the problem. MPFs take the major hit from the customers and leadership for the problems that are sometimes out of the MPF's control; i.e system failures. Most solutions take time to implement, and sometimes get shelved because leaders either move offices or move bases before the next leader can fill the position. MPFs need a tool that is easy to use, and can help produce recommendations for the MPF to implement.

#### 1.2 Problem Statement

Currently, MPFs are having a problem with prolonged customer wait times. MPFs see over 100 customers a day, on average, and are resourced minimally while working with unreliable systems. The purpose of this analysis is to determine which factors are most significant in reducing the customer wait times, and to use the simulation model to provide recommendations for improving MPF operations.

#### 1.3 Organization of the Thesis

The second chapter reviews queuing simulations and theories used in other organizations related to solving similar queuing problems. Chapter 3 lays out the day-to-day operations of an MPF, and the issues that create longer customer wait times. Chapter 4 describes the methodology used to provide the analysis and insights explained in Chapter 5. Chapter 6 summarizes the conclusions and expounds upon further recommendations to improve this research.

# II. Literature Review

The Military Personnel Flight (MPF) provides essential administrative services to military and civilian members. The MPF suffers from long customer wait times, something that is often examined in terms of queues of customers awaiting service. There is not a lot of research on the topic of MPF queues, but one can relate the problem to military operations in maintaining security, transporting supplies, or maintaining aircraft. The topic of queues and simulations are widely researched in many different disciplines, mainly in restaurants, healthcare production or manufacturing, even in cyber security networks. Any business that has wait times can utilize a queue in their business model and can benefit from researching queuing theory and simulations. The biggest challenge is the "[w]idespread public demand for improved access, political pressure for shorter wait times, a stretched workforce, an aging population and over-utilized equipment and facilities" (Patrick and Puterman, 2008). This literature review examines different methods of modeling a queuing system using queuing theory and simulations.

#### 2.1 Queuing Theory and Simulation

Queuing theory is used in many applications, such as transportation and production lines. The most common type, M/M/1 Queuing system, represents a single line with a single server and is not only quite applicable, but also easy to understand. There is a plethora of problems that can be improved by using queuing theory to understand the problem. Businesses utilize this method to analyze their processes to optimize their profits, or reduce wait times for their customers. Queuing theory is the study of queues and associated waiting times (Dharmawirya and Adi, 2011). "The key elements of a queuing system are the customers and servers" (Banks et al., 2014). Businesses use queuing theory to interpret their servers' capability and capacity to reduce wait times for their customers while keeping their utilization rates within reasonable ranges. A major problem is "in a queuing system, minimizing the time that customers have to wait and maximizing the utilization of the servers or resources are conflicting goals" (Fomundam and Herrmann, 2007). Businesses have to determine the balance between increasing customer satisfaction or not overworking their resources or employees.

The reason there is a need for queuing theory is because "[a] queue forms whenever demand exceeds the existing capacity to serve" (Mei and Cheng, 2015). In order to understand queuing theory, this review breaks down the components of a queue. "In a simple queuing model, the three components involved are the arrival process, service process and the queue structure" (Nilsen, 1998).

In the arrival process, customers enter the queue according to inter-arrival times that follow some distribution such as "a Poisson distribution, a Deterministic distribution, or a General distribution. However, inter-arrival times are most often assumed to be independent and memoryless" (Dharmawirya and Adi, 2011), and follow an exponential distribution. These arrival patterns can be either stationary (same rate) or non-stationary (changing rate). Most real world applications involve queues with people arriving in a non-stationary manner. Customers can arrive individually, in groups, or a combination of the two. Similarly, queuing models can have singular arrivals or batch arrivals.

One aspect that businesses having queues of customers must be aware of is the reaction of the customer(s) when entering the queue. "If a customer decides not to enter the queue upon arrival, the customer is said to have balked. A customer may enter the queue, but after a time lose patience and decide to leave. In this case, the customer is said to have reneged" (Gross et al., 2008). This is important because

businesses want to keep their customers rather than watch them leave because the lines are too long and thus lose the sale. This is where wait times and queue length matter.

Once the customer finishes waiting in line, they enter the service process. The service process uses two pieces of information: the number of servers available for the customers to use, and the service time distribution. Service processing times may differ from server to server or may be the same for each server depending on the queue being observed. A service pattern could be state-dependent, where the service depends on the number of customers waiting, or non-state-dependent (Gross et al., 2008). Queues that involve people are usually non-state-dependent, because services usually keep going no matter how many are in the queue. If there are longer queues, then the business may look into hiring more employees or buying kiosks for automated services, but this will increase costs. This is why reducing wait times and increasing the resource utilization are conflicting goals.

One pitfall to watch out for is over-utilizing resources. Dwyer (2016) stated a similar conclusion when analyzing an entry control point servicing people through the base gates, "the [Entry Control Point] cannot sustain a constant utilization greater than 1." Overall, the wait times cannot be minimized to a point where the employees never get a break or do not get to go home at the end of their shift.

The final component is the queue discipline. How are the servers choosing the customers that are served next? The analysts need to decide whether the customers can renege or balk from the queue, and there needs to be capacities in the system. To model real life situations, a system cannot support infinite customers. To make a model more adequate to fitting the real life situation, the analysts and the business owners scope these details to produce a best model with which to compute results yielding the best recommendations to help minimize wait times or increase their server

utilization rates.

Creating a simulation is often the best route to take when the goal is to find or fix problems with your queuing model. Banks (1998) states three steps to create a simulation.

- 1. Identify the specific industry needs.
- 2. Obtain data on the current processes.
- 3. Build a simulation model that is capable of examining the effects of changing various parameters on the transaction process.

To best analyze the queuing model, first build a baseline model. This model represents the current setup of the queuing system. After analyzing the results from the baseline, analysts hypothesize recommendations to change and improve the system. Next, using experimental models based on those recommendations, the analysts can compare the baseline to the experimental models. This comparison helps to determine whether to implement that change into the system or not.

A benefit of simulation is that "[simulations] of queuing systems produce precise results from measured and summarized data. These results have no variability from run to run but represent expected, average performance" (Brigandi et al., 1994). Once the simulation is built and validated as replicating the system being observed, the simulation can provide estimated wait times, utilization rates, and server idle times as a function of various system settings or configurations. This is why simulations are often the best method to use when modeling queuing systems.

#### 2.2 Applications

#### 2.2.1 Call Centers

An example of a business that uses queuing theory and simulations is a call center. "The whole point of the call-centre is to get the customer served and offline as quickly as possible" (Moran, 2004). There is a consequence for not having efficient call centers. Brigandi et al. (1994) states "Businesses establish call centers to talk to their callers; anything that impedes that process undermines the overall success and profitability of the center and erodes callers' perceptions of the business." Call centers employ queuing theory to help design and improve the efficiency of their processes to meet customers' needs as satisfying customers keep the companies competitive. To be efficient, the major goal for call centers is to reduce the wait times of the callers in the phone queue, and target the priority customers to increase company profit.

Call center analysts examine data on workers' idle time, and the number of customers that hang up after waiting too long. If there are too many customers reneging, or the idle times are too great, then the solution is to either hire more workers or replace inefficient employees with more efficient workers. There are many reasons why a call was lost though, such as, "improper personnel scheduling, insufficient personnel to answer calls, insufficient network service lines or trunks, improper or insufficient arrangement of center terminal equipment (gate arrangements), operational problems such as poor training, poor handling of various types of calls and slow data system retrieval time, limitations in space or equipment, and lack of motivation on the part of the business to handle all calls" (Brigandi et al., 1994). Using simulations as an analytic tool can help prevent these type of errors within a call center. The businesses can find the root cause of the problem, and make the best decision to fix that root problem.

AT&T used a Call Processing Simulator (CAPS) to help multiple business ac-

counts with their call centers, and "AT&T has increased, protected, and regained more than \$1 billion from a business customer base of about 2,000 accounts per year." (Brigandi et al., 1994) Using queuing theory and simulations can be very beneficial and may take a lot of work to validate and verify the model, but in the end, the rewards are great.

#### 2.2.2 Security Checkpoints

Security checkpoints are used in quite a few places, most commonly in airports and on military bases. Many of us have experienced the long queues within airports, waiting for everyone to be searched and walk through the metal detector. Airline security waits can be stressful to many, especially when experienced close to flight times. Airports have been trying to cut the security wait time by increasing the number of machines serving the queue and other methods. One method that stood out is virtual queuing.

Narens (2004) used a simulation to model airport security checkpoint queues. Two models were created. First, a baseline model of the current security checkpoint queue was created with predetermined customer arrival time distributions. Second, another model was created with an experimental virtual queuing option for the customer, where the customer is given a particular time to arrive for their check in. The results showed that virtual queuing customers were waiting less in a physical queue when they arrived at their specific time frame, and there were less overall waiting times for the security checkpoint, waiting at the gate, and waiting after boarding. The only time virtual queues did not work was when customers chose their own time. "Doing this allows a customer to conduct other activities that decreases the perceived wait time for a service" (Dwyer, 2016). Virtual queuing can reduce the stress of customers, and provide more confidence in their knowing they will make their flight. Queue efficiency is on the customer and not the employees working the queue.

#### 2.2.3 Healthcare

Another field using simulations to optimize their customer satisfaction is healthcare. Looking at healthcare clinics with multi-phase and multi-server queuing systems, Lin et al. (2017) used resource allocation and setting block appointments for different types of patients to help reduce wait times. The results showed that utilizing both methods was beneficial in increasing resource allocation for patients, and setting block appointments helped get through customers quicker. Overall, healthcare has many queuing systems to monitor and improve for their patients. Waiting too long could mean life or death for a patient. Servicing patients is a hard and stressful task, and it gets worse when a patient dies, and the family members blame the hospital staff. Using queuing theory and simulations is very beneficial for healthcare professionals to keep their patients alive and well by employing efficient and effective processing systems.

#### 2.3 Conclusion

This literature review summarized a sample of previous research employing queuing theory and simulations to help improve their queuing system. Whether it be minimizing the wait times for their customers or bulking up their servers to manage utilization rates, simulations can be a helpful in determining which policy option is best. The remainder of this thesis builds on previous research to develop a generalized model of MPF customer service systems, one that any base may use to support recommendations to reduce their customer wait times.

## **III.** Military Personnel Flight Operations

The MPF services many customers, including military, retirees, contractors, and civilians. It is a one-stop shop for personnel administrative needs. Most importantly is a customer obtaining a Common Access Card (CAC). Services for CACs bring the most foot traffic to MPF customer service. Other services include updating Military Personnel Data System (MilPDS), fixing SGLI issues, and updating Defense Enrollment Eligibility Reporting System (DEERS) for the member. This chapter describes the most common operations of the MPF, and the problems encountered, to provide insight into why customers experience long wait times during a visit to any MPF.

### 3.1 CACs

CACs are the primary reason for customers going to the MPF. CACs have many uses; an employee often cannot do their job without it. CACs primary purpose is for authentication. CACs are needed to get the member on base, and even into buildings or offices they work in. CACs are used to login into workstations and other devices in the office, like printers. Since authentication is the primary use, each member must create a PIN which is connected to their CAC to safeguard their information on the CAC. Due to the many CAC uses, there are also many issues that arise with the card. These issues include the computer chip on the CAC no longer working, the card being expired, the card was lost, a PIN needs a reset, or the member's information has changed, like rank or name. With thousands of employees working on a base, all using CACs, and only one place to go with one system to fix any issues, the MPF will experience long queues. DEERS is the only system used to fix CAC issues. This causes bottlenecks in customer service in the MPF. Furthermore, DEERS has reliability issues further complicating service.

#### 3.2 DEERS

The main system the MPF uses is DEERS. DEERS is used to access a person's information, issue some form of ID, update the customer's information or their dependents' information and their TRICARE benefits. Only MPF personnel have access to DEERS, and it is used to serve customers on a daily basis. The most common problem the MPF runs into is DEERS going down. When DEERS is down, nothing can be issued to the customer, nor information altered in the system. Customers are left waiting, and frequently with no estimated time for DEERS to be up again. This problem causes customers to renege. It is not only frustrating to the customers, but also to the MPF employees as well. When DEERS goes down, work almost comes to a standstill. Customers usually blame the MPF employees for the outage when the problem stems from above base level computer support. These situations are usually handled by sending out mass updates to the whole base. The hard part is getting the word out to the off-base civilian customers. This is where most of the customers balk when arriving and seeing the post on the door.

Another major issue the MPF encounters are the problems of maintaining the old hardware that DEERS operates on. The equipment is out of date and requires a lot of care. There is a monthly cleaning schedule to maintain the systems and devices for the DEERS terminal. Any issue with the hardware closes the terminal until the office fixes the problem. Closing a terminal can result in longer wait times for the customers. Not only are the personnel responsible for maintaining the hardware, but also they are responsible for keeping track of all consumables within each terminal to make sure they do not run out when serving customers. An MPF does not want to keep customers waiting, only to tell them they cannot receive their ID at that time because the office ran out of the consumable to make it. Ordering consumables for the terminals can also be a problem since there is commonly a long wait for a new shipment to arrive after it is ordered. The MPF must be proactive in maintaining the equipment in all the terminals, as well as keeping them stocked for making the different IDs. Even though DEERS is a huge part of the operations, there is backoffice work such as updating MilPDS, completing monthly deliverables, and other miscellaneous tasks that need to be completed. This is an area where manning issues could affect maintaining effective operations to avoid longer wait times.

#### 3.3 Limited Personnel

MPFs have a limited number of stations to serve customers requiring DEERS access. The stations are only used for DEERS and are not compatible with other Air Force systems. This creates a problem when needing to place information in other systems to keep customer's information current. For this reason, there is added work in the back-office area. Personnel in the back-office keep track of all the updates to DEERS and manually update MilPDS. Since there are other tasks to complete, the number of personnel in the office is split between helping customers and working tasks in the back-office. When the office has more personnel, they can utilize more terminals, have others do the back-office work, and allow personnel to have breaks.

The average number of personnel in the customer support office is around five. This means that most of the time, all terminals are not utilized. There are days where the customer arrivals are constant, and others where it drops off. Different MPFs have different policies in place to control customer arrival times. These policies can help or hurt the customer wait times.

#### 3.4 Customer Arrivals

There are two primary policies utilized by the MPF, and another being a mixture of the two. The first policy allows customers to schedule an appointment online or by calling the front desk. The second policy allows walk-ins during hours of operations. The third option uses both policies. There are pros and cons for both individual policies, but experience indicates that the worst thing to do is utilize both.

Using appointments only limit the customers served during each day. The average time frame for each appointment is 30 minutes. The only walk-ins allowed are those who have questions, base leadership, people who need PIN resets, and identification emergency situations. This policy is usually favored by the personnel working the terminals. Maintaining a regular schedule for breaks, lunch, and switching personnel from front office to back-office work is easier to manage and work with. This policy limits wait times for customers, increases work efficiency, but turns away most of the walk-in customers, thereby decreasing overall customer satisfaction.

Having only walk-ins increases the customer arrivals and increases wait times. This policy allows the MPF to serve more customers per day, compared to only appointments, but customers are more likely to experience longer wait times. Most days see up to 20 people waiting before the doors even open to the MPF. This keeps customer satisfaction higher since the customers do not balk or renege due to the time, they will be served. An advantage of this policy is there is a first come, first served order to serving each customer. No one cuts the line.

The customer service section can utilize both scheduling and walk-in methods, which increases the number of customers coming in, while increasing the wait times as appointments take priority. The challenge for the customer service section is that most of the day becomes "peak time". Almost the entire day, the waiting room is full. High customer satisfaction is hard to maintain when you serve a newly arriving customer in front of a full room because they have an appointment. It is demoralizing, and customers tend to feel like it is unfair since that will most likely add another 30 minutes to their wait time. Using both policies allows the MPF to serve the most customers, but personnel breaks are sacrificed to get through all the customers as quickly as possible. Even when using all the terminals, the employees often end up working past closing time to finish all customers and have to come in early to finish the back-office work that was not completed the day before. This dual policy option often hurts office morale and customer satisfaction.

#### 3.5 Conclusion

The MPF's goal is to serve customers as quickly and efficiently as possible. The various problems described increase customer wait times. Other important issues are the office morale and completing all other back-office work. Using just appointments will increase office morale, work efficiency, and decrease the number of customers seen in a day. Using just walk-ins increases number of customers and increases customer satisfaction. Using both, in most cases, hurts customer satisfaction, increases number of customers, and hurts office morale. This research focuses on finding the best solutions to these problems.

# IV. Methodology

#### 4.1 Overview

This chapter details the simulation built to represent a standard MPF office's workflow of customers. The software used to build the simulation was Simio. The chapter describes how the simulation was built to best represent a real MPF. Then the assumptions underlying the simulation and data used are discussed. The chapter closes discussing model validation and verification, and the experimental scenarios used to produce recommendations for MPFs to best reduce customer wait times.

#### 4.2 Simulation Model Overview

The simulation model represents the day-to-day operations of the MPF customer service section. The simulation models a workday from 0700 to the time all customers are served. The simulation stops when all customers who entered the queue are serviced. To account for customers arriving before the MPF opens, arrivals start at 0700. Customers are not serviced until 0800 and stop arriving after 1600. This represents the MPF closing their doors before close-of-business to make sure the personnel do not stay too late servicing the rest of the customers. It is common to work past 1800 due to the high volume of customers.

Airmen and civilian employees work in MPFs. There are a limited number of DEERS terminals to serve customers. Each airman/civilian employee and each of the DEERS terminals are represented as resources. Employees stagger their lunch breaks. Half will go at 1100, while the other half will go at 1200. There are two resources with work schedules to represent the employees with different lunch hours. The third resource represents the DEERS terminals.

The model follows a streamlined approach. Customers enter the office, sign into

a kiosk or front desk, wait for service, seize the resources they need to complete their task, release the resources upon completion, and then exit the system. Figure 1 depicts the model flow.

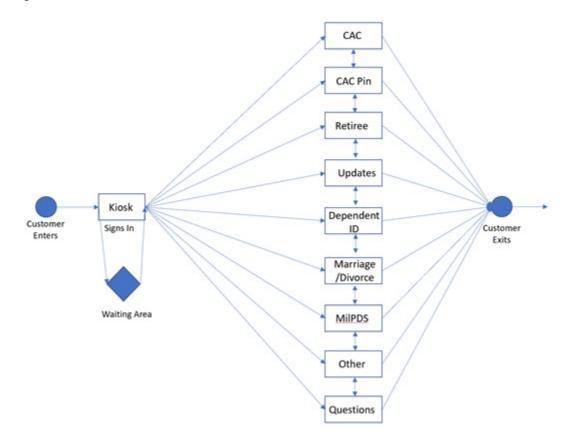


Figure 1. MPF Simulation Flow Model

The model simulates ten different tasks. The first server is the Kiosk or front desk to sign in customers. A decision is made for the customer at this point, where the customer is either serviced immediately or told to wait for service. Customers will wait until an employee resource is available, whereupon service starts. The other nine servers represent the different tasks the MPF provides a customer. Certain tasks need a DEERS terminal and an employee to complete, while other tasks just need an employee. The tasks needing a DEERS terminal are: creating a CAC, resetting a CAC pin, issuing a dependent ID, issuing a retiree ID, updating a marriage or divorce, and updating anything else other than marriage and divorce. The tasks that just need an employee are: updating MilPDS, asking questions, or any other inquiry not related to DEERS.

All the tasks are represented in the simulation by servers with their own processing time. The kiosk server characterizes customers signing in at the front desk, and only takes a minute, and does not require an employee. To determine the processing times of the tasks that require resources, a triangular distribution was utilized for each server defining the minimum, the median, and the maximum time. Processing times used are in Table 1. The data includes extreme service times, well beyond the average processing time. These extremes are often caused by system failures. An MPF can encounter system failures at any time during the day. System failures put a strain on the average wait times because it stops all work and allows no service for any customer needing a terminal. The current simulation represents an MPF operation with no system failures. To account for no system failures in the simulation, the maximum processing times were reduced to more reasonable amounts which is described in Table 1, the Reduced Processing Time.

| Task             | $\begin{array}{c} {\rm Processing \ Time} \\ {\rm (min)} \end{array}$ | Reduced<br>Processing Time<br>(min) |
|------------------|---|-------------------------------------|
| CAC              | Tri(10, 24, 120)  | Tri(10, 24, 45)                     |
| CAC PIN          | Tri(3, 11, 60)  | Tri(3, 11, 30)                      |
| Retiree          | Tri(2, 15, 120)   | Tri(2, 15, 45)                      |
| Updates          | Tri(1, 12, 107)   | Tri(1, 12, 50)                      |
| Dependent ID     | Tri(8, 18, 90)  | Tri(8, 18, 45)                      |
| Marriage/Divorce | Tri(10, 19, 120)  | Tri(10, 19, 45)                     |
| MilPDS           | Tri(1, 12, 98)  | Tri(1, 12, 30)                      |
| Other            | Tri(0, 10, 92)  | Tri(0, 10, 30)                      |
| Questions        | Tri(5, 24, 133)   | Tri(5, 24, 30)                      |

Table 1. Processing Time Distributions

To make the model more realistic, the servers must finish any task they start. This means employees postpone breaks to complete a customer service. A key aspect considered was the efficiency rate at which the employees complete a task. For the simulation, efficiency is represented as a multiplier to processing times. An interactive data sheet was created to calculate this efficiency parameter. Employees work more efficiently when they are not encumbered with a lot of customers and the MPF is staffed properly. Also, employees work better when they are comfortable in their work environment. These factors are hard to quantify, but are of interest to leadership. Efficiency values were chosen by changing the values until realistic results were produced. This allows an MPF to represent their office's circumstances that could affect the efficiency rate of their employees. When this efficiency variable is above one, the processing time is increased indicating reduced efficiency, and when the variable is below one, the processing time is decreased to indicate increased efficiency.

The customers are represented in the simulation as entities. A list of customer types was created with different sequences of tasks assigned to the customers. Sequence tables were used to model the sequence by giving each customer a certain path to follow. A total of 13 customers types were created to represent the different tasks of interest in this study. The customers separate by sequence to those needing terminals and employees, and those who just need an employee. To simulate a customer requiring multiple tasks, 4 customer types were defined with multiple tasks in their sequence, and the other customer types only have one task. Using the data collected, proportions of each customer type were determined. The most common task for a customer is for CACs at 40%. The next two common tasks were issuing dependent IDs and resetting CAC pins at 24% and 19%, respectively. The other tasks were around 1-7%. The simulation entities seize employees as each customer's required resource, and if required, a terminal. The full details of all customer types and the percentage of each type are in Table 2.

| Customer<br>Type | ${\rm Task}({ m s})$              | $\begin{array}{c} \mathbf{Percentage} \\ (\%) \end{array}$ |
|------------------|-----------------------------------|--|
| 1                | CAC/Marriage/Divorce/Dependent ID | 0.5  |
| 2                | Questions/MilPDS                  | 0.5  |
| 3                | CAC PIN                           | 18   |
| 4                | CAC PIN/Questions                 | 0.5  |
| 5                | Updates/Retiree                   | 0.5  |
| 6                | $\operatorname{CAC}$              | 40   |
| 7                | Retiree                           | 4  |
| 8                | Updates                           | 7  |
| 9                | Dependent ID                      | 24   |
| 10               | MilPDS                            | 1  |
| 11               | Marriage/Divorce                  | 2  |
| 12               | Questions                         | 1  |
| 13               | Other                             | 1  |

Table 2. Customer Types and Percentages

A basic approach was used to capture the arrival rate of the MPF. The data collected 25,800 customers' details over 254 days. Each customer was put into a bin of the hour they entered the MPF. Each bin was divided by 254 to find the number of customers per hour in one day. The average of all the bins in a single day is 11. For this queuing simulation, a Poisson distribution is assumed, which makes the interarrival times exponential with an average of 1/11 per hour.

The metric recorded is the waiting time of each customer entity. Once an entity enters the queue to the MPF, an entity state value is assigned the exact time in the simulation. Once that entity exits the kiosk, a tally is collected recording the time it leaves the kiosk minus the original time the entity entered the kiosk queue. The average wait times are recorded for subsequent analysis and compared to the different experimental scenarios that are considered in this study.

#### 4.3 Assumptions

The current simulation cannot account for all situations in an MPF. Assumptions help scope the simulation development and best fit the real-life operations of an MPF. First, all employees are trained to complete all the same tasks. In practice, employees have varied skill levels; the current simulation model does not differentiate employees by skill level. Thus, all entities experience the same processing types regardless of employee skill or experience.

In the operational world, MPFs can be busy to the point where there is almost no time to allow for breaks. Usually, for busy days, the breaks are spread out throughout the time after lunch. For simulation purposes, the employees stick to their schedule of a 1100 or 1200 lunch break, if they are not already helping a customer.

Balking is a common trait in queue simulations and empirical evidence suggests balking occurs at an MPF. However, there was no recorded data on the length of times a customer was willing to wait in the queue before reneging. The assumption made was that customers balk 7% of the time. Allowing balking helps the simulation run a more realistic number of customers and represents the customers who are not willing to wait in the long queue.

The simulation does not account for the type of day of the week. Each day of the week has a different number of customers, and different peak times. For example, Mondays are often the busiest day of the week for MPFs. This simulation models a generic day, but accommodates an experimental scenario testing different arrival distributions to see what changes need to be made on those certain days of the week.

The final assumption is perfect reliability of the systems used to service the customers. MPFs often deal with system failures. This could mean one or more terminals are down, reducing service accordingly. This would inevitably affect average wait times, and the resources' utilization rates. This also applies to the tasks that do not need a terminal, such as a MilPDS update. The current study focuses on average wait times during days where systems are working.

#### 4.4 Data

The data were collected from the MPF at Langley-Eustis AFB over a one-year period, from April 2018 to April 2019. The data consisted of a list of each customer that signed in for service, listing their task, waiting time, and processing time. The data provided the average processing rates of each task, and the probabilities of the different type of customers. Previous work was able to build a valid simulation using the MPF data. The data were well modeled by a Poisson distribution for the number of customer arrivals using an exponential distribution to model the interarrival time. The previous work used deterministic processing times to replicate the operations of the Langley-Eustis MPF. The model was verified and validated by the MPF leadership.

The data were reevaluated to build this current simulation. The arrival distribution was confirmed to follow a Poisson distribution. All the averages were recalculated and used in the model. The data consisted of over 27,000 customers. The data was cleaned by removing the customers that visited the MPF for any other task besides the ones listed previously. There were some data that were deleted due to having an unrealistic processing time or waiting time. The threshold used was 180 minutes for processing times, but no threshold was applied to the waiting times because some customers did get serviced after waiting a whole day. To avoid skewing the average wait times, these customers were not deleted.

#### 4.5 Validation and Verification

Validation and verification are crucial to ensure a working simulation represents a real system. The approach is to build small test models representing customer arrivals and server utilization, and then compare the test results to the actual results. This project had access to the results from a previous modeling effort. Since the previous model was validated and verified by the MPF leadership, that model was deemed credible to compare the current model's results to the previous simulation's results for verification.

To validate the current simulation, a thorough walk-through of the process was conducted. First, reevaluating the historical data's averages and distributions produced the metrics to build smaller models of the queuing system. Then the results were compared to the previous simulation results for validation.

The average wait time based on the historical data was 72.2 minutes. The previous simulation goal was 70 minutes, and the same goal is used to compare and validate the average wait times of the current model. The current model has an average wait time of 58.8 minutes and a 95% confidence interval of (44.3, 73.2). The goal of 70 minutes is within the 95% confidence interval which validates the wait times. From this comparison and subject matter expertise review, the model was deemed validated and verified for the purposes of this particular analytical research project.

#### 4.6 Experiments

MPFs have a hard time processing customers when situations are out of their control, such as DEERS going down. Simulation experiments help explore options for the MPF to consider to minimize their customer wait times. The experimental focus is to test and determine what change of policies might help an MPF reduce their current customer wait times. The first set of experiments change the number of terminals available to observe the utilization rate of the terminals. MPFs have an average of four terminals, which is used as the baseline. The experiments will use a range of five to seven terminals. This range helps distinguish behavior in wait time and terminal utilization rate curves. Acquiring permission for another terminal is hard because of the strict rules set by Defense Manpower Data Center. The utilization rate needs to be over 80% over a period of a year for all terminals for the MPF to receive another terminal. These experiments will show MPFs if they can ask for another terminal, and if wait times would be reduced.

The second set of experiments changes the number of personnel working the MPF. MPFs only have a certain number of people in their office based on the Unit Manning Document. However, MPFs can manage where and how many people are assigned to each section. The model uses a baseline of three personnel in each work schedule. The experiments test the range from four to eight employees. These experiments quantify the effect of adding or removing employees on customers' wait times and if schedules need to be reworked to manage employee utilization rates.

The final set of experiments changes the global efficiency metric. If MPFs are not able to acquire new resources, then maybe they can change the environment their personnel work in. The experiments investigate the impact of the MPF making personnel more comfortable in the workplace. This could be making sure the air conditioning or heater are working when needed, the personnel are well staffed and are able to take breaks, or the personnel have comfortable chairs when working. These experiments can guide MPFs on how climate changes may help to reduce wait times.

#### 4.7 Summary

The model was built to simulate the operations of an MPF for a generic day. The simulation considers different types of customers with different tasks, and different factors such as personnel efficiency, and different lunch schedules. The discrete event simulation does not capture every situation that could happen but is deemed validated and verified to account for most of the day-to-day operations as considered in this particular research project. The simulation explores ways the MPF may reduce customer wait times using a data sheet read by the simulation software facilitating an MPF input of their own unique metrics for the model.

## V. Results Analysis

#### 5.1 Overview

In this chapter, the baseline model is analyzed to understand the current operations of an MPF. Different experimental scenarios are used to explore the relationship between the number of employees, the number of terminals, and the work efficiency rate with average customer wait times. The analysis determines which factors are significant to reducing average customer wait times. Based on the analysis, recommendations are made to improve MPF operations.

#### 5.2 Baseline Analysis

The model was designed to represent any MPF, and to allow users to input specific values for the input or parameter variables. Every MPF may have different resource levels for the different factors, but the baseline model is based on subject matter expert's experience working in the MPF. The baseline model runs are replicated 15 times and each run reflects the operations of the MPF working for a single generic day. 15 replications was used because the 95% confidence interval for average customer wait time included the goal of 70 minutes from the historical data. The input parameters for the baseline model are listed in Table 3.

| Table 3. Baseline | Parameter | Settings |
|-------------------|-----------|----------|
|-------------------|-----------|----------|

| Number of Employees | Number of Terminals | Work Efficiency Rate |
|---------------------|---------------------|----------------------|
| 6                   | 4                   | 1.0                  |

The output data were analyzed to determine the average wait time for a customer and the utilization rates of the resources. The baseline model indicates an average customer wait time of 58.8 minutes with a 95% confidence interval of (44.3, 73.2).

| Factor                              | Utilization<br>Percentage | 95% Confidence<br>Interval |
|-------------------------------------|---------------------------|----------------------------|
| Number of Employees<br>w/1100 Lunch | 70.5                      | (67.6, 73.5)               |
| Number of Employees<br>w/1200 Lunch | 72.2                      | (69.8, 74.7)               |
| Number of Terminals                 | 83.7                      | (81.9, 85.6)               |

Table 4. Factors' Utilization Percentages and Confidence Intervals

The Defense Manpower Data Center sets the standards for utilization rates of DEERS terminals. MPFs may request more terminals if the terminals are over 80% utilized for an extended period of time. From Table 4, the terminal utilization rate is 83.7%. According to the baseline model, MPFs need more than four terminals to reduce customer wait times and manage the customer throughput with six employees.

The employee utilization rate for the 1100 and 1200 lunch schedules are 70.5% and 72.2%, respectively. Since there are less terminals than employees, the employee utilization rates are lower than the terminals' utilization rates. This makes the number of terminals a limiting factor in the MPF. Since more customers need a terminal for service, the extra employees can help the customers who do not need a terminal. The percentage of customers not needing a terminal for their task is 3.5%. Thus, employees have a lower utilization rate with a limited number of terminals.

Another observation is that including two different resources to represent different lunch schedules does not affect the utilization rates of the employees in each of the lunch break time groups. A paired t-test, with a p-value of 0.4345, showed no significant difference in their means. Overall, both sets of employees are utilized at the same rate.

The experiments help understand how the work efficiency rate affects the customer wait times. The baseline keeps efficiency at 1.0 to represent the normal working operations. The experiments show how significant the influence of resources are on the average wait times by changing the number of terminals, number of employees, and the efficiency rates.

Experiments help to find the relationships between resources and the average customer wait time. Each initial experiment is compared to the baseline results to determine a better setup for an MPF. Final experiments examine changing multiple factors simultaneously to reducing wait times and managing resource utilization rates.

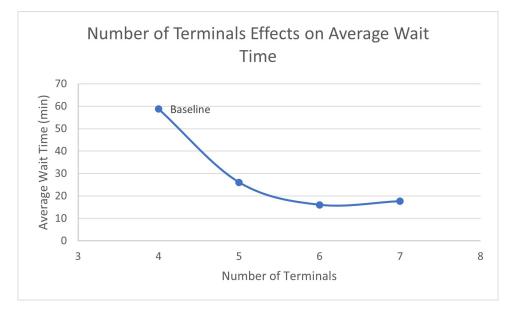


Figure 2. Number of Terminals Effects on Average Wait Time

The number of terminals located at the MPFs vary in the Air Force. The experiments examined a range from 4 to 7 terminals. Figure 2 depicts the significant drop and diminishing returns in average wait times as the number of terminals increase. Average wait time starts leveling off after six terminals because the number of employees (i.e. 6) stayed the same throughout the experiment. The six employees became a limiting factor. After six terminals, the average wait time increases very little when adding one more terminal. Clearly, you can add terminals, but personnel are needed for the terminals to reduce the average wait times. More terminals also cause a decrease in terminal utilization.

As expected, the average terminal utilization rate decreases with more terminals.

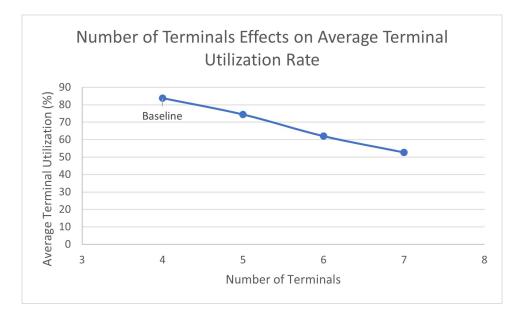


Figure 3. Number of Terminals Effects on Average Terminal Utilization Rate

Figure 3 shows a steady decrease as the number of terminals increase. As mentioned above, manpower is the limiting factor. As more terminals are added, the more likely the terminals are not used, since there may not be personnel available to work the extra terminals.

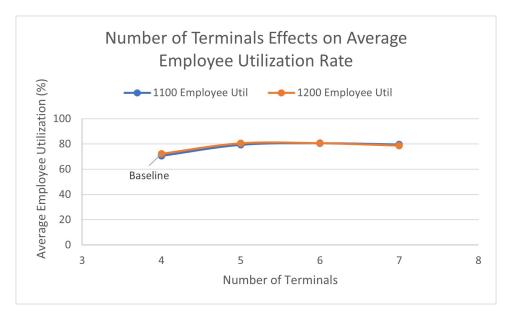


Figure 4. Number of Terminals Effects on Average Employee Utilization Rate

Figure 4 displays the effects on the average employee utilization rate as the number

of terminals increase. Adding just one more terminal raises the employee utilization rate to 80%. With six employees, the utilization rate stays the same with 5 or more terminals. In the real system, the utilization rate would increase on average because each employee would be able to utilize a terminal to service customers. Employee utilization rates are affected more significantly when changing the number of employees in the system.

Four experiments varied the number of employees in each work schedule. Table 5 summarizes the experimental settings while Figure 5 plots the results.

| Scenario     | Number of<br>Employees with<br>Lunch at 1100 | Number of<br>Employees with<br>Lunch at 1200 | Total Number of<br>Employees |
|--------------|--|--|------------------------------|
| Baseline     | 3  | 3  | 6                            |
| Experiment 1 | 4  | 4  | 8                            |
| Experiment 2 | 3  | 4  | 7                            |
| Experiment 3 | 3  | 2  | 5                            |
| Experiment 4 | 2  | 2  | 4                            |

 Table 5. Employee Number Breakdown

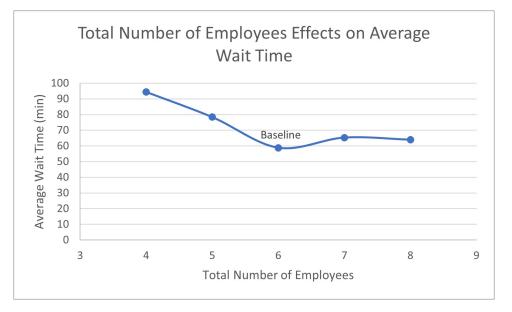


Figure 5. Total Number of Employees Effect on Average Wait Times

Figure 5 suggests that an MPF does have maneuverability with personnel scheduling.

When restricted to just 4 terminals, an MPF with 5 employees has an average wait time of around 79 minutes. Increasing to 6 or more employees drops average wait time to around 63 minutes. MPFs can determine if there is a need for another person to improve their customer support.

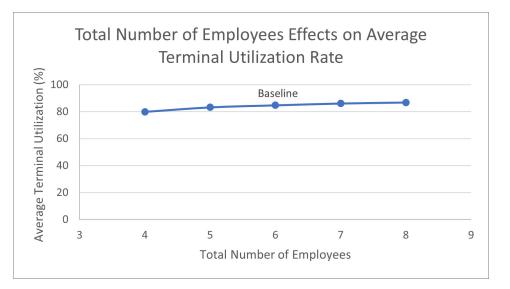


Figure 6. Total Number of Employees Effects on Average Terminal Utilization Rate

The total number of employees is found to influence average terminal utilization rate, but not significantly. Over the range of number of employees considered, a total of a 7% increase in utilization rate was noted. The number of terminals is the limiting factor. No matter how many employees are in the MPF, all terminals are used. There is less down time between the different employees utilizing the terminals resulting in the small increase to the utilization rate. The most interesting observation is the employee utilization rate shown in Figure 7.

Adding more employees is found to help employee utilization rate. The MPF is busy the entire day, with little time to give personnel breaks. Most MPFs do not have the luxury of having excess personnel compared to the number of terminals. Employees typically work through either part of their lunch or through an entire break. Looking at the simulation results in Table 6, having only 4 employees means

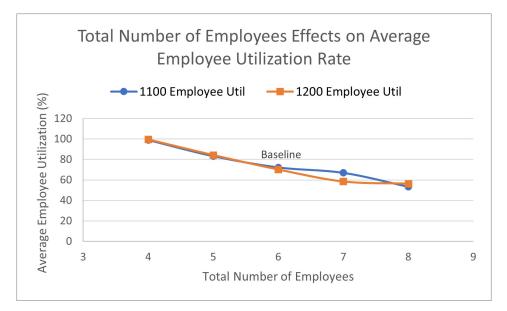


Figure 7. Total Number of Employees Effects on Average Employee Utilization Rate

| Scenario     | Employees with<br>Lunch at 1100<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1200<br>Utilization Rate<br>(%) |
|--------------|--|--|
| Baseline     | 72.2   | 70.3   |
| Experiment 1 | 53.3   | 56.4   |
| Experiment 2 | 67.0   | 58.5   |
| Experiment 3 | 83.3   | 84.4   |
| Experiment 4 | 99.0   | 99.6   |

 Table 6. Employee Utilization Rates

they are utilized on average 99% of the time. Adding just one employee drops the utilization rate to 83%. This personnel increase allows for small breaks, but it remains difficult to allow for a full hour for a lunch break. Generally, MPFs have 4 to 5 personnel working and, on the very busy days, must let employees take lunch whenever they get a small break, such as when the number of customers arriving slows down. MPFs are better suited with 6 or more personnel, which will also increase moral and work efficiency.

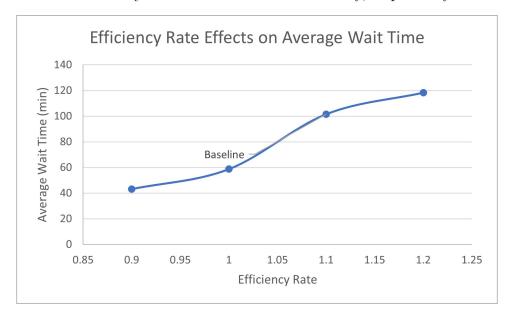
The simulation model does not consider the different population sizes each base services. Some bases may cover larger populations such as Langley-Eustis AFB, while Keesler AFB, which covers a large area, services small population sizes. MPFs may need more personnel compared to others depending on the location of the base to help manage customer wait times.

An experiment examined two ways to explore a total of 7 employees. Table 7 provides the utilization rates when changing how many of the seven are on each schedule. The utilization rates of the different shifts are compared to see if there was a significance for which shift should have more people. A paired t-test with a p-value of 0.3154 determined there is no statistically significant difference in the utilization rate of each shift with the same number of employees. There is a difference in utilization rate in the shifts in each experiment. The decrease of the employee utilization rate in the shift with more personnel follows the same conclusion of the other employee experiments, where more personnel decreases the employee utilization rate. This allows that shift with more personnel have more time for breaks, or take turns having a full hour for lunch. This is only viable if the total number of employees are larger than the number of terminals.

|            | Number of       |             | Number of       |             |
|------------|-----------------|-------------|-----------------|-------------|
|            | Employees with  | Utilization | Employees with  | Utilization |
| Experiment | Lunch at $1100$ | Rate $(\%)$ | Lunch at $1200$ | Rate $(\%)$ |
| 1          | 3               | 67.0        | 4               | 58.5        |
| 2          | 4               | 57.1        | 3               | 66.3        |

Table 7. Comparison of Utilization Rates with 7 Employees

The next set of experiments examine employee work efficiency and how improving personnel attitudes may improve average wait time. The efficiency rate is a variable used to focus on an employee's work efficiency. Greater efficiency is generally associated with comfort in the office, and sufficient training. To capture this effect, the global variable efficiency rate is multiplied by the task completion to increase or decrease the time to complete a task. For this experiment, a realistic range for the efficiency variable was set from 0.9 to 1.2. These values equate to roughly a 10%



improvement in efficiency to a 20% reduction in efficiency, respectively.

Figure 8. Efficiency Rate Effects on Average Wait Time

Figure 8 plots efficiency rate based on average customer wait times. At a rate of 1.1 and larger, the average wait time increases by over 40 minutes. An office with model employees is ideal, but people have different personalities. This variety could affect employees' work efficiency. Some people are hardworking while others have a hard time focusing or not trained as well. Many factors play into people's work performance. Thus, this experiment focused on its effect. An MPF may need to look at those factors to affect work efficiency. Overall, the results show that the efficiency rate is the most significant factor that affects average customer wait times. The range of the average customer wait times due to efficiency rates varies from 43.2 minutes to 118.4 minutes, which is wider than the range on average customer wait times caused by the number of personnel or terminals.

Figures 9 and 10 examine the efficiency rate effects on resource utilization and show a relatively flat line for each utilization rate. Overall, work efficiency affects average customer wait time. There is a slight increase as the efficiency rate reaches 1.2. If the time is extended to process a customer, then that terminal is being used

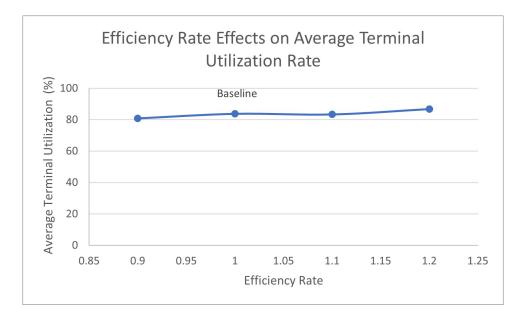


Figure 9. Efficiency Rate Effects on Average Terminal Utilization Rate

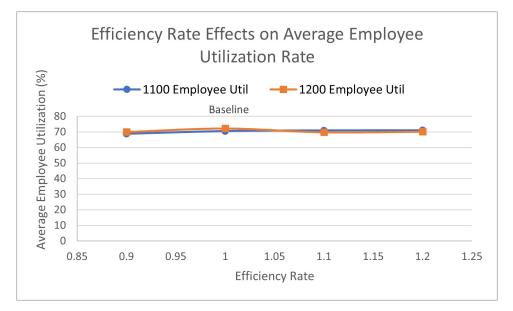


Figure 10. Efficiency Rate Effects on Average Employee Utilization Rate

longer. Longer processing times mean greater utilization of the terminals. Employee utilization rates do not fluctuate. Efficiency rates are linked with the employees, since it is a global variable applied to process times and and would not affect employee utilization rates as much as customer wait times.

The last few experiments mix the factor levels to see if there are any relationships

that can determine an optimal set up for the office. The details of the experiments' parameters are listed in Table 8. There are four mixes in the experiment. Mix 1 and 2 use less employees than terminals, but vary efficiency rates. Mix 3 and 4 use more resources, and efficiency rates are slightly off from normal of 1.0.

|          | Number    | Number of       | Number of       |             |
|----------|-----------|-----------------|-----------------|-------------|
|          | of        | Employees with  | Employees with  | Efficiency  |
| Scenario | Terminals | Lunch at $1100$ | Lunch at $1200$ | Rate $(\%)$ |
| Baseline | 4         | 3               | 3               | 1.00        |
| Mix 1    | 5         | 2               | 2               | 0.85        |
| Mix 2    | 6         | 3               | 2               | 1.20        |
| Mix 3    | 7         | 4               | 4               | 0.95        |
| Mix 4    | 6         | 4               | 5               | 1.05        |

### Table 8. Mix Experiments' Parameter Settings

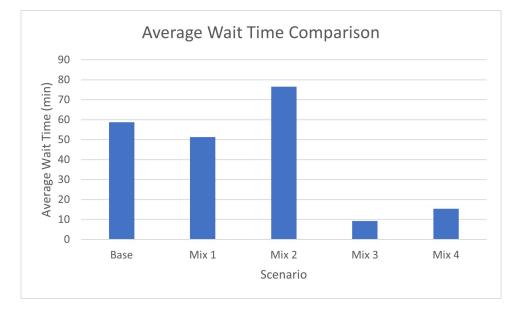


Figure 11. Average Wait Time Comparison

Comparing the Mix experiments to the baseline results in Figure 11, Mix 1 slightly reduces the average wait time. From the previous experiments, the efficiency rate is the most significant factor. Mix 1 has an efficiency rate of 0.85, which helps reduce average wait times despite limited resources. Having only 4 employees, and still reducing the average wait time to less than the baseline, indicates that the work efficiency rate is helpful. Mix 1 shows that an office with low manning can still reduce wait times, but must look at how to improve their workers' efficiency rates.

Mix 2 has more resources, but the efficiency rate value is high at 1.2. The average wait time is 76.5 minutes. Comparing Mix 1 and Mix 2, the efficiency rate is the only thing that is worse in Mix 2. Yet, this had a significant impact to the average wait time. This illustrates how number of resources can help, but if the resources are not efficient, then it will not help the overall service objective.

Mix 3 and 4 are more unlikely setups but used to show how varied setups affects the average wait time. Mix 3 has a larger resource pool with a slightly better efficiency value. The average customer wait time was reduced to 9.2 minutes. This is a preferred situation for an MPF. Mix 4 has one less terminal than Mix 3, but one more employee. Due to the larger efficiency value, and one less terminal, the average wait time increases to 15.4 minutes. Still, this is significantly better than the baseline results. The mix experiments depict how the average wait time is affected by the efficiency value but can be managed by increasing other resources. Overall, having an inefficient team does not mean average wait times cannot be reduced. An MPF may just need to find other avenues to either help the team work more efficiently or add more resources.

Figure 12 compares the experiments to the baseline average terminal utilization rates. All the experiments reduce terminal utilization, but the baseline has 4 terminals while the experiments have 5 or more. The most interesting comparison is Mix 2 to Mix 4. Mix 4 has a better average wait time, but terminal utilization is slightly worse. Mix 2 only has 5 employees, so one terminal will not be used, which reduces terminal utilization significantly. This is the same reason why Mix 1 has a smaller terminal utilization rate than Mix 2. The good thing is that all these experiments do have a utilization rate less than 80%, so another terminal is not a viable alternative. Having

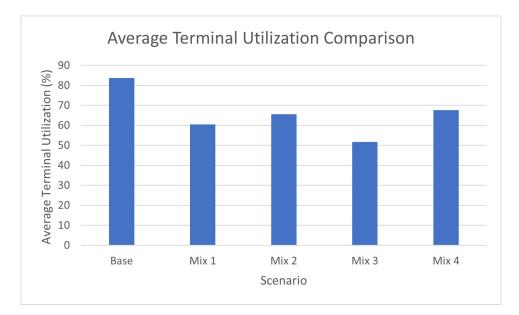


Figure 12. Average Terminal Utilization Comparison

5 or more terminals is beneficial for any MPF to reduce their average customer wait times.

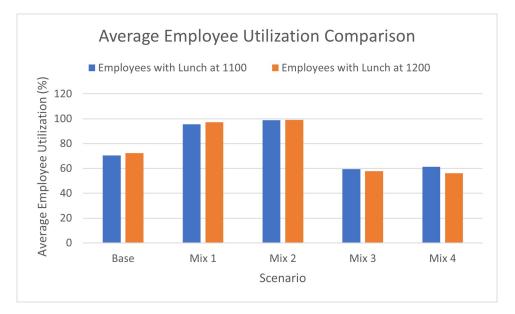


Figure 13. Average Employee Utilization Comparison

Figure 13 depicts the major issue with Mix 1 and 2. The employee utilization rates are almost 100%, which is not good for employees' moral. These situations can be managed by looking at MPF resource needs. For Mix 1, low resources cause the

high utilization rate. For Mix 2, the problem is more focused on the high efficiency value. The resources could be improved, but taking care of the employees will improve the efficiency value. The high efficiency value is increasing the average wait times, which in turn increase how long the employees are working. Mix 3 and 4 have good utilization rates. Even though there are differences in the number of terminals and number of employees, the employee utilization rates are similar.

## 5.3 Conclusion

The analysis provides insights on how the controllable factors affect average customer wait times in the operations of an MPF. Exploring the different situations an MPF could encounter helps determine what can be done to help improve average wait times, and their resources' utilization rates. Based on the analysis, it is clear the main contributor to reducing the average wait time is the work efficiency rate of the personnel, followed by the number of terminals, and then the number of employees. Taking care of the personnel is important, but many situations can arise that may affect average wait times. This simulation can be used as a tool for all MPFs to find better solutions to reducing average customer wait time.

# VI. Conclusions and Recommendations

#### 6.1 Overview

This chapter summarizes the analysis results, and recounts what solutions are possible for MPFs. The next section describes the future research using the simulation that was constructed and how the simulation could be improved to provide a more detailed analysis on MPF operations.

#### 6.2 Results Summary

The purpose of this research was to build a representative simulation model with which to test specific factors that are controllable within an MPF to potentially reduce average customer wait times. Over all the Air Force bases, MPFs have different setups for their operations of the customer support section and most suffer from long customer wait times. The simulation was concieved and built based on subject matter expert's knowledge and data collected at Langley-Eustis AFB. The goal was to build a tool for MPFs to use to provide insight on how to improve their current operations.

The main insight gained from analyses using the simulation is that the work efficiency of the personnel is important and affects average wait times the most. Making sure the employees are happy in their work environment is crucial. Whether it be keeping the scheduling as fair as possible for working the terminals, or having the building temperatures comfortable, or even allowing for small breaks during the day other than lunch, can help employees work more efficiently. The number of terminals available helps in reducing average wait times. Adding more terminals to an MPF helps in reducing average wait times, but does require personnel to work those terminals. Lastly, the number of personnel does affect average wait times, where less people will result in large average wait times, and more employees result in smaller average wait times. Additionally, more employees does help keep employee utilization rates lower. It also helps with keeping the workload spread out enough to keep the personnel happy, resulting in a more work efficient group. The best MPF configuration appears to be more than 5 terminals and 6 or more personnel with a working efficiency value of 0.95 or less.

#### 6.3 Recommendations for Future Research

The discrete event simulation was built to represent the customer service operations of an MPF. A model built to account for DEERS system failure and maintenance will give more insight into terminal utilization, and how system failure will affect average wait times. Systems can fail at any time, and accounting for these events will make the model more accurate.

The model could expand to include employees with different skill levels. The rank structure of an existing customer support section could be used as a guide to determining the differing skill levels of the personnel in the section. Varied skill levels could assist examining employee utilization; i.e, which employees need more help or guidance. Finally, more advanced resource scheduling could examine staggered breaks and lunches to the personnel in the MPF.

The current model uses a homogeneous Poisson process; one arrival rate to the full working period. Creating an hourly arrival rate table would provide a non-homogeneous arrival process and thus offer a more accurate representation of customer arrival flow. The MPF sees different influxes of customers during certain hours. For example, lunch time from 07:00 to 10:00 usually have the highest volume of customers, while from 15:00 to 17:00 has the lowest volume. This would yield more accurate MPF insights.

Another recommendation is to include appointments in the simulation. The cur-

rent model only accounts for walk in traffic. Most MPFs have either appointment only, walk-ins only, or a mixture of the two policies. Finally, the model should expand to provide customer reneging. Currently, some percentage of arrivals immediately leave or balk. In practice, some customers leave after some waiting period.

## 6.4 Summary

In the end, the simulation model helped provide insights on how to improve an MPF to reduce the average customer wait time. Varying scenario experiments provide analyst insight into ways to change MPF operations to help improve customers' satisfaction, while also increasing working personnel satisfaction. The results are reliable, but assumptions and simplifications of the model were necessary to more accurately represent the real-life system. Creating this generalized simulation may help any MPF benefit from the analysis process using their own specific data and distributions.

# Appendix A. Experiments Detailed Results

| Scenario     | Average Wait<br>Time (min) | Terminal<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1100<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1200<br>Utilization Rate<br>(%) |
|--------------|----------------------------|-------------------------------------|--|--|
| Baseline     | 58.8                       | 83.7                                | 72.2   | 70.3   |
| Experiment 1 | 26.1                       | 74.4                                | 79.3   | 80.6   |
| Experiment 2 | 16.1                       | 62.0                                | 80.6   | 80.7   |
| Experiment 3 | 17.7                       | 52.7                                | 79.6   | 78.8   |

# Table 9. Terminal Experiment Results

#### Table 10. Employee Experiment Results

| Scenario     | Average Wait<br>Time (min) | Terminal<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1100<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1200<br>Utilization Rate<br>(%) |
|--------------|----------------------------|-------------------------------------|--|--|
| Baseline     | 58.8                       | 83.7                                | 72.2   | 70.3   |
| Experiment 1 | 63.9                       | 86.8                                | 53.3   | 56.4   |
| Experiment 2 | 55.7                       | 84.1                                | 57.1   | 66.3   |
| Experiment 3 | 78.3                       | 83.2                                | 83.3   | 84.4   |
| Experiment 4 | 94.4                       | 79.9                                | 99.0   | 99.6   |

## Table 11. Efficiency Rate Experiment Results

| Scenario     | Average Wait<br>Time (min) | Terminal<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1100<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1200<br>Utilization Rate<br>(%) |
|--------------|----------------------------|-------------------------------------|--|--|
| Baseline     | 58.8                       | 83.7                                | 72.2   | 70.3   |
| Experiment 1 | 43.2                       | 80.9                                | 68.9   | 70.0   |
| Experiment 2 | 101.6                      | 83.3                                | 70.9   | 69.8   |
| Experiment 3 | 118.4                      | 86.8                                | 71.0   | 70.2   |

| Scenario     | Average Wait<br>Time (min) | Terminal<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1100<br>Utilization Rate<br>(%) | Employees with<br>Lunch at 1200<br>Utilization Rate<br>(%) |
|--------------|----------------------------|-------------------------------------|--|--|
| Baseline     | 58.8                       | 83.7                                | 72.2   | 70.3   |
| Experiment 1 | 51.3                       | 60.5                                | 95.5   | 97.2   |
| Experiment 2 | 76.5                       | 65.6                                | 98.9   | 99.1   |
| Experiment 3 | 9.2                        | 51.8                                | 59.4   | 57.7   |
| Experiment 4 | 15.4                       | 67.6                                | 61.4   | 56.1   |

 Table 12. Mix Experiment Results

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|---|---|--|---|
| 1. REPORT DATE (DD-MM-YYYY)   | 2. REPORT TYPE  |  | 3. DATES COVERED (From — To)  |
| 25-03-2021  | Master's Thesis   |  | August 2019 — March 2021  |
| 4. TITLE AND SUBTITLE   |   | 5a. CON  | ITRACT NUMBER   |
| Reducing Military Personnel Flight Wait Times Using a Simulation  |   | 5b. GRANT NUMBER                                 |   |
|   |   |  | GRAM ELEMENT NUMBER   |
| 6. AUTHOR(S)  |   | 5d. PRC  | DJECT NUMBER  |
| Cornman, Matthew D., Capt, USAF   |   | 5e. TASK NUMBER                                  |   |
|   |   | 5f. WOF  | RK UNIT NUMBER  |
| 7. PERFORMING ORGANIZATION N  | AME(S) AND ADDRESS(ES)  |  | 8. PERFORMING ORGANIZATION REPORT<br>NUMBER   |
| Air Force Institute of Technology<br>Graduate School of Engineering and Management (AFIT/EN)<br>2950 Hobson Way<br>WPAFB OH 45433-7765                            |   |  | AFIT-ENS-MS-21-M-148  |
| 9. SPONSORING / MONITORING AG   | GENCY NAME(S) AND ADDRESS(ES)   |  | 10. SPONSOR/MONITOR'S ACRONYM(S)  |
| DANTE C. REID, Major, USAR<br>ACC/A1MI  | · ·   |  | ACC/A1MI  |
| Bld 635, 114 Douglas St, Suite 133<br>Joint Base Langley Eustis, VA 23665<br>DSN 574-0874 / Comm (757) 764-0874   |   |  | 11. SPONSOR/MONITOR'S REPORT<br>NUMBER(S)   |
| 12. DISTRIBUTION / AVAILABILITY   | STATEMENT   |  |   |
| DISTRIBUTION STATEMENT<br>APPROVED FOR PUBLIC RE  | A:<br>LEASE; DISTRIBUTION UNLIMITED   |  |   |

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## 14. ABSTRACT

A shortage of resources and system failures have put a strain on Military Personnel Flights (MPFs) being able to service their customers in a timely manner. Prolonged customer wait times are becoming a common problem in most MPFs creating problems between the relationship of the customers and leadership. This research uses historical data of an MPF to develop a simulation model of daily operations in an MPF. Subject matter expertise of current MPF operations and resource levels were used to provide a baseline model of the MPF queuing system. The analysis examines the effects of number of Defense Enrollment Eligibility Reporting System (DEERS) terminals, the number of personnel and their work efficiency rating on average customer wait times. The goal is to produce a simulation model that an MPF can utilize. The simulation model will provide insights in how to improve the current operations of the MPF to reduce customer wait times. The results recommended MPFs have 5 terminals with 6 or more personnel with an efficiency rate of 0.95 or less to significantly reduce the customer wait times, and manage the resources' utilization rates.

#### 15. SUBJECT TERMS

queuing theory, simulation, wait times

|   | CLASSIFICATION D. ABSTRACT | - | ADSTDACT |    | 19a. NAME OF RESPONSIBLE PERSON<br>Dr. Raymond R. Hill, AFIT/ENS                              |
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