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THESIS

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Abstract

Customers at Military Personnel Flights (MPFs) have been experiencing long wait times. These customers are typically employees of the United States Air Force and every moment spent waiting for service is a moment they are away from their actual jobs. By reducing the mean wait time of MPF customers, manhours can be saved and customer complaints may be alleviated. This research uses data collected from an MPF to build a discrete-event simulation model of an MPF. A full factorial experimental design was conducted in the model using five factors. The factors included the total number of employees, the total number of terminals designated for walk-in customers, the total number of terminals designated for appointment customers, the minimum number of employees working during lunch, and different appointment policies. The outputs of the experiment were used to generate regression models that estimate the mean wait time for walk-in and appointment customers. The regression formulas were also analyzed to determine relationships between the factors and the mean wait times. Additionally, several experimental scenarios were tested for reductions in mean wait time. The analysis showed that the number of employees working has the largest impact on mean wait times when compared against other factors. Further, it is recommended to alter baseline model with an increase of number of employees working from five to six, with a simultaneous increase in designated walk-in terminals from four to five, to achieve a significant reductions in mean walk-in wait times and mean appointment wait times.

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To my beautiful wife and my furry friends.

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Nicholas C. Anderson

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MILITARY PERSONNEL FLIGHT CUSTOMER WAIT TIME REDUCTION MODEL USING SIMULATION

I. Introduction

1.1 Background & Motivation

Long wait times for customers can be common at United States Air Force (USAF) Military Personnel Flights (MPF), which are units that provide services related to individual's identification and personnel records. Excessive waiting results in unhappy customers and hinders the day-to-day mission of the USAF by keeping personnel away from their jobs for longer than needed. These long wait times are symptoms of several factors that, when happening together, cause delays. These factors include system outages, service priorities, and high volumes of traffic.

Naturally, we desire for a system to have shorter queue times, more customer throughput, adequate server utilization rates, and maximum profit. While the system analyzed in this thesis, an MPF, does not make profit, the commander of an MPF is still concerned with accomplishing the mission using an optimal allocation of available resources. While talking more generally about the Air Force in his inaugural address as the 22nd Air Force Chief of Staff, General Brown said, "We need to remove any of the internal impediments that will stop us from moving forward" (Brown, 2020). Having Airmen, Department of the Air Force civilians, and contractors waiting in a queue to be able to perform their job is an internal impediment that is hindering the Air Force from accomplishing its mission.

MPFs are responsible for several different tasks in support of all personnel affiliated with the USAF. These personnel include military servicemembers, government civilians, contractors, military dependents, and military retirees. The responsibilities of an MPF include issuing military identification cards, referred to as Common Access Cards (CAC), resetting CAC personal identification numbers, issuing dependent and retiree identification cards, updating changes in personnel records such as marital status, and assisting customers with questions pertaining to their personnel record.

MPFs operate with several limited resources. MPF employees are both military and non-military personnel with varying skill levels, duties, and experience. Most face-to-face interaction with customers is done by young enlisted Airmen who usually have limited experience. Employees typically help one customer at a time so they an MPF is limited in how many customers it can service simultaneously. Additionally, some tasks require an employee to use a Dependent Enrollment Eligibility Reporting System (DEERS) terminal. DEERS stores identifying information used for issuing identification cards, updating dependents' information, and updating TRICARE benefits. DEERS is subject to system outages that could cause backups in serving customers.

Customers typically arrive to an MPF and sign-in via a check-in kiosk in the waiting area. Signing in lets the employees know the type of customer and what service they are there to receive. Once the appropriate resources are available, employees bring customers back to be served for their particular task. After completion, the customer immediately exits the MPF and the employee begins helping the next customer.

Performance of an MPF can be measured by several different criteria such as mean wait time, maximum wait time, or total customer throughput. In this research, we are concerned with the mean wait time for a customer at an MPF. Reducing mean wait time would save manhours, which can help the overall USAF mission.

Simulation techniques, specifically discrete-event simulation (DES), offer the capability to model a generic MPF, test different policies, and determine improvements with statistical precision before expending resources in executing a change in the real world.

1.2 Problem Statement

Military Personnel Flights are seeing high volumes of customer traffic and are unable to serve every customer in a timely manner, which results in negative impacts to the overall Air Force mission and low customer satisfaction. This problem is exacerbated by limited MPF resources and system outages. Current data from an MPF shows a mean wait time of 76 minutes for walk-in customers and 15 minutes for appointment customers. Air Force leadership needs a generalizable solution to test the effectiveness of potential administrative policies and employee practices, with respect to MPF operations, before fully committing to a drastic change. There are opportunities to use data analysis to identify administrative policies and practices that can be implemented to improve the efficiency of MPFs.

1.3 Research Questions

The objective of this thesis is to develop a generalizable model that can be used to answer questions regarding the analysis and implementation of new administrative policies and practices. The key questions we explore in this thesis are:

1. What changes to an MPF achieve the largest reductions to mean wait time?

2. How much is mean wait time reduced if a resource is increased? (This could be hiring more employees or acquiring more terminals.)

3. What interactions exist between variable factors?

Answers to these questions will identify courses of action that reduce mean wait times, determine how much reduction in mean wait time is achieved for each resource type, and how interactions between factors can help or hinder the problem.

1.4 Scope

There are many areas where effort could be exerted to improve an MPF. This section will identify areas we exclude from the current research to make the model more generally applicable.

The model covers a normal five-day work week. It does not account for holidays, early release, or random events that result in base closure or work stoppages such as weather or exercises. The model also does not account for employees taking leave, being late, being sick, or having to leave work during the day for any reason other than the allotted lunch break.

Additionally, this model does not account for emergency walk-ins that arrive for a time-sensitive issue. These occurrences are not modeled due to the lack of data on their frequency.

Further, this model only accounts for the customer service section of the MPF and excludes passport, special leave accrual, and 100% VA disability services.

Failures of DEERS terminals will be modeled as total DEERS network outages. Other general computer outages or slowdowns will not be modeled.

Lastly, the utility of a simulation model DES is limited by how closely the model can replicate the real world. Significant changes to the system outside of well-defined state changes are not included in the model.

1.5 Summary of Contributions

Analysis prior to this thesis was done by Cornman (2020) to determine which factors are significant in reducing wait times at an MPF. His findings revealed that employee morale, number of terminals operating, and number of employees available were the main contributors to impacting wait time. This thesis builds upon Cornman's work and generalizes the DES model.

The research in Chapter 3 of this thesis generated a working DES of an MPF that can be used to test alternative MPF structures. Chapter 4 of this thesis found that the total number of employees and total number of designated walk-in terminals were the main factors that contribute reducing mean wait time by using regression modeling and confidence intervals. Moreover, this thesis also highlighted the impact of how those two factors interact with each other and cannot be ignored when considering changes. Additionally, two policy changes, increasing minimum lunch time manning and serving appointment customers earlier, showed a reduction in mean wait times. Lastly, the addition of a CAC PIN reset machine at the check-in kiosk also showed a drastic reduction in mean wait times.

1.6 Organization of Thesis

The second chapter reviews existing pieces of literature related to simulation and other techniques utilized in this thesis. Chapter 3 covers the methodology of creating the model and the process of verification and validation. Chapter 4 presents the analytical methods, the results of those methods, and insights gathered from those outputs. Chapter 5 provides a summary of this thesis and sets forth possible future improvements to this research.

II. Literature Review

2.1 Introduction

Simulation has a right time and wrong time to be utilized. With MPFs being a small niche of the world, other applications of simulation to similar types of systems must be studied so their processes and methodologies can be applied to the MPF system. The studying of queues and service times commonly occurs in service industries like transportation, restaurants, and even healthcare. An MPF has several analogous aspects to these service industries and are candidates for improvement with simulation. In this literature review, several different applications of simulation, queuing theory, and modeling approaches are examined for their use in properly modeling an MPF and expanding upon previous work.

2.2 Queuing Theory

Queuing theory can be used to gain insight into basic system performance. Simple queuing systems are generally described by the distribution of the arrivals, the distribution of the service times, and the number of servers in the system. With those parameters, it is possible to compute theoretical values to, for example, maximize profits or minimize wait times. While theoretical, Banks states that "queuing models, whether solved mathematically or analyzed through simulation, provide the analyst with a powerful tool for designing and evaluating the performance of queuing systems" (Banks, Carson, Nelson, & Nicol, 2010).

The first foray into queuing theory was in 1908 when Agner Erlang began studying holding times on a telephone switch (Dharmawirya & Adi, 2012). In his analysis, he determined that the number of phone calls received followed a Poisson distribution and the holding time was exponentially distributed.

When using queuing theory, the intent is often to measure the waiting time for a typical customer, the length of queues, total number of customers in system, or how often the servers are busy. However, Shortle et. al. state that "since most queueing systems have stochastic elements, these measures are often random variables, so their probability distributions – or at least their expected values – are sought" (Shortle, Thompson, Gross, & Harris, 2018).

To fully understand a queueing situation, it may be beneficial to describe the system in queuing theory terminology and notation to obtain a baseline. From this baseline, modifications can be proposed, such as varying numbers of servers or different arrival and service distributions. Dwyer did this for military entry control points by first establishing his baseline model, and then creating three alternative systems to compare against. His comparisons included differing numbers of guards (i.e., servers) and variations on the behavior of customers entering the system. This work resulted in statistically significant findings that identified possible policies to implement that can improve service, such as utilizing parallel servers rather than tandem servers (Dwyer, 2016).

Queuing theory tends to have shortfalls when systems become more complex. Joustra and Van Dijk say that these "[queuing theory] formulas represent so-called steady state situations" (Joustra & Van Dijk, 2001). Many systems that open and close everyday, or have highly varied demand over time, do not fit this assumption. These issues do not render queuing theory useless, however they do require careful consideration when applied to a system under study. Joustra and Van Dijk also state that "queuing theory remains useful for the verification and validation of a simulation model. In the experimentation-phase, theory proves to be valuable in defining experiments as well as analysing results."

2.3 Simulation

Queuing theory provides good results for simple systems, however, often a system becomes too complex to be adequately modeled by queuing theory. The advent of computing technology has allowed computer simulations to model these complex systems and provide insight that was unobtainable before. Banks states, “many real-world systems are so complex that models of these systems are virtually impossible to solve mathematically” (Banks et al., 2010). The model of a standard Air Force MPF can be more accurately modeled with simulation due to the various types of customers, work schedules, and general stochastic nature of arrival and service times.

Banks defines *simulation* as “the imitation of the operation of a real-world process or system over time” (Banks, 1998). Computers and software today can imitate complex systems over long periods of time in moments. However, simulation models are imitations and cannot be a perfect substitute for the real thing. Vincent says, “often, the goal of simulation input modeling is to provide a model that is reasonable, given the goals of the simulation” (Banks, 1998). In examining a simulation model, it is important to understand that the results may vary from reality. If built correctly, a simulation model can produce useful insights into the actual system.

While simulation cannot make exact predictions, it can be used to overcome limitations of queuing theory. Joustra and Van Dijk state that “simulation offers the freedom of using arbitrary distributions for check-in processing time and arrival patterns” and make it “possible to test alternative check-in methods, e.g., dynamic opening and closing of counters” (Joustra & Van Dijk, 2001).

2.3.1 Discrete-Event Simulation

Banks defines *discrete-event simulation* as “the modeling of systems in which the state variable changes only at a discrete set of points in time” (Banks et al., 2010). Further, a DES is analyzed by numerical methods rather than analytical; the difference being that analytical methods use deductive reasoning to achieve a solution, whereas numerical methods employ computational procedures that are akin to "running" a model as opposed to "solving" it.

A direct application of DES was accomplished in 2018 on a Virginia Department of Motor Vehicles (DMV) building where the authors were interested in improving the wait time for customers (Arnaout & Bowling, 2018). Using data collected by observing this DMV, a DES was constructed and used to test two different alternatives regarding methods of customers checking in and employee allocation across the facility. Their results indicated that the alternatives tested were not statistically significant in their differences from the baseline. Results like these indicate that it may not be worth spending resources to alter to system to one of the proposed alternatives.

2.4 General Applications

Queuing theory and simulation are only practical if they can be successfully utilized to help some real-world system. Many businesses and government services operate in an environment of cost-cutting and doing more with less. Such organizations are interested in how to allocate their resources to improve their services. Cornman states that "businesses have to determine the balance between increasing customer satisfaction or not overworking their resources or employees" (Cornman, 2020). The rest of this section looks at several applications of queuing theory and simulation to identify best practices and improvements.

Given that one measure of interest is wait time, it may be prudent to identify when and where the wait time is the shortest. From the perspective of the customer, if the customer can look up average wait times at different places offering the same service, then they could choose the location with the shortest one. In 2013, research was conducted on California Department of Motor Vehicles (DMV) locations and wait times (Zhang, Nguyen, & Zhang, 2013). Several different prediction techniques were utilized to inform customers how long the wait would be at each DMV when a customer arrived from their current location. With this information, the customer could drive to a DMV a little farther from their location and end up waiting less time. Their analysis showed that linear regression was the most accurate technique for forecasting wait times at these DMV locations.

Restaurants fall under the purview of queuing theory applications, because many often have a queuing area and a counter where customers place an order. Dhamawirya and Adi studied a sushi restaurant that exhibited exponentially distributed arrival and service times (Dharmawirya & Adi, 2012). The restaurant was observed during peak hours and theoretical values were compared to observed values. It was shown that due to the high server utilization rate, the queue was longer on average and led to potential customers balking the queue. This study highlighted the importance of keeping a queue short so that customers are willing to wait, rather than going to a competing restaurant.

Properly scheduling employees becomes a daunting task when confronted with fluctuating demand at different areas and times in the system. Transportation systems are good examples of complex systems with difficult scheduling problems. Systems like transportation have varying arrival rates throughout the day at different stations, several different technologies for collecting fare, and unexpected shutdowns. Understaffing a busy station while simultaneously overstaffing another station could be detrimental to revenue and customer satisfaction.

The subway metro in Santiago, Chile, was the subject of a 2018 study on staff scheduling. The metro uses multiple types of fare collectors scheduled throughout the day. The analysis begins with identifying potential schedules via an integer programming optimization model and then uses discrete-event simulation on different scheduling schemes to determine an optimal solution. The authors of the study state, "the optimization model determines the number of fare collectors of each type to schedule at each station booth and the type of shifts to satisfy service and operational requirements while minimizing the total staffing cost" (Miranda, Rey, Sauré, & Weber, 2018). The metro model developed was successful in reducing the time required to plan schedules from days down to hours and was implemented in the Santiago Metro. The utilization of different techniques to achieve real-world resource savings is indicative of the potential to save in other areas.

2.5 Healthcare Applications

Healthcare operations have recently become candidates for simulation techniques due to healthcare facilities attempting to meet increasing demands with limited resources, similar to the problem Air Force MPFs are facing. Peter and Sivasamy state, "[q]ueuing theory and simulation methods are analytical techniques that are increasingly accepted as valuable tools to be used in modeling and analyzing the inter-arrival and service times for patients coming to a health facility" (Peter & Sivasamy, 2019). The delays that occur can typically be attributed to a disparity between the demand and current capacity. The authors note the need to apply queuing theory to healthcare due to the variability of interaction between the arrival and service processes, as well as the desire to improve service standards.

An example of a healthcare simulation from 2015 involves a Sacramento hospital with a goal to determine the optimal number of operating rooms to keep open at different times of the day. The authors used Monte Carlo simulation with patient arrival data and surgical procedure lengths to build a generalizable model that could guide decisions on how to balance resources. The simulation output average and median wait times for different types of patients and assisted decision makers in determining the number of operating rooms need to be devoted to non-elective surgeries (Antognini, Antognini, & Khatri, 2015).

Emergency rooms also suffer from overcrowding and can be examined with queuing theory and simulation. Xu and Chan modeled an emergency department using arrival behavior and predicted future patient information (Xu & Chan, 2016). With this information, different policies were tested to divert patients to alternate medical facilities in the area based on the predicted patient treatment. While the authors acknowledge some assumptions in their modeling may not reflect reality perfectly, this example highlights that queuing theory and simulation give decision makers the flexibility to not only allocate their servers, but to also modify administrative polices to improve system operations.

Applying these simulation techniques to any system poses challenges. Healthcare applications can be even more difficult due to the nature of the healthcare. Patrick and Puterman ((Patrick & Puterman, 2008)) outline some of the challenges regarding wait times:

- Patients are not homogenous. Different trauma levels receive different priorities.
- Wait times are calculated from the time the service was requested, not when the service was needed.
- Averages do not give enough information as wait time distributions tend to be skewed.
- Accurate wait time data can be difficult to obtain based on how the data is collected and stored.

These data challenges are not unique to healthcare and apply to other areas. Patrick and Puterman also used several different techniques, including simulation, to identify that “even if more capacity is required, managers must first ensure that current capacity is used to its fullest potential” (Patrick & Puterman, 2008).

2.6 Appointments

Having customers arrive via walk-in is often an oversimplification in some systems. For example, many healthcare systems have appointments as well as walk-ins and attempt to service both sets of patients. Wang, Liu, and Wan state that “without careful planning for walk-ins, daily service operations may be interrupted, resulting in long patient waits, provider overtime work, and, ultimately, poor service quality” (Wang, Liu, & Wan, 2017).

Similar to scheduling appointments, some systems may find virtual queuing to be feasible. Airports and amusement parks are candidates for this method. Narens describes a virtual queue as “an invisible line passengers wait in before entering a physical queue” (Narens, 2004). More specifically, a virtual queue allows customers join the queue from a computer or phone, displays a position in queue and estimated wait time, and gives the customer the flexibility to show up when they are about to be served, instead of waiting in a physical line for the entire duration. Virtual queues allow the managers of the system to smooth the demand by distributing it over the course of the day and attempt to utilize the entire operating time period to its maximum capacity.

2.7 Summary

This chapter highlighted recent applications of queuing theory and simulation to the study of real-world systems with the goal of extracting information to allow managers to make decisions that improve their business or service. It was shown that simulation is about knowing arrival and service times, as well as about resource allocation and setting policies that benefit the system. Finally, the concept of applying an appointment scheme to a system was examined and shown to have potential to improve a system when applied appropriately.

This research intends to take parts from the literature discussed above and apply them to the problem of long wait times at MPFs. The methodology may differ from the discussed applications, but uses a combination of techniques to determine better alternatives to the system in question.

III. Methodology

3.1 Overview

This chapter explains the methodology and tools used for this analysis. The desired outcome was to accurately model a USAF MPF unit in Simio using real-world data collected from Langley-Eustis (L-E) Air Force Base from April 2018 to April 2019. The parameters of this model are called the baseline parameters. Once verified and validated, alternative scenarios can be tested against the baseline parameters and used to answer the research questions from Chapter 1 to potentially help a real-world MPF reduce wait times for customers. This chapter contains a model overview, assumptions made for the model, data examination, and the verification and validation process.

3.2 Model Overview

This model represents a USAF MPF customer service section providing various services to customers each day. The simulation covers a Monday-to-Friday work week with operating hours of 0730 to 1600. After 1600, arrivals are halted as the MPF no longer accepts new customers for that day, but the employees are modeled to stay on shift until either all customers in the system have been serviced or 1930 hours, whichever comes first. The simulation begins in an empty and idle state at 0730 on Monday and it ends on Friday at 1930 hours. Figure 1 depicts a schematic view of the baseline model.

3.2.1 Customer Types

Customers are represented as ten different types of entities. Each type of entity corresponds to the service the customer is there to receive and is determined by a

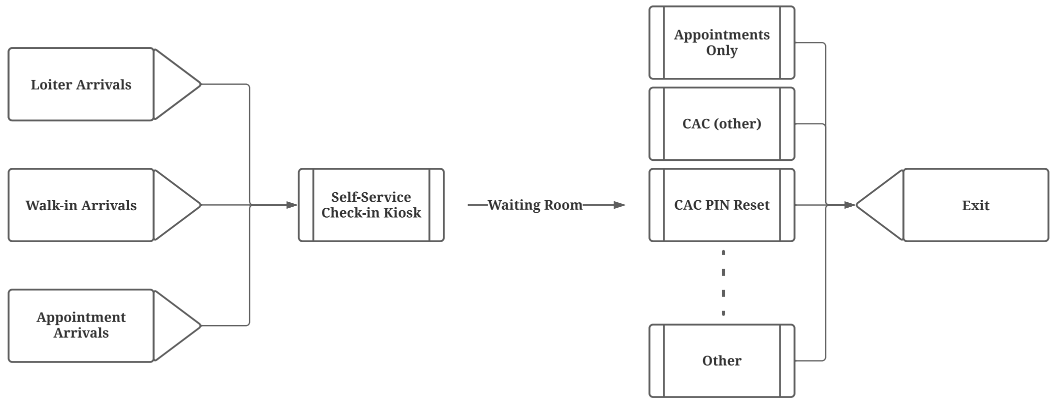

Figure 1. The schematic of the model shows the flow of the system from a customer entering until they exit the system after service.

random draw proportional to the number of customers requesting each service type from the Langley-Eustis Air Force Base MPF data. Similarly, arrival rates follow probability distributions fit to the same data.

Entities arrive through three different arrival nodes. The first arrival node is for *loiters*: customers that arrive prior to 0730, queue up outside, and file in at the start of business each day. The second arrival node is for walk-in customers arriving throughout the workday from 0730 until 1600. The third arrival node is for customers with an appointment. Appointments are scheduled for every 30 minutes starting at 0730 and ending at 1530 allowing for 17 daily appointments per terminal. The proportions of each type of customer generated from loiter and walk-in arrival nodes are shown in Table 1.

The number of loiter arrivals at the start of each day are drawn from a Poisson distribution, where the parameter is the average number of customers per hour that checked in on that particular weekday before 0735 throughout the time period of data collection. This cutoff was to account for loiters who may have arrived at 0730, but were unable to check-in immediately as they were not at the front of the queue. The walk-in arrivals are modeled as a non-homogeneous Poisson process with varying arrival rates based on the real-world data, binned into 30-minute intervals. Due to

Table 1. Proportions of Walk-in and Loiter Types

Service Type	Proportion
CAC (Other)	0.402
Dependent ID	0.215
CAC PIN Reset	0.214
DEERS Update	0.067
Retiree ID	0.047
Marriage/Divorce	0.024
Other	0.017
Questions	0.008
MilPDS Update	0.006

varying arrival rates on different weekdays, arrivals are fit to different distributions for each weekday. Outside of operating hours, arrival rates are set to zero. Arrival times of appointment customers are based on a schedule with a stochastic element to account for customers arriving early or late. During the data collection period, only one terminal was designated for appointments; however, appointment customers waiting longer than 15 minutes past their scheduled appointment time can be serviced by terminals not specifically designated for them in the model.

3.2.2 Service Types

The model has one server node for the check-in kiosk and ten additional server nodes, one for each type of service. The ten services are: *Appointments*, *Retiree ID*, *CAC (other than Marriage/Divorce updates)*, *CAC PIN Reset*, *DEERS Update*, *Dependent ID*, *Marriage/Divorce*, *MilPDS Update*, *Questions*, and *Other*. Due to the absence of data, we assume the self-service check-in kiosk to have a constant one-minute service time. The processing time for each service, other than the check-in kiosk, follows its respective empirical probability distribution using the L-E MPF data.

3.2.3 Model Flow

Upon arrival, a customer entity checks in at the self-service check-in kiosk and, if unable to be serviced immediately, moves to a waiting area until resources become available. This model uses a first-come, first-served policy for walk-in customers with one exception where the model prioritizes the next customer serviced with the currently available resources. This mirrors real-world MPF policies for walk-ins as well as situations where a certain resource has failed, but a customer farther back in the queue can be serviced with currently available resources. Appointment customers are serviced as soon as resources become available. Once the required resources become available, the resources are seized, and the customer is transferred to, and serviced at, the appropriate service node. If an appointment customer is still waiting fifteen minutes after their scheduled appointment, model logic will bring the customer into service next regardless of the status of any appointment terminals. Fifteen minutes is an assumed value called *Appointment Wait Threshold* in the model. Upon finishing service, the resources used are released and the entity immediately exits the system at the exit node.

Each customer entity type is assigned a *Resource ID* property, which designates the resources it requires for service. When an entity enters the waiting room or exits the MPF, the model checks the *Resource ID* of the next waiting customer and evaluates the available quantity of each resource to determine if they can be serviced (Figure 2). If so, the next customer is immediately transferred to its respective service node. If not, the model checks if any customer can be serviced with the available resources.

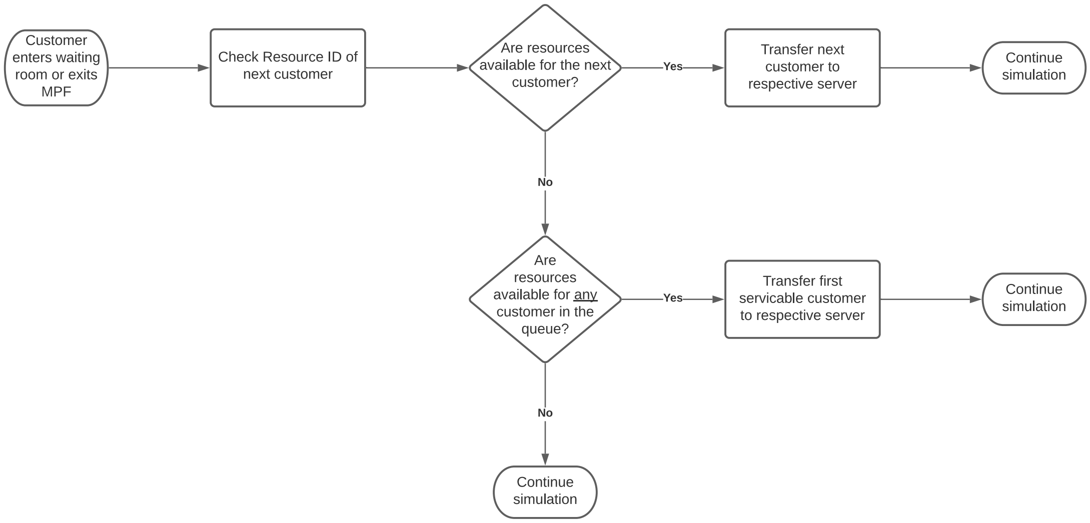

Figure 2. Model logic flow when an entity enters the waiting room or exits the MPF.

3.2.4 Model Resources

The employees and service terminals of an MPF are limited resources and are modeled as such. Both resources are modeled separately, as the employees take a lunch break, which leads to reduced manning in the middle of the day, and to designate terminals for appointment or walk-in customers. After each service, each employee is delayed from returning as an available resource to account for any short cleanup actions or rest breaks.

The availability of the DEERS network is modeled as a resource due to the potential of system outages. The DEERS resource must be seized to begin any task requiring DEERS, but the capacity is large enough to never be exhausted. Upon a DEERS outage, no DEERS tasks may be started, but any DEERS tasks in progress are continued.

All services require an employee resource. All services except for *Questions* require a terminal resource. Only *MilPDS Update* and *Other* require just an employee and terminal resource. Table 2 shows the resources required by each service type.

Table 2. Resources Required by Service Type

Type	Employee	Terminal	DEERS
Appointment Only	Yes	Yes	Yes
CAC (Other)	Yes	Yes	Yes
CAC PIN Reset	Yes	Yes	Yes
DEERS Update	Yes	Yes	Yes
Dependent ID	Yes	Yes	Yes
Marriage / Divorce	Yes	Yes	Yes
MilPDS Update	Yes	Yes	No
Other	Yes	Yes	No
Retiree ID	Yes	Yes	Yes
Questions	Yes	No	No

3.2.5 Baseline Model Parameters

The discrete-event simulation was created to model the Langley-Eustis MPF at the time of data collection. The discrete-event simulation using the values from the Langley-Eustis MPF, called the baseline model parameters, as input parameters is called the baseline model. These values were formulated in conversations with the MPF personnel or by assumption. Table 3 shows the value of each parameter used in the baseline model.

Table 3. Baseline Model Parameters

Parameter	Value
Number of Walk-In Terminals	4
Number of Appointment Terminals	1
Number of Employees	5
Minimum Number of Employees During Lunch	3
Appointment Wait Threshold (minutes)	15

3.2.6 Baseline Outputs

The outputs of the model when using the baseline parameters are shown in Table 4. These are discussed in Section 3.5. Figures 3-6 show proportional histograms of the frequency of wait times in the simulation and in the data.

Table 4. Outputs from the model when using the baseline parameters

Measure of Interest	Output (minutes)
Mean Wait Time - Appointments*	13.66
Mean Wait Time - Walk-ins*	74.94
Mean Maximum Wait Time - Appointments	83.53
Mean Maximum Wait Time - Walk-ins	207.05
* - Validated	

Due to data availability, the baseline model is only validated on the two measures of mean wait time. However, it is important to observe the mean maximum wait times that are output from the model because unexpected values could indicate something happening that is undesirable. Fortunately, the mean maximum wait times seem reasonable compared to the empirical distributions used to build the model. True values for maximum wait times are unknown, due to the omission of large wait times from erroneous entries (Section 3.4). The validation data for mean wait times (Section 3.5) had a maximum value of 83 minutes for appointment customers and 429 minutes for walk-in customers. While the model is not validated on maximum wait times, the measure is still worth observing to ensure some semblance of reason.

3.3 Assumptions

Several assumptions were necessary to build the model. These assumptions are made to help manage unnecessary model complexity or to account for the absence of

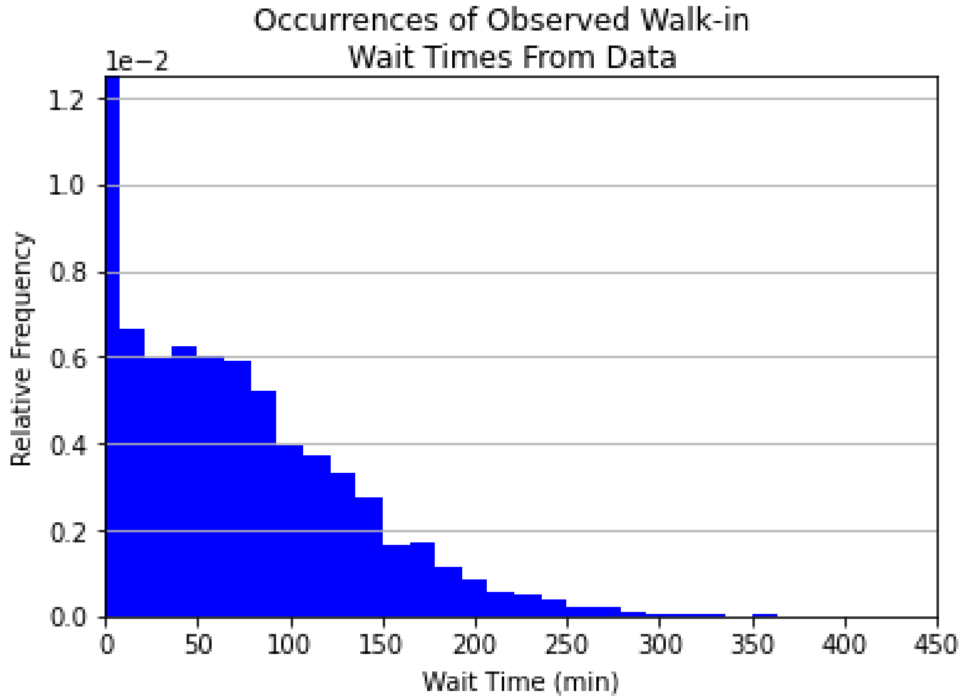

Figure 3. Frequency of walk-in customer wait times observed in the L-E MPF data.

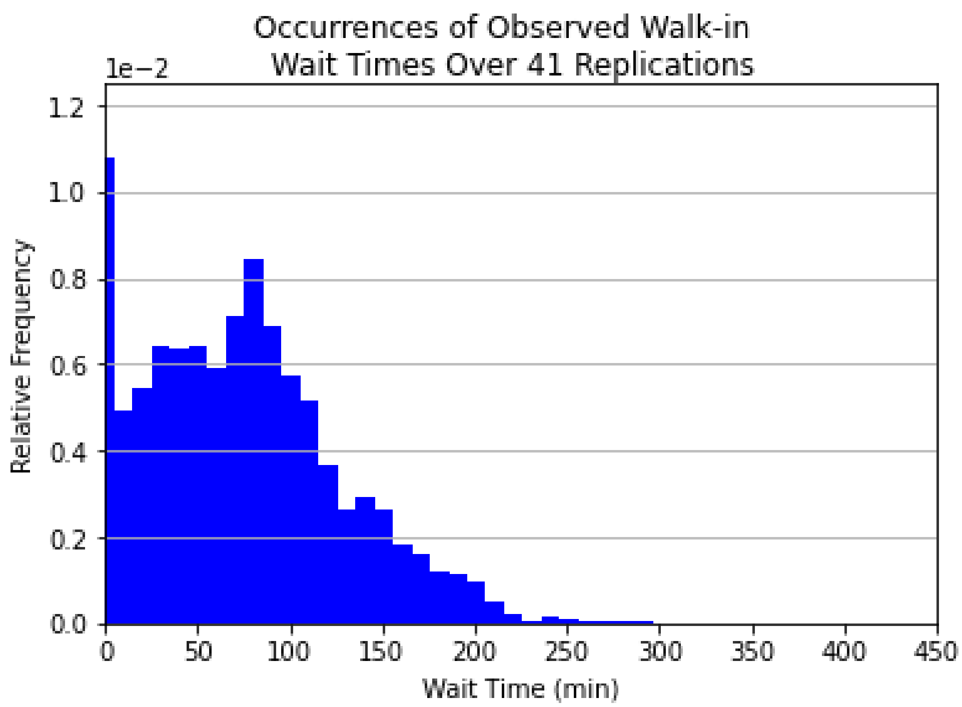

Figure 4. Frequency of walk-in customer wait times observed in 41 replications of the model.

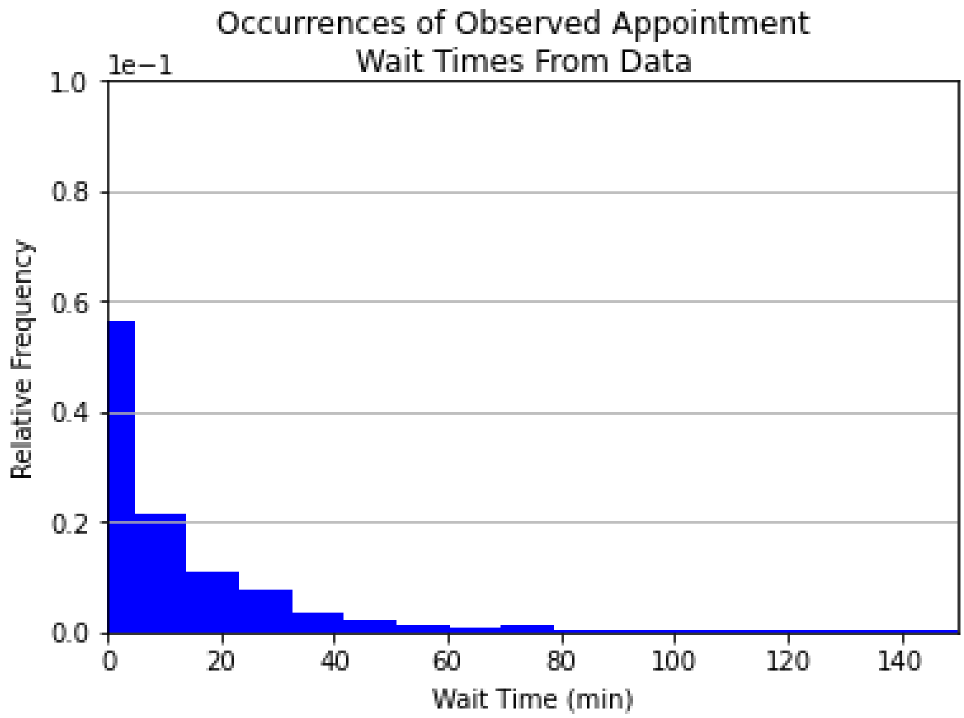

Figure 5. Frequency of appointment customer wait times observed in the L-E MPF data.

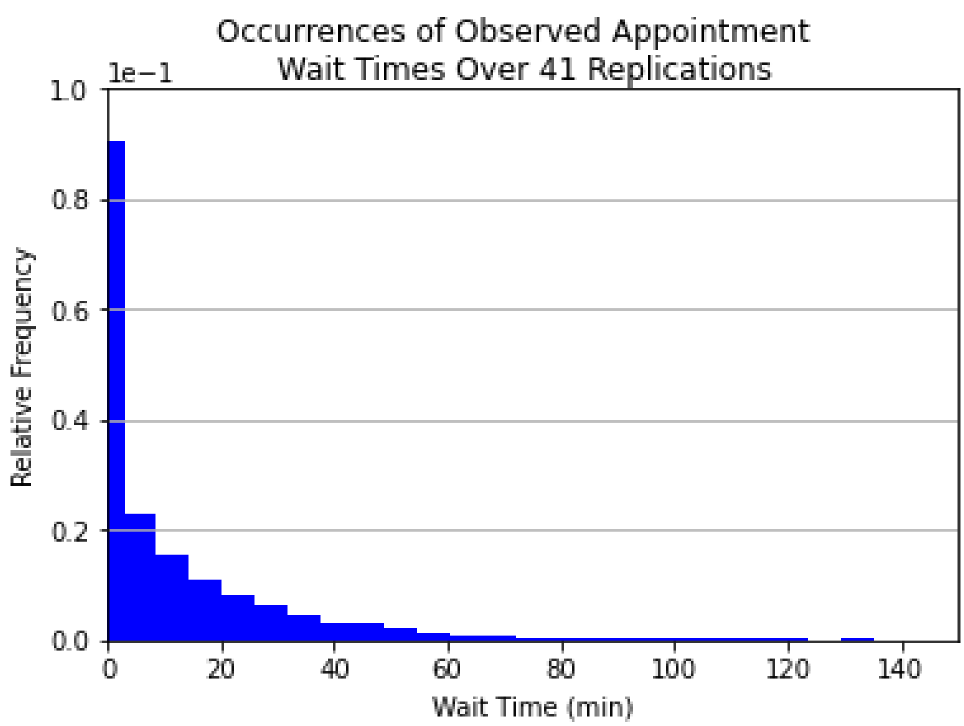

Figure 6. Frequency of appointment customer wait times observed in 41 replications of the model.

information while attempting to mimic a real-world MPF. This section presents the assumptions made and the reasoning behind each one.

1. The MPF opens everyday at 0730. In reality, some customers do arrive before 0730, but are modeled as loiters and enter the system at 0730.

2. Appointments are fully booked every day. Otherwise, available appointments would be reserved by any of the walk-in customers.

3. The skill level of all employees is the same. In reality, each employee has varying levels of proficiency at each task; however, the same employees do not work everyday. To account for the variation of employee proficiency, a random draw from the empirical distribution of service times in the data is used to determine how long each service lasts.

4. There will always be a lower bound on employees on shift at any time during the workday. This is because employees should be available for the entire duration of daily MPF operations.

5. During lunch hours (1100-1300), it is assumed that the employees make the appropriate lunch accommodations so that the number of employees on shift does not drop below the lower bound of employees.

6. The MPF will close the doors to new arriving walk-in customers at 1600 each day, but employees will always stay until the last customer in the system for that day has been serviced or 1930 hours, whichever is earlier. At 1930 hours, the remaining customers in the queue exit the system unserved. This assumption allows for the rare occurrence of an employee staying several hours past closing before departing, an event which is reflected in the original data. This cutoff was chosen to allow for employees to leave work by a reasonable time.

7. Service times greater than 180 minutes are likely an error in data entry. These data entries often came in groups and looked like they had been retroactively added to the data or that the operator did not check the customer out until the next morning.

8. Customers leave the system immediately following service. This does not allow for multiple services for a customer. The data only shows one service for each customer, so the addition of further services cannot be supported by the data. While in reality, some customers likely did show up for multiple services, the service time for those customers is present in the empirical distributions used to construct the model.

9. Due to the unavailability of DEERS reliability data, DEERS failures have been assumed to follow an exponential distribution with an average of 12 hours between failures; the restoration of DEERS service is assumed to follow an exponential distribution with an average of 15 minutes.

10. Due to the unavailability of check-in duration data, check-in durations are a constant one minute for each customer.

11. Services that are in progress when a DEERS failure occurs are not suspended. Here, we assume that any time waiting for DEERS restoration is accounted for in the service times in the original data.

12. An appointment customer waiting an unreasonable amount of time after their scheduled appointment time is serviced next. An unreasonable amount of time is assumed to be 15 minutes. These assumptions come from the notion that customer service will try to keep their scheduled appointments on track in an attempt to not fall behind.

13. Data entries occurring on a weekend represent a different population of customers than the weekday customers and are excluded from this analysis.

14. Data entries with an arrival time before 0700 or after 1600 were assumed to be an error in data entry. This is due to the normal operating hours and accounting for a 30-minute grace period where the MPF could have possibly opened for service early.

15. The reduction of employee or terminal resources to the model will increase the mean wait time. This is reasonable because reducing their totals would reduce the number of customers that can be served throughout the day.

3.4 Data

The input data for this model was collected at Langley-Eustis AFB MPF starting 10 April 2018 and concluding on 29 April 2019 and contains $29,733$ data points. The data captures twelve characteristics on each customer that arrived during that time period. The data used to develop and validate the model include: *Date*, *Check-In Time*, *Time Service Starts*, *Service Type*, *Minutes Serviced*, and *Appointments*. Previous work (Cornman, 2020) used the same data but modeled service times using triangular distributions and did not account for varying arrival times throughout the day. Upon reevaluation, a non-homogeneous Poisson process for arrival times was fit to the data with 30-minute intervals throughout the time the MPF is servicing customers. Additionally, service times were reexamined and used to generate empirical distributions for each service type.

The process of preparing data for analysis by removing or modifying data that are incorrect, incomplete, irrelevant, duplicated, or improperly formatted, is called *data cleaning*. This section describes the actions taken on the raw data to clean it and generate the arrival and service time distributions.

To create the arrival distributions, the data was cleaned starting with the raw data. The raw data was cleaned a second time to create service time distributions, entirely separate from the arrival distributions. This duplication of effort maximized the amount of usable data for both the arrival and service times. This allowed the use of rows that had invalid or incomplete data, such as a missing service time, but still had a valid arrival time, or vice-versa. Each set of cleaned data maintained over 90% of the original data. Proportions of the data used to create the model are shown below in Table 5.

Table 5. Proportions of Data Used After Cleaning

Type of Distribution	Proportion
Walk-In Arrivals & Loiters	0.915
Service Times	0.975
Walk-In Wait Times	0.964
Appointment Wait Times	0.974

For arrival times, any customers that were logged as arriving prior to 0700 were excluded as the MPF did not open that early and these points were more likely data with incorrect arrival times. Similarly, any arrivals logged after 1600 were excluded. Additionally, some entire days were removed as they did not contain an entire workday of data, contained implausible entries (e.g., consecutive customer wait times oscillating between zero minutes and four hours), or were influenced by a holiday and not representative of a normal weekday (e.g., Christmas Eve).

For service time durations, entries over 180 minutes were excluded. This modification follows from the assumption that service times greater than 180 minutes are likely to have been an error in data entry. Additionally, service times entered as zero minutes were rounded to one minute to account for service that began and ended before the clock progressed a minute.

One final adjustment was made to service times to account for some ambiguity in the data. One service type is labeled as *Appointment Only* and leaves out any mention of what actual service was conducted. Additionally, some entries have a service type and also indicate in the *Appointments* column that the customer had an appointment. In creating the empirical service distribution for the *Appointment* service, all entries containing that service type, as well as any points indicating an appointment in the *Appointments* column, were considered. For all other empirical service type distributions, all entries containing each respective service type were considered, regardless of what was indicated in the *Appointments* column. A small portion of entries were labeled as *Appointment Only* but indicated a *No* in the *Appointments* column; these were considered to be appointments.

The wait times from the data were cleaned in a similar way as arrival times. First, customers arriving prior to 0700 or after 1600 were removed. Next, any wait time that began prior to 0730 was recalculated to be the wait time once service began for that day. The final action was removing any wait times that were greater than the length of the workday or otherwise illogical in the context of the data collection (e.g., the first customer of the day was not serviced for several hours).

3.5 Verification & Validation

Building just any model is not enough to gain insight. It is important to build the correct model and accomplish the necessary actions to ensure it imitates the system of interest. These necessary actions are a process called *verification & validation* (V&V). Sargent defines *verification* as "ensuring that the computer program of the computerized model and its implementation are correct" (Sargent, 2013). Verification ensures that the actions taking place in the model are the developer's intended actions. Sargent defines *validation* as "substantiation that a model within its domain of applicability possess a satisfactory range of accuracy consistent with the intended application of the model." Validation ensures the model outputs are within a tolerance of the measurements of interest that exist in the real system. The process of conducting V&V is an iterative process throughout the development of the model.

It can be expensive in terms of resources to develop a model that imitates the real system as much as possible. Because of this, several different tests and evaluations were conducted to build sufficient confidence that the model works for its intended application. This section describes the different methods Sargent suggests for verifying and validating a model.

3.5.1 Subjective Methods

Subjective V&V methods are those that do not involve a mathematical or statistical procedure. These methods involve observations of the model under certain conditions or over time periods. Every type of scenario cannot be observed for correctness, but the modeler uses their best judgement to ensure that important design points are examined before the model is considered verified and validated.

The V&V process began with discussions with subject-matter experts that understand how an MPF works. The information gathered was used to construct the conceptual model using the appropriate conditions upon which the data was collected. These first steps helped develop the foundation upon which the V&V stands. Without the right parameters of the system when the data was collected, any analysis would be tenuous.

One method Sargent (2013) describes is observing *animation*. Sargent describes animation as "the model's behaviour is displayed graphically as the model moves through time.” The Simio software has graphical animations of the system that allow users to see what is happening throughout the simulation. This technique was used extensively during construction to ensure that entities flowing through the system are doing what the modeler intended, as well as what actually happens when a real customer flows through a real MPF. Animation was also used to ensure server and resource capacities were not violated and the values of state variables were set correctly at different times in the simulation.

A more in-depth method called *tracing* is used to ensure that model logic is correct. Sargent describes tracing as “the behaviour of a specific type of entity in a model is traced (followed) through the model to determine whether the model’s logic is correct and if the necessary accuracy is obtained.” Tracing provides a look behind the animation to see how the model is evaluating logic as the simulation runs. Simio has a trace capability that shows the checks within processes as a simulation progresses. This tool was used to verify that different types of entities in various scenarios were processing through the system as expected and that the model was accomplishing the correct processes for the current conditions. Because the trace contains too many entries to do an exhaustive check, filters were applied to observe when specific events occur. For example, in the case of a resource constraint, the model should be servicing the next customer in the queue that can be immediately helped. This is checked by filtering for the events where a resource constraint exists and verifying the model logic was evaluated correctly.

Additionally, the use of *operational graphics* were implemented as visual aids to watch dynamic information change throughout the simulation. The primary use of this technique was to ensure that customer proportions were being generated according to the proportions in the data. Table 6 shows the outputs of the operational graphic at the end of one replication compared to the actual proportions from the L-E data.

Table 6. Proportions of Walk-in and Loiter Types — L-E Data & Simulated

Service Type	Data Proportion	Simulated Proportion
CAC (Other)	0.402	0.413
Dependent ID	0.215	0.198
CAC PIN Reset	0.214	0.235
DEERS Update	0.067	0.049
Retiree ID	0.047	0.056
Marriage/Divorce	0.024	0.032
Other	0.017	0.007
Questions	0.008	0.0005
MilPDS Update	0.006	0.005

Sargent also describes *degenerate testing*, where values that result in degenerate behavior are input into the model to ensure that degenerate behavior is exhibited as expected. One test consisted of ensuring the queue grew without bound when inducing arrivals faster than the servers can manage.

Similar to the previous method, *extreme condition testing* is checking the outputs of a model when given extreme or unlikely values. When testing the scenario where resource capacities were greatly increased, the average wait time decreased to nearly zero, which is expected. Additionally, when resources were severely limited, the model showed a large increase in wait times.

3.5.2 Objective Methods

V&V would not be complete without an objective test. For Sargent's *internal validity*, two statistical hypothesis tests were conducted using the model with baseline parameters: one for mean walk-in wait time, and one for mean appointment wait time. After each interval is constructed, they are compared against the collected real-world data with the desired outcome being that the interval contains the value from the collected data. For this model, the measures of interest are the mean wait times for each of the appointment customers and the walk-in customers. These intervals are constructed using $\alpha = 0.05$.

An absolute precision of a five minute half-width was chosen for each interval. The decision to use five minutes was arbitrary but is a common acceptable window in society. The model was run for ten replications to obtain an initial estimate for the population variance. This estimate was then used to determine how many additional replications were needed to achieve the desired precision for both intervals, according to

$$R \geq (\frac{z_{\alpha/2} S_0}{\epsilon})^2. \tag{1}$$

In (1), $z_{\alpha/2}$ is the critical t-value, S_0 is the sample standard deviation after the initial ten replications, R is the number of total replications needed, and ϵ is the desired precision. Using Equation 1, we determined that an additional 31 replications were needed for a total of 41 replications. The intervals capture both of the means from the data, so the model passes this test for validation.

Table 7 shows the results of the simulation after 41 replications.

Table 7. 95% Confidence Interval on Mean Wait Times — Baseline Model ($n = 41$)

Measure of Interest	Mean (Data)	Mean (Simulation)	Interval
Mean Wait Time - Appointment Customers	14.90	13.66	(12.19, 15.14)
Mean Wait Time - Walk-In Customers	76.40	74.94	(69.65, 80.23)

3.5.3 Summary of V&V

Sargent states "there is no set of specific tests that can easily be applied to determine 'correctness' of a model." However, his methods provide confidence that this model is sufficient for the task of analyzing MPF wait times. The process of V&V indicates the model is doing what it is intended to do and that its outputs are within a statistical tolerance of the real-world data.

3.6 Summary

This chapter covered the methodology that was utilized to create a DES of a USAF MPF, including how the model logic was built, criteria for cleaning the Langley-Eustis MPF data, the V&V process, and the limitations that exist. The next chapter explores how this model was used to answer the research questions from Chapter 1.

IV. Analysis

The creation of a verified and validated model allows the testing of different scenarios to gain insights and to identify possible changes in the measures of interest. For this particular model of the Langley-Eustis MPF, we want to observe any changes to wait times for customers when we modify resource capacities or policies to help answer each research question posed in Chapter 1. A full factorial experimental design was generated and each design point was simulated in Simio. The simulation outputs of every design point were then used in a regression analysis where insights were gleaned regarding the relationships between variables. Additionally, several alternative scenarios were hypothesized, simulated, and analyzed to identify if one or more of the alternatives can help reduce mean wait times. Finally, a data excursion was conducted to observe the results of the simulation when an additional machine is added to the check-in kiosk that is able to accomplish CAC PIN resets. The analysis of each scenario and excursion will answer the first and second research questions and the regression analysis will answer the third research question (Section 1.3). This chapter explains the design of the experiments, regression, the selected design points, one analytical excursion, and the results.

4.1 Experimental Design

The Simio software can run as many scenarios as desired, as long as the time and computing power are not constrained. This allowed the implementation of a full factorial experimental design for this MPF simulation. Factors were determined by the likely impact they may have on the mean wait times for customers in the model, while the levels of each factor, or factor levels, were determined as a range of values that seemed reasonable to implement.

4.1.1 Factors & Factor Levels

For the design of this experiment, five factors were selected: the numbers of walk-in terminals, appointment terminals, total employees, employees to remain on shift during lunch hours (1100-1300), and the *Appointment Wait Threshold*. Each of these factors can be modified in the simulation and may affect the mean wait times for customers in the simulation.

The factor levels for each factor are shown in Table 8. Some combinations of factor levels would only require shifting current resources or policies in an actual MPF, however most combinations would require an MPF to acquire additional resources.

Table 8. Factors and factor levels for the full factorial design of the MPF model

Factors	Factor Levels
Number of Appointment Terminals	0, 1, 2, 3, 4, 5, 6
Number of Walk-In Terminals	0, 1, 2, 3, 4, 5, 6
Number of Employees	5, 6, 7, 8
Number of Lunch Time Employees	3, 4, 5
Appointment Wait Threshold (minutes)	0, 5, 10, 15, 20

When the number of appointment terminals was changed from one, the arrival rate of walk-in customers was scaled proportionally (Table 9). Because the appointments are always fully booked, the number of appointment customers scales proportionally with the number of appointment terminals. The final assumption here is that when five or more terminals are designated for appointments, the MPF is closed to walk-in customers.

The full factorial design considered every possible combination of *feasible* factor levels. Infeasible combinations were omitted, namely those where the number of lunch time employees was greater than total employees. Also omitted were design points where fewer employees than designated appointment terminals existed, as those

Table 9. The scaled rate of walk-in customers based upon the number of designated appointment terminals

Number of Appointment Terminals	Scaled Rate
0	1.25
1	1
2	0.75
3	0.5
4	0.25
5 or more	0

combinations are unlikely to be used in a real MPF. The last set of omitted design points were redundant points that occurred when the MPF was appointment only, but gained additional walk-in terminals. In total, 220 design points were omitted and 2720 were used for analysis. The number of replications for each design point ranged from 10 to 650 to achieve an absolute precision of five minutes. Confidence intervals were not obtained for each scenario, however, enough replications were completed to ensure the mean wait times were within a statistical tolerance of five minutes. The outputs of the simulation, including mean wait time for appointment and walk-in customers, are used to conduct the rest of the analysis in this chapter.

4.2 Regression

Regression helps identify and characterize the relationships between inputs and responses. Using regression for this problem helps determine which parameters influence the mean wait time for an MPF and the magnitude of the effects. This section utilizes partial first derivatives to analyze how modifying different factor levels affects the mean wait times.

The regressors in this regression analysis are the input parameters for the simulation model (Table 8). The response variable is the mean wait time for customers, however the data show a large difference between how long walk-in customers wait and how long appointment customers wait. Because of this, we split mean wait time into two different response variables — the mean wait time for walk-in customers and the mean wait time for appointment customers — and accomplished two separate regression analyses.

The full factorial design results in a wide variety of design points. The design points used to generate this regression analysis happen to only be cases in which the MPF keeps the same amount of resources as the baseline model, but shifts them around, or where the MPF gains resources. A loss of resources was not accounted for in the regressions to restrict the domain to alternatives that would not increase mean wait times. The 2,720 design points and their outputs from the factorial design were migrated into the JMP software to generate each regression.

4.2.1 Mean Wait Time — Walk-In Customers

Building the regression formula to analyze the mean wait time for walk-in customers started by using every variable and interaction term available — up to four-way interaction and up to third-power polynomial terms. From that point, a backwards regression was performed.

The response variable, mean walk-in wait time, was transformed using the natural logarithm function such that the model's estimation for the mean walk-in wait time is e^{W_w}. The resulting regression equation is

$$9.492 - 0.266x_1 + 0.088x_2 - 1.132x_3 - 0.074x_1x_3 + 0.064x_1^2 + 0.078x_3^2 = W_w \quad (2)$$

where the log mean walk-in wait time (W_w) is expressed as a function of the numbers of walk-in terminals (x_1), appointment terminals (x_2), and employees (x_3). Table 10 shows the detailed regression parameter estimates. In addition to the first-order terms, there is one interaction term between x_1 and x_2 and two second-order polynomial terms — one for x_1 and another for x_3.

Table 10. Parameter estimates for the regression to estimate the mean wait time for walk-in customers when at least two terminals are designated for walk-in customers

Term	Estimate	Error	t-ratio	p-value
Intercept	9.492	0.334	28.45	<0.0001
Walk-in Terminals (x_1)	-0.266	0.036	-7.39	<0.0001
Appointment Terminals (x_2)	0.088	0.005	19.21	<0.0001
Number of Employees (x_3)	-1.132	0.010	-11.34	<0.0001
x_1x_3	-0.074	0.004	-17.75	<0.0001
x_1^2	0.064	0.003	20.37	<0.0001
x_3^2	0.078	0.008	19.21	<0.0001

This regression model has an $R^2 = 0.796$ and is statistically significant, with $p < 0.0001$, which indicates that at least one of the regression coefficients can explain the response variable. Additionally, each of the parameter estimates are statistically significant with $p < 0.0001$.

The addition of walk-in terminals lowers the response, which is an intuitive effect because more available terminals will allow more customers to be serviced simultaneously. Similarly, hiring more employees to service customers also lowers the response. However, adding appointment terminals and holding all other factors constant marginally increases the mean walk-in wait time, perhaps due to the increased allocation of resources away from walk-in customers. By changing the single appointment terminal in the baseline model to a walk-in terminal, the estimated mean walk-in wait time changes from 75.9 minutes to 65.5 minutes. The first order effects make sense on the surface, but the second-order polynomial terms and the interaction need to be taken into account to understand the full effect.

Partial derivatives show the instantaneous rate of change when increasing the respective variable. The partial first derivatives of the regression function help identify the relationships between the variables when the regression formula includes interaction terms or polynomial terms. While the first derivative shows the *instantaneous* rate of change and not the exact amount of change received, the values of the partial derivatives show the direction the response variable is trending when changing the respective variable. These trends show the relationships between the regressors and themselves, as well as between the regressors and the response variable.

The first derivative of the regression function shows the change in the response with respect to the change the chosen variable. The partial first derivative must be taken twice, once for x_1 and another time for x_3. The first partial derivative with respect to x_1 is

$$\frac{\partial y}{\partial x_1} = -0.266 - 0.074x_3 + 0.128x_1 \tag{3}$$

and the first partial derivative with respect to x_3 is

$$\frac{\partial y}{\partial x_3} = -1.132 - 0.074x_1 + 0.156x_3 \tag{4}$$

.

Both partial first derivatives have a similar form, however Equation 4 shows that the number of employees (x_3) has over double the impact on mean walk-in wait time than number of walk-in terminals (x_1) in the domain of values tested (Table 8). In both partial first derivatives, the interaction term has a negative coefficient and the second-order term has a positive coefficient. These values indicate that a large increase in one term, while holding the other term constant, will have a smaller impact than the impact the estimate would receive if there was a small increase to both terms. One takeaway is that the increase in mean wait time from each equation is offset by the magnitude of the other variable. In other words, it helps to increase both the number of walk-in terminals and employees by one, as opposed to an increase of two or more to one of the variables.

Table 11. Regression estimates for mean walk-in wait time when modifying the baseline parameters

Modification	Walk-in Terminals (x_1)	Appointment Terminals (x_2)	Employees (x_3)	Regression Estimate (mins)	Percent Change
Baseline	4	1	5	81.0	N/A
x_1 + 1	5	1	5	77.1	-4.8%
x_2 + 1	4	2	5	88.4	+9.2%
x_3 + 1	4	1	6	45.8	-43.4%
x_1 + 1 & x_3 + 1	5	1	6	40.5	-50.0%

Table 11 shows regression estimates for mean walk-in wait time and the percent change from the baseline. Each row shows the regression estimate when each factor is increased by one, except the last row where both x_1 and x_3 are increased by one. These results help corroborate the importance of increasing the number of employees before adding any terminals. Notably, adding a walk-in terminal has a marginal reduction on the estimated mean walk-in wait time while adding an appointment terminal increases the estimate.

4.2.2 Mean Wait Time — Appointment Customers

Similar to the regression analysis for mean walk-in customer wait times, we began with every possible regressor and used backwards regression to remove insignificant regressors. As before, the response variable, mean appointment wait time, was transformed by the natural logarithm function. The estimate for mean appointment wait time is e^{W_a}. The resulting regression equation is

$$3.404 + 0.412x_2 - 0.212x_3 - 0.115x_4 - 0.094x_2x_4 = W_a \tag{5}$$

where the log mean appointment wait time is expressed as a function of the numbers of designated appointment terminals (x_2), employees (x_3), and the minimum number of employees during lunch time (x_4). Table 12 shows the detailed regression parameter outputs.

Table 12. Parameter estimates for the regression model to estimate the mean wait time for appointment customers

Term	Estimate	Error	t-ratio	p-value
Intercept	3.404	0.061	56.14	<0.0001
Appointment Terminals (x_2)	0.412	0.013	32.89	<0.0001
Number of Employees (x_3)	-0.212	0.006	-37.31	<0.0001
Minimum Lunch Time Employees (x_4)	-0.115	0.014	-8.49	<0.0001
x_2x_4	-0.094	0.003	27.64	<0.0001

This regression model has an $R^2 = 0.820$ and is statistically significant at $p < 0.0001$, which indicates that at least one of the regression coefficients can explain the response variable. Further, each regression coefficient in the model is statistically significant with a $p < 0.0001$.

The coefficients show that increases in each factor reduce the mean wait time, with the exception of the term for appointment terminals. As with mean walk-in wait times results, the number of employees have the largest effect on reducing mean appointment wait times. The positive term for appointment terminals is explained by the interaction term with the minimum number of lunch time employees. The first partial derivative with respect to x_2 is

$$\frac{\partial y}{\partial x_2} = 0.412 - 0.094x_4 \tag{6}$$

and the first partial derivative with respect to x_4 is

$$\frac{\partial y}{\partial x_4} = -0.115 - 0.094x_2 \tag{7}$$

.

Equation 6 shows that by adding an additional appointment terminal, mean appointment wait time will rise, unless it is offset by at least five employees working through lunch. Because the simulation model schedules appointments during lunch hours, the reduction in manning creates a bottleneck that increases the mean appointment wait time. Equation 7 is important because it shows that increasing the minimum lunch time manning will reduce appointment wait times, because there is a negative intercept and a negative coefficient for the x_2 term.

Table 13. Regression estimates for mean appointment wait time when modifying the baseline parameters

Modification	Appointment Terminals (x_2)	Employees (x_3)	Minimum Lunch Time Employees (x_4)	Regression Estimate (mins)	Percent Change
Baseline	1	5	3	8.4	N/A
$x_2 + 1$	2	5	3	9.6	+13.8%
$x_3 + 1$	1	6	3	6.8	-19.1%
$x_4 + 1$	1	5	4	6.8	-18.8%
$x_3 + 1$ & $x_4 + 1$	1	6	4	5.5	-34.4%

Table 13 shows the regression estimates and percent change in mean appointment wait time from the baseline. As expected, adding an appointment terminal does increase the estimate because there are too few employees during lunch time. Increasing total employees provides the largest reduction, however an increase to minimum lunch time manning gives close to the same effect. Combining those two changes almost doubles the reduction.

4.2.3 Regression Insights

The regression analysis indicates that the number of employees typically has the largest effect on reducing the mean wait time for walk-in and appointment customers, however, the other terms should be taken into account when considering changes. For mean walk-in wait time, increasing the total number of employees while simultaneously increasing the number of walk-in terminals is beneficial because of the way they interact. For mean appointment wait times, total employees also has the largest reduction, but the bottleneck caused by the minimum number of lunch time employees does have a powerful impact, as well. Employees are important to both measures of interest because they are a shared resource between the two customer types. Hiring more employees is an intuitive solution to reducing mean wait time, but it is important to keep in mind that the total throughput of appointment customers is fixed by the number of appointment terminals.

The mean appointment wait times are not very high relative to the mean walk-in wait times. In the baseline model, the mean walk-in wait time is over five times greater than the mean appointment wait time and because there is only one appointment terminal, there are many more walk-in customers to be served. The total time saved will likely be greater when attention is given to the mean walk-in wait times. Adding to the importance of the total number of employees, x_3 does show up in both regression formulas and provides the largest reduction to mean waiting times per unit increase in both. The analysis indicates that by investing in an additional employee, mean walk-in wait time would be reduced by 43.4% and mean appointment wait time would be reduced by 19.1%.

4.3 Design Point & Data Excursion Analysis

4.3.1 Design Point Analysis

Some select design points from the experimental design are highlighted in this section due to the minor changes required to implement them into an MPF. The simulation outputs from each selected design point are examined in this section. The number of replications for each design point was calculated, separate from each other, to achieve an absolute precision of five minutes at the 95% confidence level after running 10 initial replications. Table 14 shows the parameters used in each scenario, and Tables 15 and 16 show the results.

The first design point is adding one employee and one walk-in terminal. This should naturally reduce wait times but comes at the cost of hiring a new employee and purchasing an additional terminal.

The second design point is increasing the lunch time manning from three employees to four. This scenario has the potential to cost nothing except the effort to ensure employees have sufficient time for their lunch break, and it will likely decrease mean wait times as the bottleneck caused by the lunch time manning is widened.

The third through sixth design points modify the number of terminals designated for appointments from anywhere between two and five, inclusive. As in the regression analysis, an assumed proportional decrease in the arrival rate of walk-in customers is applied based on how many terminals are designated for appointments (i.e., 25% decrease from the baseline per additional appointment terminal) (Table 9). These scenarios could highlight an optimal number of designated appointment terminals when only five total terminals exist.

The seventh design point modifies the *Appointment Wait Threshold* from fifteen minutes to zero minutes. This requires appointments be serviced as soon as their appointment time passes and resources become available. This should reduce the mean appointment wait time but may potentially increase the mean walk-in wait time.

While the model was not validated on mean maximum wait times (i.e., the mean of each replication's maximum wait time), those values are included in Appendix B to highlight the effect these scenarios do have on the model. The focus of this analysis

Table 14. Selected Design Point Model Parameters

Scenario	Walk-In Terminals	Appointment Terminals	Employees	Lunch Employees	Appointment Wait Threshold (mins)
Baseline	4	1	5	3	15
1	5	1	6	3	15
2	4	1	5	4	15
3	3	2	5	3	15
4	2	3	5	3	15
5	1	4	5	3	15
6	0	5	5	3	15
7	4	1	5	3	0

Table 15. Selected Design Point Estimates — Walk-in Wait Times

Scenario	Mean Walk-in Wait Time	Percent Change	Regression Walk-in Wait Time	Percent Change
Baseline	74.9	N/A	81.0	N/A
1	33.3	-55.5%	40.5	-50.0%
2	59.0	-21.2%	81.0†	0.0%
3	155.3	+107.3%	105.5	+30.3%
4	284.3	+279.6%	156.3	+93.1%
5	415.0	+454.1%	263.2	+225.1%
6	N/A	N/A	N/A	N/A
7	75.4	+0.6%	81.0†	0.0%

† The factors in the regression formula are the same as the baseline parameters for these design points.

Table 16. Selected Design Point Estimates — Appointment Wait Times

Scenario	Mean Appointment Wait Time	Percent Change	Regression Appointment Wait Time	Percent Change
Baseline	13.7	N/A	8.4	N/A
1	10.2	-25.9%	6.8	-19.0%
2	12.4	-9.5%	6.8	-19.0%
3	8.8	-35.8%	9.6	+14.3%
4	7.4	-46.0%	10.9	+30.0%
5	9.2	-32.8%	12.4	+47.6%
6	13.2	-3.7%	14.1	+67.9%
7	5.5	-59.9%	8.4†	0.0%

† The factors in the regression formula are the same as the baseline parameters for these design points.

is on mean wait times, therefore other possible effects to the system are outside the current scope of work.

4.3.2 Scenario Comparisons

Table 15 results indicate that the only reductions in mean walk-in wait time from the baseline scenario happen in scenarios 1 and 2. Table 16 results indicate that scenarios 1 and 7 have the largest decrease to mean appointment wait times, while not increasing the mean walk-in wait time from the baseline. All other scenarios either increase the mean walk-in wait time or have a negligible effect on the mean appointment wait time. With this information, four comparisons are made against the baseline scenario's outputs to identify which scenarios reduce mean wait times and by how much. The four comparisons are scenario 1 and 2's mean walk-in wait times, and scenario 1 and 7's mean appointment wait times. The mean appointment wait time for scenario 2 and the mean walk-in wait time for Scenario 7 were omitted from the confidence interval analysis to minimize the number of tests computed to increase the statistical power of those tests.

Common random numbers were used for each design point to reduce the variance and thereby improve the comparisons. Using common random numbers means every scenario will be exposed to the same random number streams. This helps reduce the variance between scenarios to achieve more narrow confidence intervals. However, the use of common random numbers makes the samples not independent of each other. Because of this, each comparison was done with a paired t-test. Table 17 shows the 95% joint confidence intervals for the difference between the experimental scenarios and the baseline model. We are 95% confident that the actual difference in mean wait times between the scenario are the baseline are contained in each interval, therefore any scenario's interval that only contains numbers strictly less than zero can be said to reduce the mean wait time.

Table 17. 95% Joint Confidence Intervals — Difference Between Experimental Scenarios and Baseline

Scenario	Mean Walk-In Wait Time (mins)	Mean Appointment Wait Time (mins)
1	(-43.1, -25.0)	(-13.1, -3.6)
2	(-20.7, -1.4)	—
7	—	(-10.0, -6.3)

Based on the results, in Table 17, scenario 1 reduces both the mean walk-in wait time by between 25.0 and 43.1 minutes and the mean appointment wait time by between 3.6 and 13.1 minutes. Scenario 1 requires the addition of a terminal and employee, which may be prohibitively expensive. However, the magnitude of the mean walk-in wait time reduction, at least 25 minutes, is relatively large compared to the simulated baseline model's 74.9 minutes and the data's 76.4 minutes.

Additionally, scenario 2 reduces the mean walk-in wait time by between 1.4 and 20.7 minutes. Scenario 2 utilizes the current resources of the MPF and only requires shifting lunch time employees to ensure that at least four employees are working during lunch time.

Lastly, scenario 7 reduces mean appointment wait time by between 6.3 and 10.0 minutes. This scenario also utilizes only the currently available resources of the MPF but adjusts how appointment customers are handled upon arrival.

4.3.3 Excursion — CAC PIN Reset Station at Check-In

This analytical excursion explores the addition of a CAC PIN reset station at the check-in kiosk. This design change uses the same parameters from the baseline model but adds the functionality for a CAC PIN reset to be accomplished while a customer is checking into the MPF for service. This functionality was implemented in the simulation model by immediately transferring customers that require a CAC PIN reset from the check-in kiosk to the CAC PIN reset service node without the seizure of an employee or terminal. If another customer requiring a CAC PIN reset arrives while the additional CAC PIN reset station is in use, they are transferred to the normal waiting room until either the CAC PIN reset station is available or until resources become available to help them as usual, whichever comes first.

Table 18 shows the simulation outputs after 20 replications of the model to achieve an absolute precision of five minutes. The mean maximum wait times are included in Appendix B to highlight the effect of this modification on metrics from the model.

This excursion was also compared to the baseline scenario using a paired t-test. The comparison was only done on the mean walk-in wait times to keep a 95% joint confidence level with the intervals in the previous section. The 95% joint confidence interval on the difference between the excursion and the baseline is (-38.5, -21.6).

Table 18. **CAC PIN Reset Station at Check-in — Simulation Outputs**

Scenario	Mean Walk-In Wait Time (mins)	Percent Change	Mean Appointment Wait Time (mins)	Percent Change
Baseline	74.9	—	13.7	—
Excursion	40.1	-46.5%	10.9	-20.4%

With 95% confidence, the addition of a CAC PIN reset machine at the check-in kiosk would reduce the mean walk-in wait time between 21.6 and 38.5 minutes.

4.3.4 Design Point & Excursion Insights

The design point analysis showed three alternative scenarios with statistically significant reductions in mean wait times. While the two largest differences come from a scenarios that have a cost to implement, two of the design points require no additional funds to implement. The increase of minimum lunch time manning from three to four employees showed a reduction in the mean walk-in wait time by between 1.4 and 20.7 minutes. Additionally, servicing appointment customers as soon as possible once their appointment time has passed, reduced mean appointment wait times by between 6.3 and 10.0 minutes.

Further, the analytical excursion showed that by adding a CAC PIN reset machine at check-in, the mean walk-in wait time could be reduced by between 21.6 and 38.5 minutes from the baseline model. This particular modification to an MPF would require some expenditures, including the purchase of a CAC PIN reset terminal and the hiring of an administrative clerk to work the check-in kiosk. However, this change is significant because it highlights how impactful it can be to expend resources servicing a common customer, one that accounts for over 20% of total customers. The data collected from Langley-Eustis shows that over 60% of CAC PIN resets take under ten minutes, while overall, 27% of service times are under ten minutes. This change is an attempt to focus effort towards a large proportion of the customer base that typically have shorter service times.

Figures 7 and 8 show the 95% confidence intervals for the differences in mean wait times from the baseline model. Appendix A graphically displays the simulated mean wait times for each scenario and excursion.

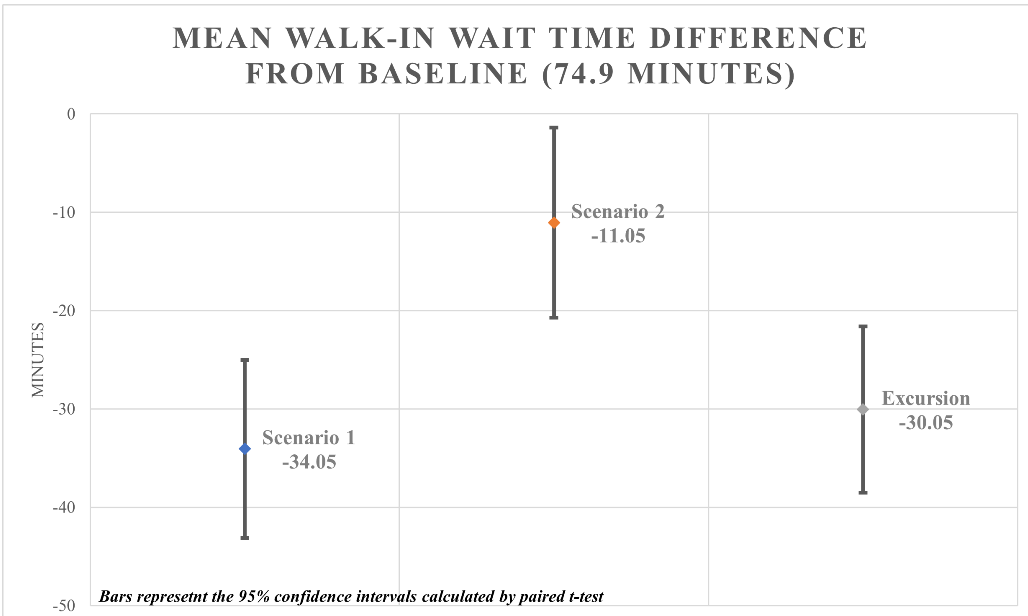

Figure 7. Shows the change in minutes from the baseline model mean walk-in wait time for scenarios 1, 2, and the analytical excursion to add a CAC PIN reset machine at check-in.

Lastly, the outputs from the simulation showed several alternative scenarios that would likely increase wait times. These scenarios were the reduction of walk-in terminals to three or fewer while increasing appointment terminals so that the total number of terminals remained at five. A notable exception is the scenario where walk-ins are no longer accepted and all customers must have an appointment. The simulation of this scenario showed similar outputs to the baseline model, but has the benefit of the MPF being able to control their total throughput and essentially regulate the "busyness" throughout the day.

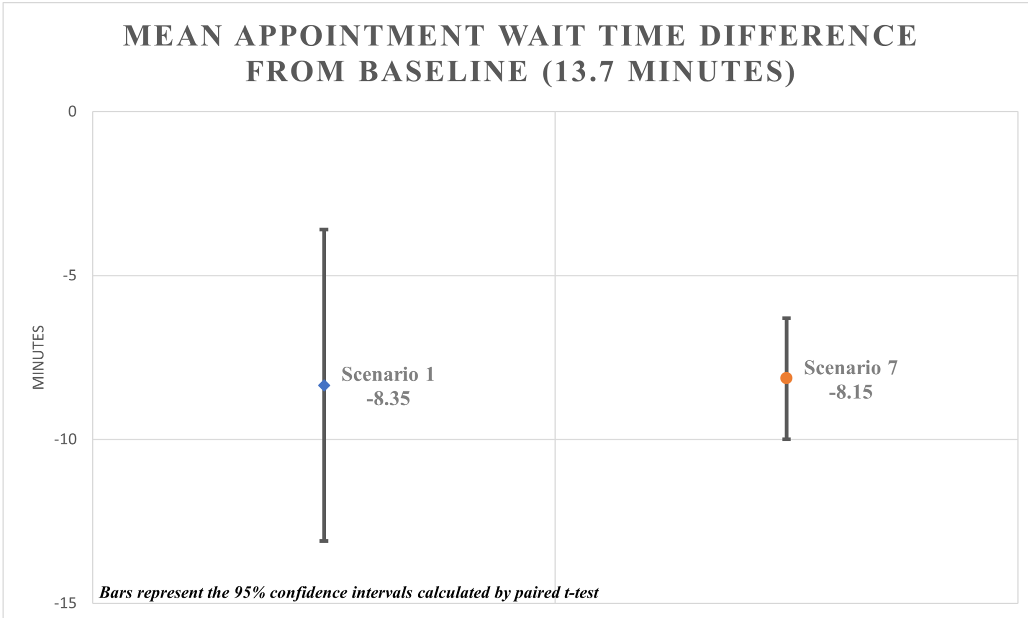

Figure 8. Shows the change in minutes from the baseline model mean appointment wait time for scenarios 1 and 7.

4.4 Summary

This chapter explored different analytical techniques applied to simulation outputs to gain insight into possible solutions aimed at reducing the mean wait time for customers in an MPF. The output of a full factorial experimental design was used to generate regression models that identify relationships between factors and their effects on mean wait times. The analysis showed that the total number of employees greatly affects the mean wait times, especially when combined with the addition of walk-in terminals. Additionally, several design points were selected for statistical comparison against the baseline model to highlight the potential changes in mean wait times when implementing reasonable alternative resource levels. The analysis in this chapter showed that the number of employees working usually has the largest effect on mean wait times. Additionally, it showed that increasing lunch time manning to four employees and immediate servicing of appointment customers were two policy alternatives that reduce mean wait times at no monetary cost to the MPF.

V. Conclusions

This chapter summarizes the initial problem statement, insights from Chapter 4, provides recommendations based on those insights, and presents several ideas for future work on the problem of high mean wait times at MPFs.

5.1 Revisiting the Problem

The problem examined in this research was motivated by long wait times for customers at MPFs and how those long wait times cost the USAF resources and hinder the overall USAF mission. Since customers cannot accomplish their USAF mission while waiting in an MPF, the cumulative man-hours spent waiting is a cost and a reason to resolve the problem of high wait times. Three research questions were posed in Chapter 1 and are repeated below:

1. What changes to an MPF achieve the largest reductions to mean wait time?
2. How much is mean wait time reduced if a resource is increased? (This could be hiring more employees or acquiring more DEERS terminals.)
3. What interactions exist between variable factors?

5.2 Summary of Insights

This analysis covered a regression approach to identify relationships between the controllable factors (Table 8) and the mean wait times, as well as how the factors interact with each other. Additionally, this analysis included statistical tests on several alternative design points and a different MPF setup that showed potential to reduce mean wait times. This section will first summarize the regression insights, and conclude with the design point statistical analysis insights.

5.2.1 Regression

The regression analysis provided several key insights, the first being that the total number of employees working has a profound effect on the mean wait times for walk-in and appointment customers. Further, there does exist a non-negligible amount of interaction between the total number of employees and the number of designated walk-in terminals. More specifically, it helps to increase the total number of employees, but it is more helpful to increase the total number of employees and the number of designated walk-in terminals simultaneously.

The regression analysis also showed that while increasing the number of walk-in terminals marginally reduces the mean walk-in wait time, increasing the number of appointment terminals increases the mean walk-in wait time. This is likely due to the increase in appointment customers it will cause, which will pull the shared resources (i.e., employees) away from the walk-in customers.

The final insight is the minimum number of lunch time employees creates a bottleneck that increases both mean wait times. It is important to consider how lunch time manning might affect customer wait times, especially if more appointments are scheduled than there are employees to service them.

5.2.2 Design Point & Excursion

The statistical analysis conducted on the selected design points and the analytical excursion identified four alternatives that reduce mean walk-in wait time, mean appointment wait time, or both (Table 17 & 18). The key insight gleaned is that the number of employees has the largest impact to mean wait time reduction, which reinforces what was shown in the regression analysis. Additionally, it was shown that there are policy changes that can be implemented to reduce mean wait times with no resources added to the MPF. The final insight is that using resources to streamline service to a large proportion of the customer base has a significant impact on the entire system.

5.3 Recommendations

The purpose of this research was to identify potential solutions to help reduce wait times at MPFs by analyzing the data collected at the Langley-Eustis MPF and using simulation to examine alternatives for MPF operations. The insights gained yield these recommendations for MPFs that have a similar current set up as the baseline model with high mean wait times.

The first recommendation is to hire one additional employee to work full time. Additionally, if possible, add a terminal for walk-in customers, however adding one employee should be the first priority. Adding one employee was shown to be extremely effective at reducing the mean walk-in wait time and mean appointment wait time in the simulation. While there is a cost to implement, the cost could possibly be offset by the number of man hours saved in wait time reduction.

The second recommendation is to increase the minimum number of lunch time employees from three to four. This change alleviates the impact of the lunch time bottleneck on the mean wait times with potentially no additional cost to implement.

The last recommendation is to consider shifting to a service model that accommodates appointments only. While this may lower total customer throughput, it will help remove the customer's uncertainty of not knowing how long they will have to wait and allow the MPF to regulate how many customers they want to serve in a day.

5.4 Limitations

This section identifies the limitations of this MPF DES as well as the model accommodations to reduce the impact on analysis.

This MPF was modeled for a normal 5-day work week with service starting at exactly 0730 and new arrivals being turned away after 1600. There are exceptions to these rules that are not modeled, such as the MPF opening earlier, or a walk-in customer arriving after 1600 and needing assistance before the start of the next business day. These exceptions likely have an impact on the mean wait time if they occur too often.

DEERS system time between failure and restoration are assumed, due to the absence of DEERS system reliability data. An hours-long DEERS system failure would certainly lead to much longer wait times in real life and skew any outputs from the model. The decision to have shorter DEERS system failures was to highlight the effects of short-term service stoppages that do exist without giving them too much influence.

Every data entry from the Langley-Eustis data has a *Check-In Time*, *Time Service Starts*, and *Minutes Serviced*. The decision to omit reneging and balking in the model was made because the data used to build the model did not show any of that behavior.

Similarly, the data for *Service Type* only holds one type of service for each data entry. It is unknown if a customer was helped on just one task or for several tasks. The decision to have entities only serviced for one task aligns with the data collected.

In the experimental design, the walk-in arrival rate was scaled down proportionally to the number of appointment terminals added to the system. This assumption is to account for the customers that would have been walk-ins but were then able to reserve an appointment. The rate of scaling could be adjusted with future data collection to achieve more accurate results.

Finally, it is recommended to revisit the regression insights when considering a potential change. While the recommendations provided in the previous section may work for the MPF that was modeled, other MPFs may need a different approach and the regression models can assist in finding the right direction to move towards.

5.5 Future Work

This section contains ideas for future work to better MPFs. The first two are suggestions to achieve greater fidelity to the discrete-event simulation model. The last four are additional avenues of analysis that may be useful to know when considering changes to an MPF.

The current simulation model does not account for emergency walk-in customers, such as a late arriving walk-in needing assistance before the start of the next business day. These do occur in reality but are not captured in the data or in the model. Adding this possibility into the model would provide insight into how these customers influence the system and what policies regarding emergency walk-ins may benefit the MPF the most.

The simulation model does account for DEERS outages through an assumption of how often DEERS fails and how long it takes to be restored. Collecting data on DEERS outages and restorations and implementing it into the model would help bring the simulation outputs closer to the actual outputs of the MPF.

The analytical excursion of adding a CAC PIN reset machine at the check-in kiosk was shown to reduce the mean wait times, however it was omitted from the regression analysis. Because the excursion is a large change to the model, accomplishing a regression analysis with the CAC PIN reset machine at check-in may provide better insight into how that particular model can be improved.

Next, it is recommended to conduct statistical analysis on combinations of the scenarios that were shown to reduce the mean wait times. While each scenario does reduce the mean wait time, the interactions between the factors shown in the regression analysis, could have effects that should be considered.

Additionally, the mean wait times are not the only important metrics to consider when gauging how well an MPF is performing. Other outputs that may be worth considering in follow-on work include the mean maximum wait times, total customer throughput, or server utilization rates. Using additional measures of interest may help MPF leaders determine a wider breadth of impacts to any changes they implement.

Lastly, an in-depth cost-benefit analysis should be conducted to give decision makers relevant information to resolve the problem while staying within their own budgetary constraints or advocating for additional funding. Specifically, how many man-hours are put back into the USAF mission per dollar spent on increasing a resource to the MPF (e.g., hiring an additional salaried employee).

Appendix A. Mean Wait Times — Bar Charts

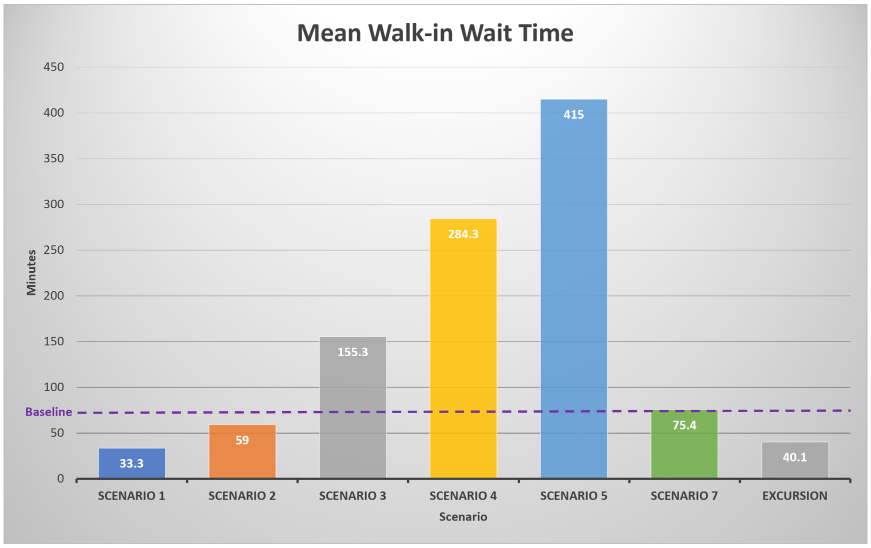

Figure 9. Shows the simulated mean walk-in wait time for each scenario and excursion from Chapter 4. These are the values after enough replications to achieve an absolute precision of five minutes.

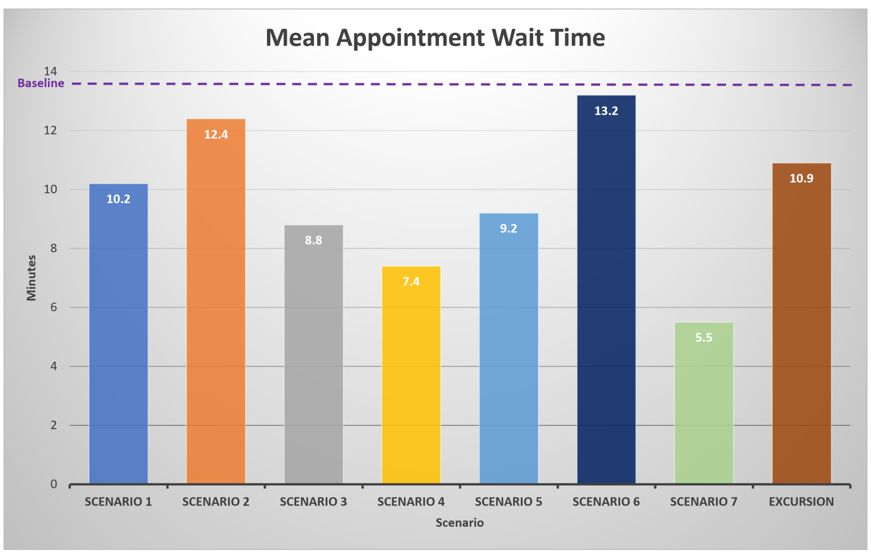

Figure 10. Shows the simulated mean appointment wait time for each scenario and excursion from Chapter 4. These values all have an absolute precision of less than five minutes.

Appendix B. Design Point Simulation Output

Table 19. Selected Design Point Estimates — Walk-in Wait Times

Scenario	Mean Walk-in Wait Time	Percent Change	Mean Max Walk-in Wait Time	Percent Change
Baseline	74.9	N/A	207.0	N/A
1	33.3	-55.5%	133.3	-35.6%
2	59.0	-21.2%	173.0	-16.4%
3	155.3	+107.3%	331.8	+60.3%
4	284.3	+279.6%	545.1	+163.3%
5	415.0	+454.1%	686.5	+231.6%
6	N/A	N/A	N/A	N/A
7	75.4	+0.6%	211.6	+2.2%

Table 20. Selected Design Point Estimates — Appointment Wait Times

Scenario	Mean Appointment Wait Time	Percent Change	Mean Max Appointment Wait Time	Percent Change
Baseline	13.7	N/A	83.5	N/A
1	10.2	-25.9%	67.2	-19.5%
2	12.4	-9.5%	86.0	+2.3%
3	8.8	-35.8%	52.1	+-37.6%
4	7.4	-46.0%	46.7	-44.1%
5	9.2	-32.8%	51.6	-38.2%
6	13.2	-3.7%	65.5	-21.6%
7	5.5	-59.9%	31.4	-62.4%

Table 21. CAC PIN Reset Station at Check-in — Simulation Outputs

Scenario	Mean Walk-In Wait Time (mins)	Mean Max Walk-in Wait Time (mins)	Mean Appointment Wait Time (mins)	Mean Max Appointment Wait Time (mins)
Baseline	74.9	207.0	13.7	83.5
Excursion	40.1	153.7	10.9	71.9

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14. ABSTRACT

Customers at Military Personnel Flights (MPFs) have been experiencing long wait times. These customers are typically employees of the United States Air Force and every moment spent waiting for service is a moment they are away from their actual jobs. By reducing the mean wait time of MPF customers, manhours can be saved and customer complaints may be alleviated. This research uses data collected from an MPF to build a discrete-event simulation model of an MPF. A full factorial experimental design was conducted in the model using five factors. The factors included the total number of employees, the total number of terminals designated for walk-in customers, the total number of terminals designated for appointment customers, the minimum number of employees working during lunch, and different appointment policies. The outputs of the experiment were used to generate regression models that estimate the mean wait time for walk-in and appointment customers. The analysis showed that the number of employees working has the largest impact on mean wait times when compared against other factors.

15. SUBJECT TERMS

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