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Abstract

The objective of this study is to model operations at an airport passenger terminal to determine the optimal service capacities at each station given estimated passenger flow patterns and service rates. The central formulation is an open Jackson queueing network useful to any USAF AMC terminal regardless of passenger type mix and flow data. A complete methodology for analyzing passenger flows and queue performance of a single flight is produced appropriate to be embedded in a framework to analyze the same for multiple departing flights. Queueing network analysis (QNA) is used, as compared to discrete-event computer simulation (DES), because no special software license or methodological training is required, results are obtained in a spreadsheet model with computational response times that are instantaneous, and data requirements are substantially reduced. However, because of the assumptions of QNA, additional research contributions were required. First, arrivals of passengers are time-dependent, not steady-state. Theoretical results for time-dependent queue networks in the literature are limited, so a method for using DES to adjust for arrival time-dependency in QNA is developed. Second, beyond quality of service in the network, a key performance measure is the percentage of passengers who do not clear the system by a fixed time. To populate the QNA mean value system sojourn time, DES is used to develop a generic sojourn time probability distribution. All DES computations have been pre-calculated off-line in this thesis and complete a hybrid DES/QNA analytical model. The model is exercised and validated through analysis of the facility at Hickam AFB which is currently undergoing redesign. For larger flights, adding a server at the high-utilization queues, namely the USDA inspection and security screening stations, halve system congestion and dramatically increase

throughput. The policy of forcing arrival in advance with controlled release to the input queue has very little improvement over the policy of allowing passengers to arrive freely as in a civilian airport.

To my mom, and sister, for not gloating that I'm the last to get a graduate degree of us three. To my wife and son who always, well usually greeted with a smile, and simply enjoyed me when I was home, and I them. To the AFIT-*12M class, I wish everyday was 11:00. To my friends and neighbors near and far, sometimes a "like," a "share," or a "wall post" really goes a long way. And last, but not lest to all of my instructors who provided a great experience of learning. Here's to lesser wrong, and more interesting great things!*

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Meredithe A. Jessup II

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USING HYBRID SIMULATION/ANALYTICAL QUEUEING NETWORKS TO CAPACITATE USAF AIR MOBILITY COMMAND PASSENGER TERMINALS

I. Introduction

1.1 Background

Queues (more commonly called waiting lines in the US) are a societal element of interest to individuals and organizations alike. Because providing infinite amounts of service—staff, computer workstations, lanes on a highway, etc.—is physically and economically infeasible, lines of customers awaiting service inevitably form and dissipate over time. The adventure of queueing is then a exercise of patience, futility, hope, competition, politeness, avoidance, community, duress, resignation, frustration, requirement and myriad other mentionable (and vulgarly inappropriate) adjectives. It can also be quite expensive when long waits lead to lost customers, high costs, and poor perceptions of an organization by investors or executives.

Airports experience such issues in three dimensions as demand on its facilities come from the air as well as the ground. Over the last 50 years, researchers have taken many approaches to quantify the impact of increasing demand and changing policies in the aviation industry. Aviation professionals generously fund and eagerly adopt developments in computer science, mathematics, sociology, and management science that engender safer operations, higher quality service, and more robust processes. The US Air Force has analogous interests to those in the civilian air industry, and can equally benefit from those analytical advancements. A particular interest is the performance in their air passenger terminals.

The United States Air Force's 735th Air Mobility Squadron (735th AMS) operates the Joint Base Hickam-Pearl Harbor's Air Mobility Command (AMC) passenger terminal. The terminal is not open to the public, only serving military and other Department of Defense (DoD) authorized personnel as detailed in regulation DoD 4545.13–R [24]. Though differing in some key aspects, functions and policies at AMC terminals are similar to typical civilian terminals. Preparing to remodel major portions of the facility, the commander and staff of the 735th are interested in exploring new processes and establishing policies, which could enhance their organization and better serve their customers. If regulatory guidance is a main cause for bottlenecks, quantitative evidence may effect policy change for other AMC passenger terminals as well.

1.2 The Airport Terminal

The terminal is a principle element of airport infrastructure that performs three main tasks. It accommodates the passengers' movement from one aircraft to another, since few air trips are made directly from origin to destination. Through various facilities, it also provides controlled processing of passengers and their belongings. Lastly, terminals provide holding space for arriving and departing passengers awaiting processing or transportation. A successfully designed terminal performs all of these tasks while meeting the needs and expectations of those using them, which includes at minimum: passengers, their accompanying well-wishers, air carriers, and the terminal staff. Multiple facilities are required to provide smooth movement, timely processing, and adequate waiting space for transiting passengers.[5]

Airport functions are classified as either *airside* or *landside* operations. The airside is described as including runways, taxiways, and all air traffic control systems (e.g., navigation and landing systems, etc.) used by aircraft and pilots, whereas the landside consists of those facilities and services used by passengers (e.g., gates, terminal buildings, parking structures, etc.) [1]. Within the context of the research presented here airside operations are considered peripheral.

1.3 Definition of Terms and Notation

The following is a summary of terms and symbolic notation used throughout this paper, which will facilitate understanding of the analysis presented.

1.3.1 Definitions.

Airside—Any passenger terminal facilities located beyond security screening.

AFB—Air Force Base

AMC Terminal—Air Mobility Command (AMC) is responsible for all transportation missions in the Air Force, which including military air passenger terminals. Thus, this is a common term used for an Air Force passenger terminal.

IID—Independent and identically distributed, referring to conditions on a random variable.

Landside—Includes all portions of an airport terminal before and including the security inspection. In general this may include additional facilities, such as baggage claim, and sometimes gates, however these are excluded from the scope of this research.

LOS—Level of Service. Entails either server utilization or processing time for a passenger.

Passenger Terminal—Also referred to as a *Pax Terminal*, is the facility of an airport in which passenger processing holding, and transit occur to and from aircraft as well as to and from ground transportation. Used synonymously with *air terminal* or simply *terminal*.

PSC—Passenger Service Center is the hub of passenger processing at the 735th AMS.

Utilization—Measure of relative usage of a particular facility as a function of the arrival rate and available service.

1.3.2 Symbols.

$c_i \equiv$ Number of servers at process i.

$CV \equiv$ Coefficient of variance. The ratio of the standard deviation,$\hat{\sigma}$, to the mean, $\bar{x}$, value of a random variable, $\frac{\sigma}{\bar{x}}$ (i.e., waiting or processing time).

$L \equiv$ Mean number of passengers in system.

$L_{q,i} \equiv$ Mean number of passengers awaiting service at process i.

$p_{0,i} \equiv$ Empty system probability for process i.

$r_i \equiv$ Offered load, $\frac{\lambda_i}{\mu_i}$ or equivalently $c_i \rho_i$, at node i. Not to be confused with r_{i0} or r_{ij}

$r_{i0} \equiv$ Probability that a passenger leaves the system from process i.

$r_{ij} \equiv$ Probability that (or proportion of) passengers leaving process i and entering process j.

$\mathbf{R} \equiv$ Matrix of routing probabilities excluding r_{i0}'s.

$T_{tot}(t) \equiv$ Adjusted mean total time spent in system by time t.

$W \equiv$ Mean total time in system.

$W_i \equiv$ Mean total time in process i.

$W_i(ADJ) \equiv$ Adjusted mean total waiting time.

$W_i(M/M/c) \equiv$ Analytical mean total waiting time.

$W_{q,i} \equiv$ Mean waiting time in queue at process i

$\boldsymbol{\gamma} \equiv$ Vector of exogenous arrivals into the system.

$\gamma_i \equiv$ Mean rate of exogenous passengers arriving to the system at process i.

$\boldsymbol{\lambda} \equiv$ Vector of passenger flow rates.

$\lambda_i \equiv$ Mean passenger flow rates from process i.

$\boldsymbol{\mu} \equiv$ Vector of service rates.

$\mu_i \equiv$ Mean service rate at process i.

$\rho_i \equiv$ Utilization at process i.

$\tau \equiv$ Delays through a system due to traveling between nodes

1.4 Problem Statement

A passenger terminal can be described as a stochastic system involving a non-stationary, terminating, arrival distribution. Of interest here is the ability to take advantage of limited available data—average service times and a general arrival profile—to estimate the average passenger throughput time, as well waiting times at individual facilities.

1.5 Research Objective and Scope

The objective of this study is to model the current operations of a passenger terminal, the 735th AMS's passenger terminal in particular, using a hybrid of simulation and analytical methods. The challenge, then, is to determine the optimal capacity given estimated passenger flow patterns and service rates for each processing station (node) in the system when processing passengers for a single flight. A proposed framework for modeling performance for loading multiple flights is also presented. Insight into optimal manning levels, given the stochastic nature of arrivals, enables decision makers to make informed decisions regarding the design and staffing of the 735th's terminal as well as other passenger terminals throughout AMC.

II. Review of Related Literature

Air transportation industry planners have heavily invested in studies focused on how best to improve customer service quality for decades. Increases in demand, physical land constraints, inadequate investment, uncertainty towards future requirements, among many other factors [11] drew the attention (and funding) of academic institutions, private organizations and government agencies alike. What resulted were a succession of approaches to identify airport landside concerns, adopt standard measures of performance, and develop assessment method. Several issues encountered by all approaches are:

- Airport terminals are complex systems with interdependent subsystems.
- The number of customers arriving to a terminal is random, but may have seasonality.
- System performance is measured, in general, by customer perceptions of comfort and timeliness.

Accounting for such characteristics, analysts have taken various avenues to model of landside operation. Earlier models, particularly prior to the mid-1980's, were primarily analytical. As computing technology advanced and became more widely accessible, simulation became the dominant practice. Analytical methods, however, continued to persist, particularly as inputs to, or modules within, larger integrated models and simulations.

2.1 Deterministic Modeling Approaches

Deterministic methods generally follow an approach detailed by Newell [23], who treated customer flows as a fluid with deterministic arrival and departure rates. Park used this approach, relating passenger flows from one facility into another through functions dependent on empirical arrival patterns, service times, and distributions of intervening activities (restaurants, shops, etc.) [26]. His approach partially follows, but did not fully utilize the results of stochastic open networks available in queueing theory.

The Simple Landside Aggregate Model (SLAM) was created to provide estimates of capacity and delays as affected by altering airport configurations. This model uses basic equations to relate passenger flow, service time, and physical size of a given facility to a predefined Index of Service (IOS) for a given facility [3].

2.2 Simulation

Simulation is a flexible tool for modeling airport operations, which has made the method a staple for airport systems analysts. Animation features of some simulations also provides researchers and managers a visual tool that enhances analyses and facilitates communication regarding the process under study. Mumayiz reviewed 20 models developed prior to 1990, which were mainly the FORTRAN language-based predecessors to today's modern applications [22]. He noted that models produced by (US and foreign) academic institutions, private firms, and government agencies that found success at many airports including John F. Kennedy, Dallas Fort-Worth Regional, Denver Stapleton, and many other airports of the time.

Gatersleben and van der Weij applied simulation methods to identify and solve problems of logistic bottlenecks in passenger handling through European airport terminals [10]. Their use of simulation was motivated by several aspects common to many airports. First, they observed that interdependencies among processes due to competing objectives amongst process owners, thus inadvertently causing bottlenecks elsewhere in the passenger flow. Congestion also arose during peak periods caused by airlines scheduling arrivals and departures closely to minimize connection times, thus flooding the terminal with passengers. Simulation was preferable in assessing future developments as well since scenarios and combinations of scenarios could be assessed. It also offered them a useful method to compare strategies and quantitatively estimate the robustness of a given course of action. Lastly, simulating provided insight into current methods, which could enable organizational growth by routing out obsolete processes and poor performance measures.

Hafizogullari et al. discussed how analysis via simulation was useful in reducing the number of passengers who miss connecting flights by analyzing a then planned design Delta Airlines facility at John F. Kennedy International Airport [13]. Their method determined the minimum time between connections for a passenger itinerary, which then translated into minimizing the cost associated with missed flights.

The Optimization Platform for Airports [including] Landside (OPAL) concept sought to develop a model that could evaluate and optimize airside and landside airport operations simultaneously, as well as provide a common platform to utilize different performance models within a single integrated facility [36].

Manataki and Zografos Asserted that many modeling techniques are over-simplistic and that simulation platforms are often overly detailed or too macroscopic. They proposed a system dynamics-based "mesoscopic model" to strike a balance between flexible features and useful performance measures [17]. They validated the model's capabilities by analyzing Athens International Airport's terminal. Suryani et al.'s system dynamics model developed was used to forecast passenger demand as well as explore how various policy scenarios (e.g., changes in airfare, etc.) and proposed terminal expansion passenger affect demand [32].

Mumayiz opines that"no set of equations can be derived to define the characteristics of the airport terminal and describe the nature of the systems [sic] operation", which makes discrete event simulation a preferable tool [22]. The volatile input or service mechanisms in the real world, the complexity of large scale systems, difficulty in mathematically quantifying queue discipline, or any combination of these factors can make analytical models highly difficult (or near impossible)to solve [12]. Gross et al., however, argue that simulation "is not in itself a panacea." In simulation, analysts must be concerned with assumptions regarding run length, replicates, statistical significance, and other limitations comparable to that of analysis by experimentation. This does not dispute the practicality and credibility of simulation, since a system must be simplified in some way to develop analytical models as well. It is the aim of this research to demonstrate that acceptable estimates of performance can be achieved using closed form expressions (i.e. queueing theory) by making reasonable assumptions regarding the nature of a system.

2.3 Queueing

The value of queueing theory has not been completely ceded in favor of simulation. McKelvey [20] used the framework provided by the FAA's Airport Landside Model queueing networks to analyze terminal performance at Palm International and Fort-Lauderdale-Hollywood International airports. This study assessed the impacts of proposed physical and operational modifications on service quality. However, the study assumed peak-hour demand at each processing facility and (admittedly) did not adequately consider the impact of delays on processors downstream. Similarly, Mehri et al. used node–by–node $M/M/c$ analysis and linear programming to analyze the passenger ticketing process at Monastir Habib Bourguiba International Airport in Monastir, Tunisia to determine the trade-offs between waiting costs and level of service [21]. This system decomposition method, however, disregards the effects of network structure on performance measures.

Real-life processes do not operate always as solitary systems, but interact with others to form complex networks. Queueing networks have received great interest in various fields such as manufacturing, computer science, transportation, medicine and communication. Gross et al. [12] explain that networks of queues can be understood as interconnected elements (nodes) , which can be any facility, station or location where customers receive a service. Each node will contain some number of servers who impart a delay on each customer before the customer proceeds to the next node or leaves the system.

Decomposing an entire system, by node, into individual queues can . This approach, however, carries two risks: (1) it may yield invalid results and (2) it may not properly account for interactions among queues [27]. In cases where customers are not contained within the system, but rather enter at least one node from an external source, traverse some number of nodes, then eventually leave the system is referred to as an open network.

2.3.1 Open Jackson Networks.

A particularly useful class of queueing networks have service times that are independently and exponentially distributed, all external arrivals are Poisson with mean rate γ_i, and customers leaving upon completion of service at node i will instantaneously enter node j with probability r_{ij} or leave the system with probability r_{i0} . Networks of this class are called *Open Jackson Networks* (OJN) as result of Jackson's work in queue performance of multi-server, complex networks with stochastic flows [14, 15]. Details regarding the solutions for performance measures are provided in Section 3.2.

2.3.2 Multiclass Open Networks.

In some cases, it is more accurate to disaggregate customers into separate types, referred to as *classes*. Each class may traverse the system differently than the others.

The simplest modification to represent such an adjustment is to solve Equation (3.1a) for each class using separate routing matrices for each class. A two class system, for instance, will have routing matrices $\mathbf{R}^{(1)}$ and $\mathbf{R}^{(2)}$ that produce flow vectors $\boldsymbol{\lambda}^{(1)}$ and $\boldsymbol{\lambda}^{(2)}$, which correspond to class 1 and class 2 customers respectively. It is a straight forward task to then calculate relative and overall performance measures for the system using Little's formulas.[12]

Whitt investigated transient behavior of open queueing networks with multiple customer classes by varying the open queue discipline and initial conditions. Specifically, he studied a $D/D/1$, two-node, four-class system with unlimited capacity, and first–in–first–out (FIFO) service discipline. He found that transient behavior his highly susceptible to initial conditions and large fluctuations in queue–length occur when large batches of short-service time customers build up in the queues. He also found that service discipline heavily influences the critical utilization and hence queue stability even when long–service time customer classes are given priority. [39]

2.3.3 Time Dependent Queueing.

Steady-state conditions are rare in real world processes. System arrival rates, customer behavior, service times, and other conditions tend to depend on an observed interval (e.g., hourly, daily, etc.) rather than being probabilistically identical in all points in time. Airports certainly fit this class of systems. Many studies have identified a particular pattern of passenger arrivals in relation to their flight departure time. Regrettably, whereas analytical solutions are readily available for stationary queuing systems, non-stationary (also called time–dependent or non–homogeneous) queues a more problematic since the rates of arrivals and/or service rates change over "large" time intervals.

Some approaches have used differential equations to approximate performance measures for complex time–dependent systems. Kleinrock's well cited technique describs the behavior of $M(t)/M(t)/c(t)$ using differential–difference equations, Equation 2.1,

$$
\begin{aligned}
\frac{dp_0(t)}{dt} &= -\lambda(t)p_0(t) + \mu p_1(t) \\
\frac{dp_n(t)}{dt} &= -(\lambda(t) + n\mu(t))p_n(t) + \lambda(t)p_{n-1}(t) + (n+1)\mu(t)p_{n+1}(t) \quad \text{for } 0 < n < c(t) \\
\frac{dp_n(t)}{dt} &= -(\lambda(t) + c(t)\mu(t))p_n(t) + \lambda(t)p_{n-1}(t) + c(t)\mu(t)p_{n+1}(t) \quad \text{for } c(t) \le n
\end{aligned}
\tag{2.1}
$$

where $\lambda(t)$ is the arrival rate at time t, $\mu(t)$ is the service rate at time t, $c(t)$ is the number of servers at time t, and p_n is defined as the probability of n customers in the system at at time t [6, 30, 31]. The drawback of this method, however, is that such systems can be difficult to solve, sometimes requiring long computation times particularly for high utilization systems [30]. Zhang and Coyle used similar equations to study transient behavior of time dependent $M/M/1$ systems. They developed a method to solve for boundary conditions using Runge-Kutta algorithms on a Volterra-type equation to find expected queue sizes [40].

Mandelbaum and Massey, derived "period dependent, pathwise asymptotic expansions" to approximate queue length in an asymptotic analysis of $M/M/1$ queues "within the framework of strong approximations." Their work determined that these systems operate in one of three "exhaustive asymptotic" regions—underloaded, critically loaded or overloaded—at a given time t. In terms of a "traffic intensity function" defined by Equation 2.2a these regimes are $\rho^*(t) < 1$, $\rho^*(t) = 1$,and $\rho^*(t) > 1$, respectively. [18] Stolletz used their results and modified their equation to included time a varying number of servers in $M/M/c$ queueing systems, Equation 2.2b, which was useful in his approximation methods explained later in this section [30].

$$\rho^*(t) = \sup_{0 \le s < t} \frac{\int_s^t \lambda(r)dr}{\int_s^t \mu(r)dr} \tag{2.2a}$$

$$\rho^*(t) = \sup_{0 \le s < t} \frac{\int_s^t \lambda(r)dr}{\int_s^t c(r)\mu(r)dr} \tag{2.2b}$$

Alternatively, one can approximate transient effects using stationary techniques such as Stationary Independent Period by Period (SIPP) and Stationary Backlog Carryover (SBC), which are analytically less rigorous than differential equations. [6] In SIPP, the time frame of interest is divided into independent intervals with constant intra-period arrival and service rates. Performance measures are then calculated for each period using the stationary $M/M/c_i/\infty$ queueing model for each period i. In this manner, performance during any period is independent of periods preceding it. This approach assumes that time periods are independent, each period achieves steady-state performance, and the system is never saturated (i.e., $\rho_i < 1$). [30]

Stolletz developed the SBC approach to estimate queue performance for the passenger check-in process when arrival rates vary over time, assuming stationary arrival rates and service rates during small independent time intervals, but adjusts for a backlog of customers from previous periods [31, 30]. This technique, approximates performance in period $i + 1$ by estimating its arrival rate adjusted for backlogged arrivals from the period i (equation 2.3) [30]

$$\tilde{\lambda}_{i+1} = \lambda_{i+1} + \tilde{\lambda}_i \cdot P_i(B) \tag{2.3}$$

where $\tilde{\lambda}_i$ is the effective arrival rate for period i with initial value $\tilde{\lambda}_1 = \lambda_1$ and where $P_i(B)$, blocking probability, is found by applying a stationary $M/G/c_i/c_i$ loss formula which generates the customer backlog $b_i = \tilde{\lambda}_i \cdot P_i(B)$[12]. The expected utilization for each period i having c_i servers with average service rate μ is then

$$\rho_i = \frac{\lambda_i + b_{i-1} - b_i}{c_i \mu}. \tag{2.4}$$

Using the expected utilization, SBC derives a modified arrival rate which serves as the input to the stationary $M/M/c_i/\infty$ method to approximate expected waiting time, W_q, and L_q.

Another approach is the Pointwise Stationary Approximation (PSA), which computes queueing performance measures during a particular period for the arrival rate associated with that interval [30]. PSA approximates nonstationary performance measures to a instantaneously stationary $M/M/c$ model where $\lambda = \lambda(t)$, $\mu = \mu(t)$, $c = c(t)$, and where the traffic is strictly less than 1 (i.e., $\rho < 1$) over the entirety of each interval. They found that this model performs well for low ρ, but worsens as $\rho \to 1$. Wang et al. [38] improved upon this method with their Pointwise Stationary Fluid Flow Approximation (PSFFA), which has a general equation derived from the relationship between the flow rate of change to the flows in and out of the system (see Equation 2.5).

$$\begin{aligned} \frac{dx}{dt} &= -f_{out}(t) + f_{in}(t) \\ &= -\mu\rho(t) + \lambda(t) \\ &= -\mu\Big(G_1^{-1}\big(x(t)\big)\Big) + \lambda(t) \end{aligned} \tag{2.5}$$

In 2.5, $x(t)$ represents the average number of customers in the system at time t and $\Big(G_1^{-1}\big(x(t)\big)\Big) = \rho(t)$, the average server utilization. Table 2.1 summarizes the formulations developed for single–server PSFFA models. For the time–dependent arrival models, σ is a "unique real root in the range $0 < \sigma < 1$" of the equation

$$\sigma = f_a^*(s)|_{s=\mu(1-\sigma)}. \tag{2.6}$$

The final listed formula is the Interrupted Poisson Process, which is a 2-state (state $1 \equiv$ ON and state $2 \equiv$ OFF), special case of the Markov–modulated Poisson Process with arrival rate λ and generator matrix

$$Q = \begin{bmatrix} -\sigma_1 & \sigma_1 \\ \sigma_2 & -\sigma_2 \end{bmatrix}.$$

Table 2.1. PSFFA Models [38]

Queueing System	PSFFA Equation	σ
M/D/1	$\frac{dx}{dt} = -\mu\left[(x+1) - \sqrt{x^2+1}\right] + \lambda$	
M/E$_k$/1	$\frac{dx}{dt} = -\mu\left[\frac{k(x+1)}{k-1} - \frac{k^2x^2+2kx+k^2}{k-1}\right] + \lambda$	
M/M/1	$\frac{dx}{dt} = -\mu\left(\frac{x}{x+1}\right) + \lambda$	
D/M/1	$\frac{dx}{dt} = -\mu x(t)(1-\sigma) + \lambda(t)$	$\sigma = e^{\frac{\mu}{\lambda}(\sigma-1)}$
E$_k$/M/1	$\frac{dx}{dt} = -\mu x(t)(1-\sigma) + \lambda(t)$	$\sigma = \left(\frac{k\lambda}{k\lambda+\mu-\mu\sigma}\right)^k$
IIP/M/1	$\frac{dx}{dt} = -\mu x(t)(1-\sigma) + \lambda(t)$	$\sigma = \frac{\lambda(\mu-\mu\sigma+\sigma_2)}{(\mu-\mu\sigma)^2+(\lambda+\sigma_1+\sigma_2)(\mu-\mu\sigma)+\sigma_2\lambda}$

Stolletz reviewed several other methods, which also approximate system performance assuming stationarity over short intervals. The simple stationary approximation (SSA) uses the average arrival rate over the entire interval of interest, thus ignoring nonstationarity. The average stationary approximation (ASA) compromises between the PSA and ASA by averaging arrival rates over an interval proportional to the mean service time then computing average performance using $M/G/c$ equations.

Lastly, the effective arrival rate (EAR), derives expected waiting time, $E[W_q]$, from the SSA, and then derives effective arrival rates assuming deterministic service rates. Each of these techniques are relatively successful for light traffic systems, but cannot be applied accurately when the system under study is even temporarily overloaded. [30]

2.4 Non-stationary Arrival Distributions

A challenging task in characterizing non-stationary queueing systems is to determining arrival distributions. In 1982, Newell published methods which form the basis for many future efforts in analyzing time-dependent stochastic behavior [23]. These effectively a graphical methods used empirical data to create arrival, $A(t)$, and departure, $D_q(t)$, curves based on customer flow times through a queue where

$$\begin{aligned} A(t) &= \text{the cumulative number of arrivals to the queue by time } t \\ D_q(t) &= \text{the cumulative number of departures from the queue by time } t \end{aligned}$$

and their respective inverses are

$$\begin{aligned} A^{-1}(x) &= \text{the ordered arrival time of customer } x \\ D_q^{-1}(x) &= \text{the ordered departure time from the queue of customer } x. \end{aligned}$$

The results are curves such as those in Figure 2.1, which can be used to estimate delay patterns. Brunetta et al. incorporated this approach to approximate passenger arrivals and wait times in their SLAM model [3, 4, 7]. Rather than using general curves as described in [37], the authors approximated profiles using piece-wise linear functions of time to estimate the number of arriving passengers during a particular period. Figure 2.1 is a representation of how passenger arrival and processing may evolve for a single flight at a particular processing counter using this method.

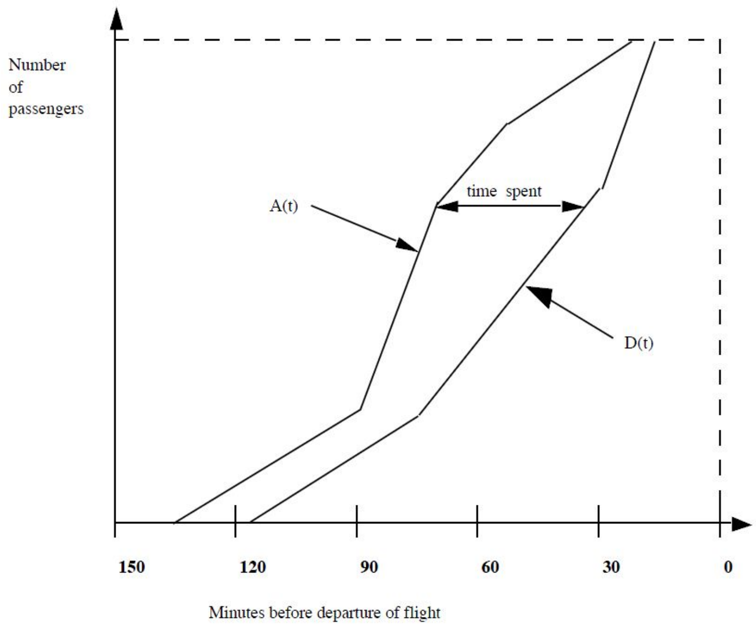


Figure 2.1. Cumulative arrival, $A(t)$, and dwell, $D(t)$, functions for a single processing facility. [37]

Upton and Tripathi employed a technique to analyze transient behavior in $M(t)/M/1$ queues by applying an $M/M/1/K$ approximation to the $M/M/1$ system and leveraging a few basic facts:

- "Over a finite interval, only a limited number of arrivals can occur; hence providing infinite buffer capacity is unnecessary.
- "Few real systems have unlimited buffer space and consequently do not exhibit true M/M/1 behavior.
- "Arrival rates equal to or exceeding the service rate can be accommodated." [35]

2.4.1 Arrivals as Renewal Processes.

An individual passenger's time between visits to an airport certainly could not be described with any accuracy by an exponential distribution. It is perfectly reasonable, then, to assume that intervals between that passenger's visits are independently and identically distributed (IID). The technical term for such a process is a *renewal* process. Collectively, the associated interarrival times of a group of passengers, then, is a superposition of renewal processes.

Thise proposition forms the the basis of a powerful theorem in queueing, Khintchine's theorem, which states that the superposition of a sufficiently large number of IID renewal processes will produce a Poisson process regardless of the actual distributions of the individual processes. This theorem is similar to the Central Limit Theorem. Instead of describing sums of random numbers being normally distributed, the collection of processes become approximately exponentially distributed. [27]

This property applies to airport arrivals since, in the limit, the arrivals for a particular flight, or even successive flights, can be approximated as exponentially distributed arrivals.

2.4.2 Distribution of Arrivals to a Commercial Terminal.

Arrival pattern models produced to address attributes specific to air travelers has been widely published. The distribution of such arrival rates is dependent on many factors including, but not limited to [31]:

- scheduled departure time
- the flight destination (e.g., long-haul or short hops)
- time of day (e.g., peak hours vs. off-peak)
- type of passengers (e.g., business or leisure)
- season (e.g., major holidays or summer travel).

Proposed methods of approximating passenger arrival profiles have included several innovative techniques. Vandebona and Allen [37] classified available passenger flow models into three categories: descriptive, analogy, and regression. The descriptive model simply characterizes an arrival pattern as a density distribution that begins as a generally increasing function, describing the interval when the passenger flow

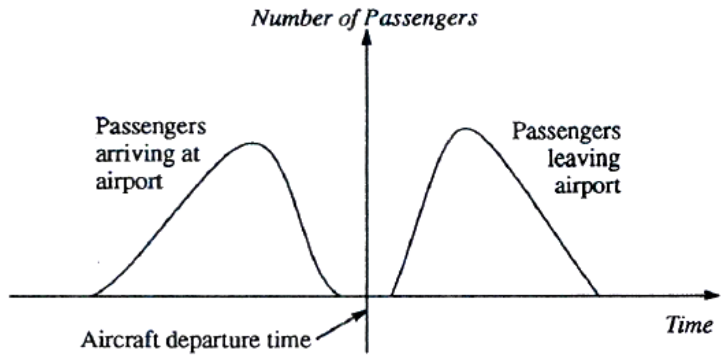
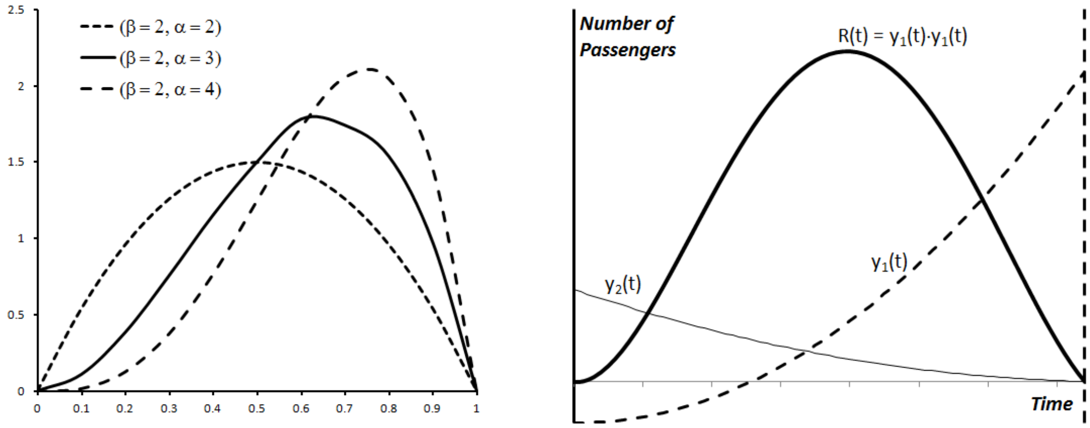


Figure 2.2. Descriptive model of passenger arrival and departure distributions. [37]

rates slowly build to a maximum. This is followed by a generally decreasing function with a slope much steeper in magnitude than that of the increasing period, describing how the arrival rate tapers off. Figure 2.2 illustrates a sample distribution for both enplaning and deplaning passengers (the former of which is simply the arrival-type pattern reflected over the y-axis). .

Analogy methods apply water runoff models to passenger flow distributions and exploit tools such as the unit hydrograph. These methods assumes that passenger can be approximated by the physical characteristics of water flowing over terrain (e.g., passenger arrivals is to storm runoff as a check-in queue is to a drainage ditch).

The next category, regression models, applies curve-fitting to determine arrival profiles. Vandebona and Allen noted that the beta distribution is often over-looked, but is appropriate for describing passenger arrival patterns. The advantage of the beta distribution is that it can assume any desirable shape by changing the values of α and β, and it has definite upper and lower bounds (see Figure 2.3a), unlike the more commonly applied gamma and log-normal distributions. The disadvantage, however, is that integrating the density function to calculate the cumulative distribution function is labor intensive compared to polynomial distributions. The polynomial method suggested by the authors attempts to satisfy the descriptive pattern and pro-



(a) (b)

Figure 2.3. (a) Beta Distributed Arrival Pattern. The values of α and β can be adjusted to achieve a form adequate to model passenger flows. (b) Polynomial Arrival Pattern. The products of $y_1(t)$ and $y_2(t)$ produce $R(t)$. [37]

vide mathematical simplicity as compared to the beta distribution. The proposed density function, $R(t)$, is the product of two quadratic functions $y_1(t)$ and $y_2(t)$ (see Figure 2.3b). Integrating $R(t)$ produces the cumulative distribution of arrivals given by equation 2.7.

$$A(t) = a_1 t^3(a_2\alpha_{n=5} - b_2\beta_{n=4}) + b_1 t^2(a_2\alpha_{n=4} - b_2\beta_{n=3}) \tag{2.7}$$

where

$$\alpha_n = \frac{t^2}{n} - \frac{2Tt}{n-1} + \frac{T^2}{n-2}$$

and

$$\beta_n = \frac{t}{n} - \frac{T}{n-1}$$

2.4.3 Distribution of Arrivals to an AMC Terminal.

Suppose, for a single departing flight, that passengers *do not* enter a queueing system to begin immediate processing upon arrival. Instead passengers arrive at a specified time prior to departure and begin entering the first queue at a more–or–less constant rate. This is the case of an AMC terminal. Instead of the increasing–decreasing arrival pattern of civilian airports, the effective arrival pattern is roughly uniform over an interval as passengers are called by name to initiate processing for their flight. This resulting queueing system is well approximated by a $D/M/c$ model for the first queue.

2.4.4 Performance of an Non-stationary Queueing Model.

Measures of performance of non-stationary queuing models are highly problematic. In general, mean value measures are estimated using approximations to simpler queueing models, but transient behavior is difficult to described since the user–friendly product form equations do not exist. Convolution methods and differential equations are often the next best available techniques. With the loss of Markovian behavior, estimates of transient behavior can be accomplished via numerical methods, since closed form-solutions are unavailable. Also sojourn times are not available to the analyst. To resolve these issues, inputs retrieved from statistical methods may assist in understanding the missing measures and allow for adjustments to a base Markovian case.

2.5 Quality of Service

2.5.1 Landside QoS Studies.

Studies have also been undertaken to explicitly define and develop measures for customer service aspects of airport terminals. In 1988, the Federal Aviation Administration (FAA) funded a study, conducted by the Transportation Review Board (TRB), to "develop guidelines for assessing the landside capacity of individual airports" [16]. The results formed the foundation of landside studies with respect to [1]:

- general guidelines for assessing an airport's landside capacity,
- basic definitions,
- a generic assessment process and a description of community factors, which influence landside performance (i.e., airport users and stakeholders in addition to passengers), and
- a collection of basic analytic methods.

Lemer concluded in his review of this study that "the effort represented a valuable first step toward definitive guidelines for capacity assessment, but much remains to be done" [9].

To identify landside issues in general and to characterize specific capacity and service capabilities/constraints, quality of service (in some literature, level of service) evaluations were conducted in many airports utilizing a variety of methods [9]. Martel and Seneviratne [19] conducted surveys of departing passengers at Montreal International Airport at Dorval to determine which factors most influence quality of service within terminal buildings. They found that, although factors differ from one element of a building to the next, in general the availability of space is a dominant concern; however for drop–off, pick–up and other "circulating elements," the availability of information was most influential. Similarly, in waiting areas, understandably, the availability of seats was most important, whereas waiting time was the main criteria in processing areas (such as ticketing and security). The authors furthered their research by developing a set of quality of service indices, marrying their original approach with the Airport Associations Coordinating Council/International Air Transport Association (AACC/IATA) framework in Table 2.2 [29].

Omer and Khan applied utility and cost-effectiveness theories to develop a framework to study "the interrelationship between space/service standards, user perceived value or utility of service, and cost" [25]. Applying this method at Montreal's Dorval as well as Toronto's Pearson International Airports, they produced composite utility

Table 2.2. IATA level of service standards [7]

LOS	Level	Description
A	Excellent	Free flow, no delays, excellent comfort level
B	High	Stable flow, very few delays, high comfort level
C	Good	Stable flow, acceptable delays, good comfort level
D	Adequate	Unstable flow, passable delays, adequate comfort level
E	Inadequate	Unstable flow, unacceptable delays, inadequate comfort level
F	Unacceptable	Cross-flow, system breakdown, unacceptable comfort level

equations for each of the airports' terminal processing facilities again utilizing the AACC/IATA criteria. This method, however, received much criticism for various fundamental flaws [9].

In addition to the research of influential factors and qualitative/statstical approaches presented above, analysts have employed many other approaches to characterize quality of service to include, but not limited to perception-response (PR) curves, fuzzy set theory, data envelopment analysis (DEA), and methods to evaluate human orientation (ability to locate destinations) within terminals.

The methods presented here, as well as the works of many others are reviewed by Correia and Wirasinghe [9]. The common results of the aforementioned studies seems to verify the intuitive conclusion that customers' perceptions of service is influenced by the value of their time spent in and awaiting service, which is dependent on the type of service being received. When awaiting service, customers prefer to be comfortable and intend to have as short of a wait as possible.

2.5.2 Capacitating Queues.

Providing customer service adequate service can be approached as in integer programming problem. From the OJN methodology, given the calculated utilization, wait times, etc., achieving target service can be achieved by simply adding servers iteratively until target performance measures are reached. Such a method is the

“One–up, One–Down” was used in by Burdick et al. [8] in a study of hospital emergency department using QNA to reduced patient length of stay.

Alternatively, especially in systems having large numbers of servers, Gross et al. [12] offer a more direct calculation

2.5.3 Summary.

Considering the literature, several points seemed clear. The problem has been of interest at many levels and continues to be studied. Simulation, though useful, is not necessarily portable or widely available and incurs considerable requirements. Queueing has been utilized but, the time–dependent nature of airport arrivals makes analytical modeling quite difficult. The unique aspect of this research is utilizing the tractability of simulation, and the ease of use of queuing network analysis to develop a simple hybrid method.

III. Methodology

3.1 Research Methodology

This research proposes a technique to estimate performance measures for a passenger terminal using a hybrid of analytical results and discrete event simulation. Measures of an analogous steady state system are computed using Open Jackson Network (OJN) methods as indicated in Figure 3.1. A simulation of the first node estimates the coefficient of variance (CV) associated with the passenger arrival pattern and service distribution. This factor is used to modify the average wait calculated using steady–state equations for the first queue, which, when combined with average waits for down–stream, produces reasonable estimates for the average total processing time per passenger.

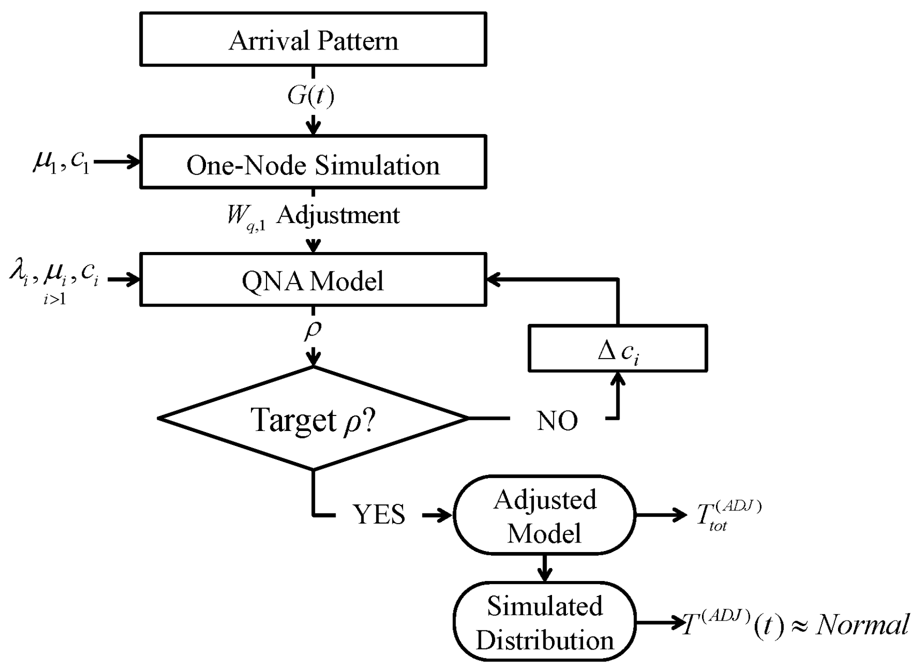


Figure 3.1. Diagram depicting general Sim-QNA hybrid methodology.

3.2 Basic Open Jackson Network Design

To analyze an air terminal as an OJN, appropriate arrival rates, service rates and passenger routing must be established. Considering reasonable assumptions for each regarding passenger and server behavior, the basic network model can be analyzed as if the system was in steady state.

3.2.1 Arrival Patterns.

Consideration of passenger arrival patterns assumes the system is never saturated ($\rho \ngeq 1$). This allows the system to be analyzed as an OJN. Interarrival times between passengers are also assumed independent and exponentially distributed with a stationary mean rate.

Equations 3.1a and 3.1b, provide the relative passenger flows for the terminal given arrival rates into the system and passenger flow probabilities to each node. This method finds the mean flow of traffic into each node using the system of linear equations known as the *traffic equations*, as follows:

$$\lambda_i = \gamma_i + \sum_{j=1}^{k} \lambda_j r_{ji}. \tag{3.1a}$$

Or in matrix form

$$\boldsymbol{\lambda} = \boldsymbol{\gamma} + \boldsymbol{\lambda}\mathbf{R}, \tag{3.1b}$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\gamma}$ are vectors of internal and exogenous flows, respectively, and R is referred to as the *routing matrix.* [12]

3.2.2 Service Patterns.

As with arrivals, all service times are assumed independently and exponentially distributed and stationary, though the number of servers may change over large intervals in accordance with staffing policy. The service discipline is assumed to be first–come–first–serve (or first–in–first–out, FIFO). The current staffing schedule at the terminal specifies three 8-hour shifts; day, swing and night shifts. The Passenger Service Center (PSC) check-in counter staff varies by shift with usually 2–3 operating during days, 2 for swings and 1–2 at night. The terminal has a total of 5 kiosks for check-in processing. At any point, and only when required, only one station is available to USDA inspection. Similarly, only one station is available for passenger security screening.

Average service times were estimated from a survey conducted from 1–10 Sept 2010 in support of a customer service analysis conducted by Air Force Smart Operations for the 21st Century (AFSO21). For the survey, a total of 100 random passengers, 10 per day over the 10 consecutive days, chosen from near the "middle" of their processing group were observed and timed as they traveled through the terminal from sign-up to security. The data is assumed to be identically and exponentially distributed though, admittedly, the true distribution may be Erlangian or even Normal. However, the intention for using this data was only to determine a point estimate of the mean given limited data, rather than to characterize the full nature service distribution.

The average service time for security screening was used as a sufficient estimate for passengers processing through the USDA inspection, since they are generally similar processes. Kiosks times were assumed to have the same average service time as the counter. The characteristics for the base case at each facility are summarized in

Table 3.1. Appendix C contains an example of the data forms as well as a summary of the data used to estimate service time averages.

Table 3.1. Base service values.

Facility	# Servers	$1/\mu$
Ag Inspection	1	1.85 min
Kiosk	5	2.74 min
Counter	3	2.74 min
Security	1	1.85 min

The actual staffing schedule will not be determined by this analysis, but, rather, the number needed to maintain a specified level of service. In fact, as airside processes take priority, staff may be drawn away from processing passengers to take on flightline tasks to the point where operations within the terminal are sparsely manned. These extenuating circumstances will not be directly addressed here, in this research, but their impact can be easily demonstrated by varying the number of servers.

3.2.3 Passenger Routing.

In general terms, passenger terminals process travelers in a feed–forward system since revisits to queues are negligibly rare. Of course passengers may re–enter the landside for a number of reasons (e.g., using a nearby restroom, retrieving a forgotten item, visiting concessions, etc.) and will then require re–processing through security. Such instances are not the norm, since necessary concessions, restrooms and even customer service are typically available post–security. This will also be treated as negligible at the Hickam terminal for analysis purposes. The terminal's current layout, however, requires passengers to exit the airside for such facilities. Ideally, passengers would have a relatively short wait before being ferried to their aircraft, and new design considerations may alleviate this concern altogether.

Ticketing can be accomplished in either one or two stages. Passengers may receive their boarding passes at the counter where they can also check baggage and then proceed to security. Alternatively, a passenger can receive a boarding pass at a kiosk, then either check baggage with an agent or proceed directly to security. Thus a small complexity is introduced. For longer flights, passengers are more likely to check baggage than those on short trips, who may only possess carry–on bags. The probability of proceeding directly from a kiosk to security is then, in part, dependent on the type of flight a passenger will board. The general routing matrix for a terminal is then

$$\mathbf{R}_{\text{OCONUS}} = \begin{bmatrix} 0 & r_{\text{bags}} & 1 - r_{\text{bags}} \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \tag{3.2}$$

where r_{bags} = proportion of passengers checking baggage at the counter. For passengers departing from Hawaii to the US Mainland (see section 4.1.3.3) the matrix routing matrix has the form

$$\mathbf{R}_{\text{CONUS}} = \begin{bmatrix} 0 & r_{\text{kiosk}} & 1 - r_{\text{kiosk}} & 0 \\ 0 & 0 & r_{\text{bags}} & 1 - r_{\text{bags}} \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{3.3}$$

where r_{kiosk} = the proportion of passengers who use the kiosk after processing at the USDA inspection.

Figure 3.2 illustrates the 735th AMS's passenger terminal in an expanded schematic form, showing all service channels. Processing facilities are represented by annotated boxes following the notation:

RC Arrivals from roll call

Ag USDA inspection

$\mathbf{K_L}$ Kiosks located in the main lobby

$\mathbf{K_P}$ Kiosks located in the PSC

T/B Ticketing counter/baggage check-in

Sec Security screening

Queues are represented by circles lined up to enter the facility. Arrows represent routing of passengers to each facility.

3.2.4 Performance Measures.

Processes in an Open Jackson Network effectively perform as if each queue were an independent $M/M/c$. In fact, so long as the described system is feed–forward; that is, no path exists allowing a passenger to revisit a process, ensuring flows between processes follow a true Poisson process. With flow rates, λ_i, to each process found using Equation 3.1b and with mean service times at each process, $1/\mu_i$, performance measures at each process can be derived by first computing the probability of that the processing station is empty, $p_{0,i}$, Equation 3.4:

$$p_{0,i} = \left(\sum_{n=0}^{c_i - 1} \frac{r_i^n}{n!} + \frac{r_i^{c_i}}{c_i!(1-\rho_i)} \right)^{-1}. \tag{3.4}$$

Measures for individual queues can be calculated directly using $p_{0,i}$, λ_i, and μ_i, or (more efficiently) using iterative computations. Equations 3.5–3.7 provide these mea-

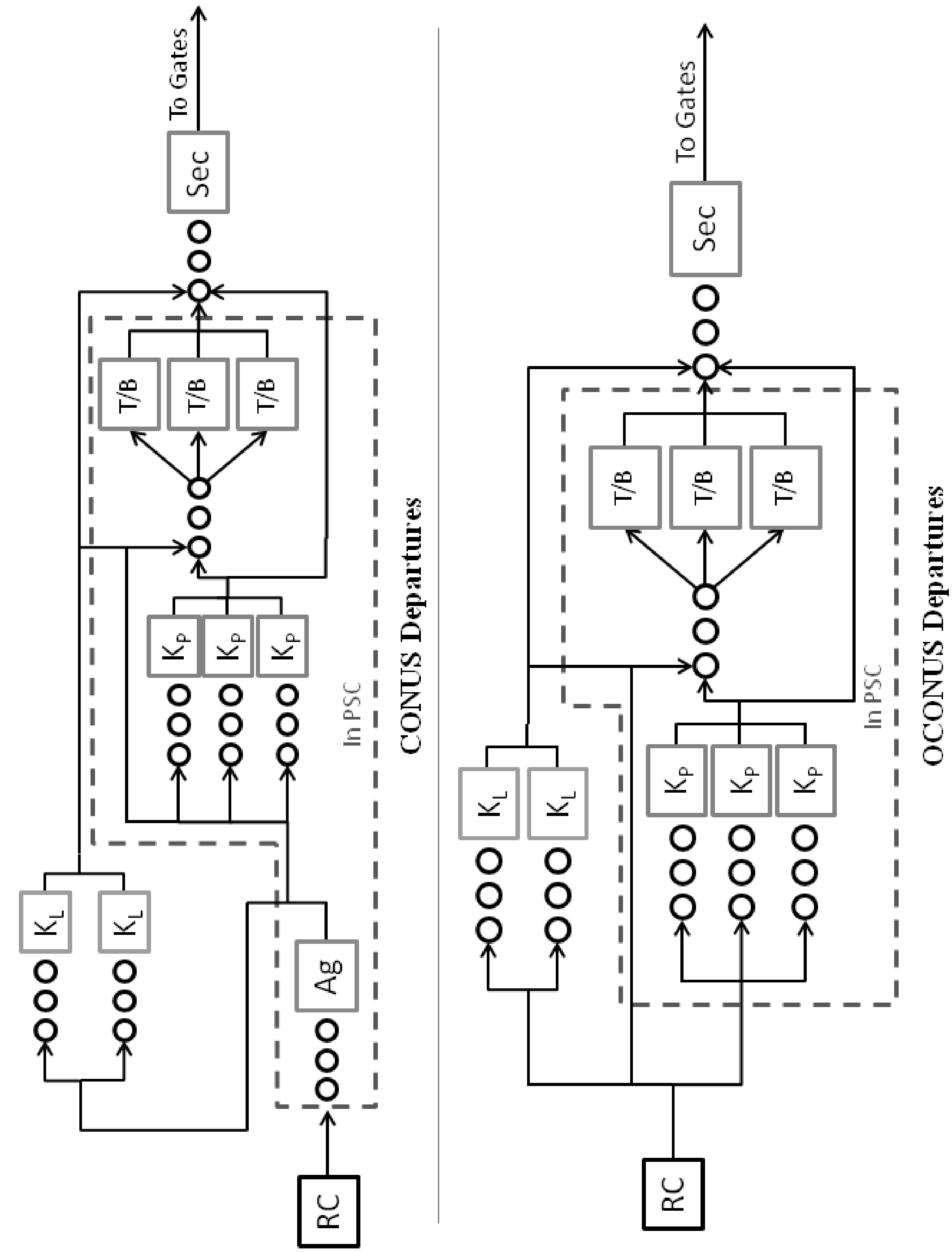


Figure 3.2. Terminal Schematic in Expanded Form.

sures:

$$L_{q,i} = \left(\frac{r_i^{c_i} \rho_i}{c_i!(1-\rho_i)^2} \right) p_{0,i} \tag{3.5}$$

$$W_{q,i} = \frac{L_{q,i}}{\lambda_i} \tag{3.6}$$

$$L_i = L_{q,i} + r_i \tag{3.7}$$

$$W_i = \frac{1}{\mu_i} + W_{q,i} \tag{3.8}$$

which are the average number of passengers awaiting service, average waiting time in queue, average total passengers, and average total time spent at node i, respectively. Then using Little's formula, Equation 3.9, for the entire system provides the overall average passenger processing time.

$$W = \frac{\sum L_i}{\sum \gamma_i} \tag{3.9}$$

where γ_i's are the average arrival rates at node i from outside the system.

3.3 Departure From Jacksonian Assumptions

In reality, an airport terminal is a non–steady–state system on a per–flight basis. Passenger flows at civilian airports follow typically follow a rather triangular or normal (sometimes skewed) pattern described in Section 2.4.2. Passengers for several flights arrive in overlapping patterns with separate and similar, but independent arrival distributions. Customer flows terminate when a flight is fully processed. Figure 3.3a shows sample paths of two such arrival patterns and their associated empirical cumulative distributions, while 3.3b illustrates the superposition of those two patterns.

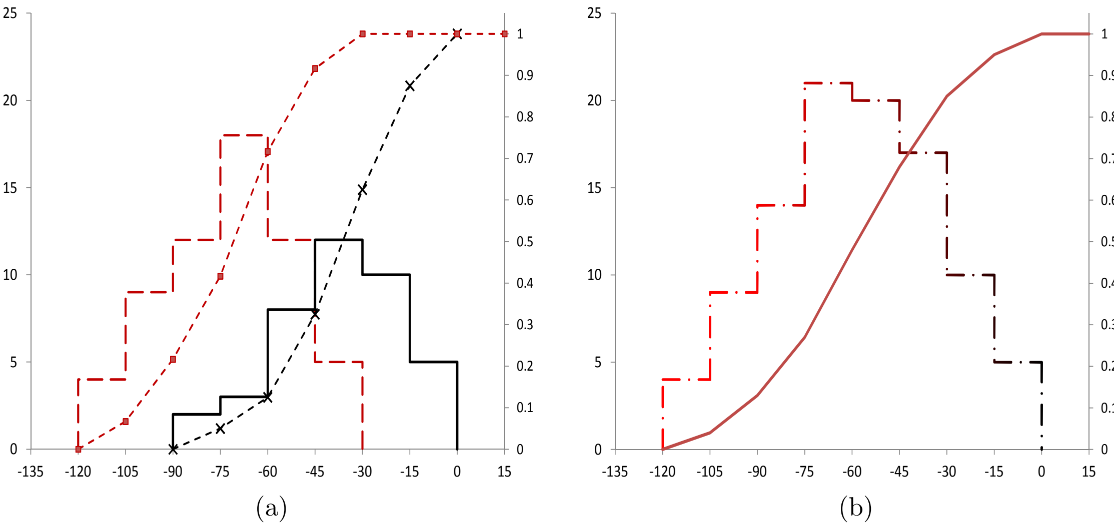


Figure 3.3. Sample paths of passenger arrivals during an arbitrary period of time with empirical CDFs. Arrivals (here shown over 15 minute intervals) discretely increase, then quickly decrease as time approaches, say, boarding time. Figure 3.3a Illustrates two separate departing flights while Figure 3.3b shows the superposition of those two flights as experienced by a check-in counter. It's CDF is approximately a convolution of the distributions of the individual flights.

The nonstationary pattern (wherein arrival rates rise fall, then terminate) renders many of the closed form solutions invalid, and inhibits transient analysis. However approximations are still possible. As shown previously, the departure process from the first queue becomes Markovian as traffic increases for so long as $\rho < 1$. In order to account for the first queue, statistical methods can be employed to estimate a factor, by which to scale W_q from the analytical model.

3.3.1 Departure Process with Low Utilization.

The fact that departures from an $M(t)/G/\infty$ queue is $M(t)$ [12, 28, 35] is a property useful for developing multi–server models and approximating their performance. The interpretation is that when a queue never forms, the distribution of the departure process is the same as the arrival process. For time–dependent processes, this is of particular interest, since in such cases customers experience no wait. The concept can be easily visualized using a simulation, which is simple to build in Arena® using a create/process/dispose process flow. Figure 3.4 illustrates the model with additional logic to collect and record statistics omitted. A contains complete figures of analysis computed using JMP®. Several figures are reproduced in this section for convenience.

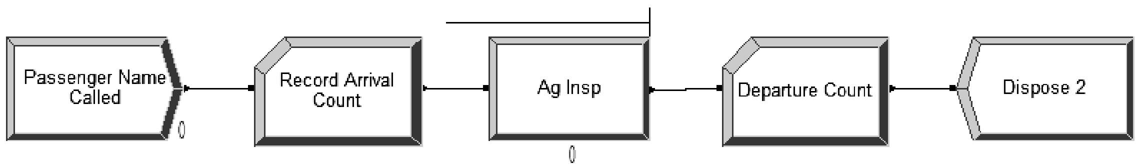


Figure 3.4. Simulation Flowchart View Model

By increasing the average service rate (thereby, decreasing utilization), a reasonable approximation for an infinite server model can be achieved without creating a large number of individual service resources. Several scenarios were run, each with a different utilization value, but only four pertinent models are shown for simplicity (additional models only reaffirmed the same conclusion demonstrated by those included here). To reduce run bias, but remain economical, the simulation was run with 10 replicates, each randomized by the internal programming logic. Both models assume 40 passengers total will be processed for a single flight.

Two arrival profiles, one with time–dependent Markovian arrivals and one with constant inter-arrival patterns, were run. The Markovian pattern assumes passenger interarrival times over 15-min intervals are stationary and sampled from an exponential distribution. The interarrival rates slowly increase over the first 60 minutes (first 4 intervals), quickly decreases for 15 minutes, then goes to zero when all 40 passengers have arrived. The schedule module built to model such a pattern is shown in Figure 3.5. The rate values chosen give the desired pattern of arrivals for each period (3, 6, 10, 13, then 8). It is unclear why a factor of 6 was necessary to achieve the appropriate mean arrival rate for each period, but the results are unaffected by

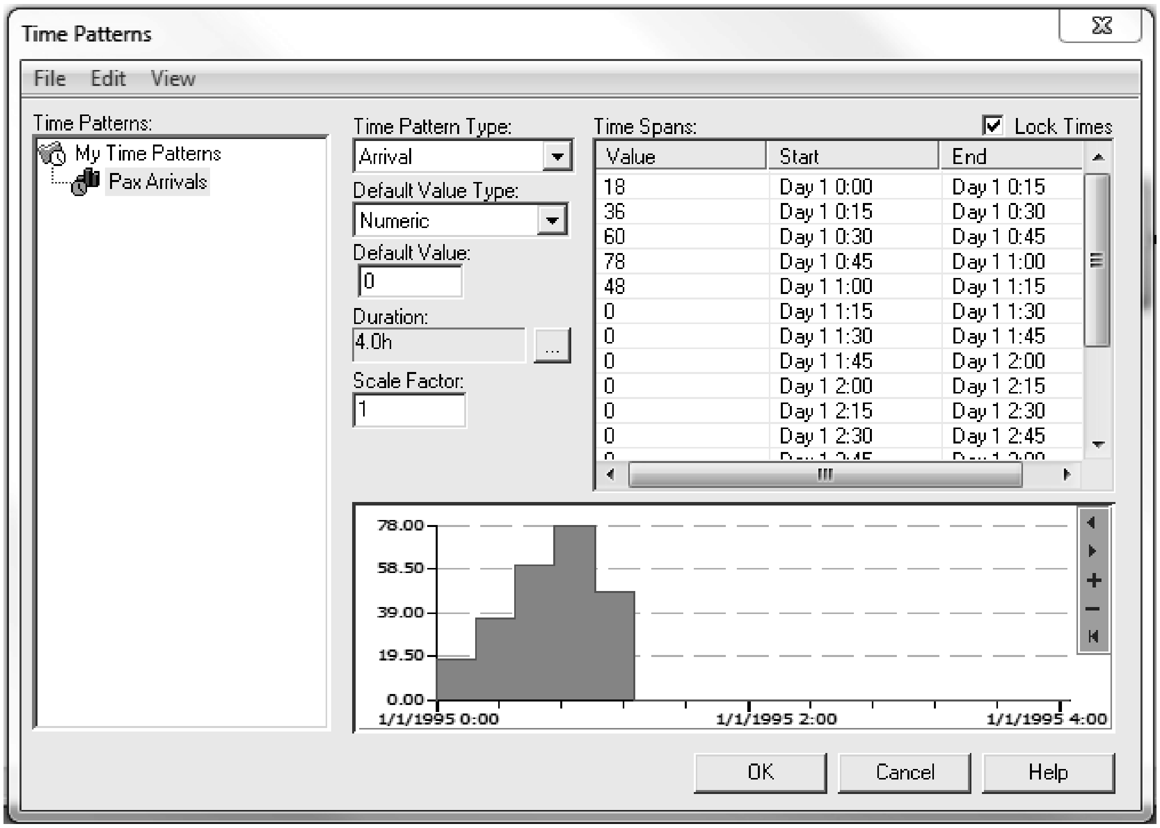
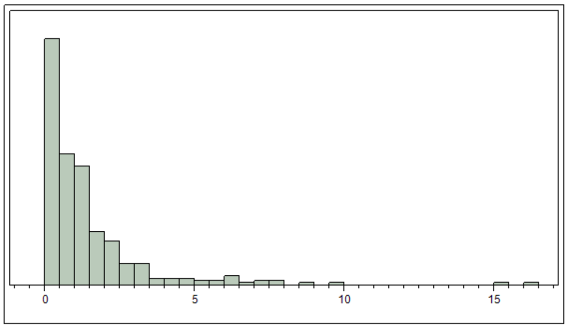


Figure 3.5. Simulation Schedule Module

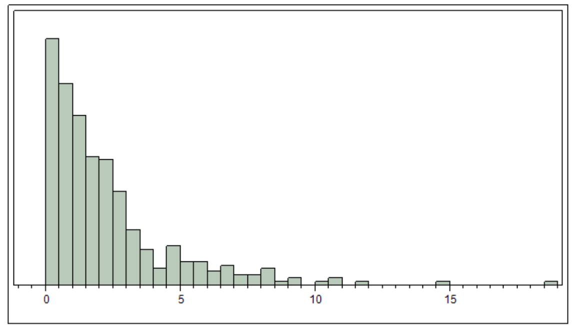
this Arena®–specific nuance. The constant rate pattern assumes passengers arrive exactly 5 seconds apart (12 per minute) until all 40 have entered the system, then arrivals terminate.

For the $M(t)$ arrivals, observed server utilizations decrease from $\rho = 0.8325$ when service time of $1/\mu = 1.85$ mins to $\rho = 0.0014$ with $1/\mu = 0.00185$ mins. The result is an evolution of the departure process away from the exponential distribution. Clearly, the distribution in Figure 3.6b is far different than that of the arrivals, Figure 3.6a, but the distribution in Figure 3.6d is nearly indistinguishable from the arrival distribution in Figure 3.6c. This is of course expected per the proposed performance.

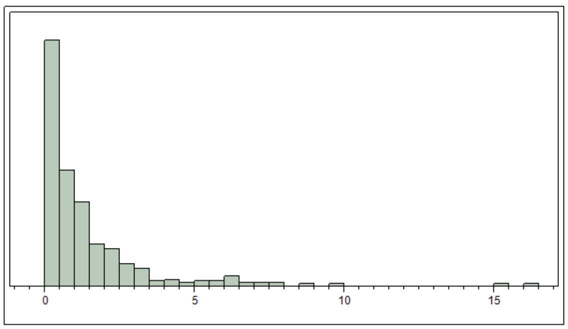
Analyzing the deterministic service model produces the same result. At an observed utilization, $\rho = 0.0000$, the departure distribution in Figure 3.6h matches the



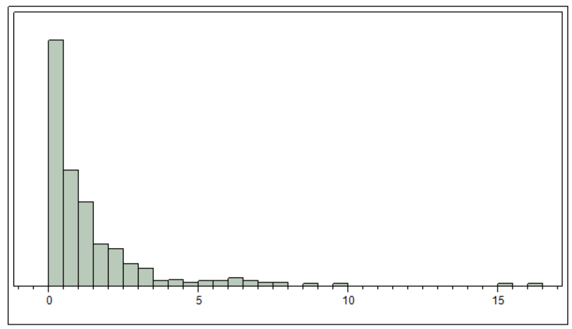
(a) Simulation 1: $M(t)$ Arrivals



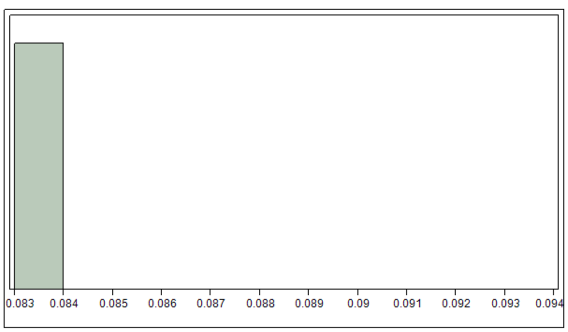
(b) Simulation 1: Departures, $\hat{\rho}_1 = 0.8325$



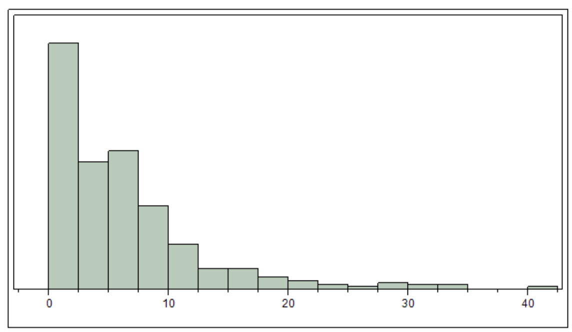
(c) Simulation 3: $M(t)$ Arrivals



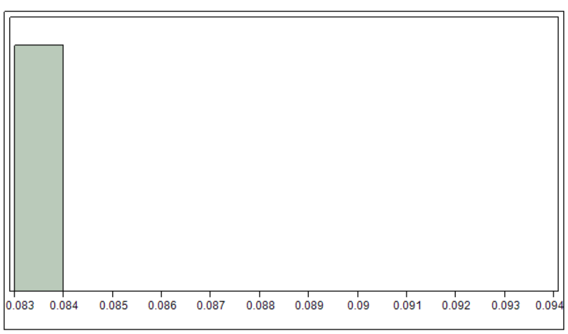
(d) Simulation 3: Departures, $\hat{\rho}_3 = 0.0014$



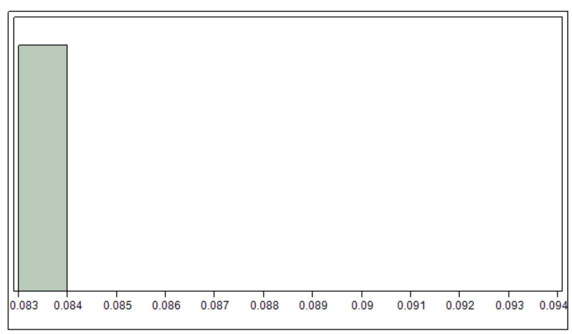
(e) Simulation 4: Deterministic Arrivals



(f) Simulation 4: Departures, $\hat{\rho}_4 = 0.8624$



(g) Simulation 7: Deterministic Arrivals



(h) Simulation 7: Departures, $\hat{\rho}_7 = 0.0000$

Figure 3.6. Simulation Results

arrival distribution, Figure 3.6g, with little error, while the distributions for the model with high utilization, Figures 3.6e and 3.6f, are wholly dissimilar. Reasonably, the character of the arrival and departure distributions would continue to converge as $\rho \to 0$ and $c \to \infty$. Thus, the simulation results are in agreement with the theoretical proposition.

3.3.2 Time-Dependent Arrival Pattern.

As described in Section 2.4, the arrival pattern to airport terminals is well studied and, in general, can be visualized graphically as a curve with an initially slowly increasing slope, which recurves to a maximum, then quickly decreases. This behavior corresponds to passenger behavior as a function of time relative to the flight departure time. That is, there is a tradeoff between a passenger's (increasing) sense of urgency to leave early to avoid missing a flight and their (decreasing) degree of liberty in avoiding long wait times within the terminal prior to departure [37]. The true shape of this curve depends on the characteristics of the flight of interest as well as the behavioral tendencies of individual travelers.

Now consider any interval of this curve, say, 5, 10, 15 mins, or the length of a service time $1/\mu$. As discussed in Section 2.4.2, reasonable approximations for a non-stationary arrival process can be found by adequately partitioning the distribution assuming constant arrival times for that time period.

3.3.3 First Queue adjustment to $G(t)/M/c$.

An approximation for general arrival queuing systems takes a bit of finesse. Various approximations are available, but deferring to statistical methods provides reasonable results. Data collection can be arranged; however, simulation (when available), especially for a relatively simple system, provides an acceptable degree of accuracy in a timely manner.

The factor of interest some constant scaling factor, SF, by which to multiply the analytical value for average wait in queue by, $W_q(M/M/c$ that will provide a reasonable approximation for the time dependent result. A suspected value is the coefficient of variance, CV, associated with the waiting time in the first queue, given $\rho_1 < 1$. The proposed method is to determine $W_{q,1}^{(ADJ)}$ where

$$W_{q,1}(ADJ) = SF \cdot W_{q,1}(M/M/c). \tag{3.10}$$

This differs from other methods of approximation, such as scaling W_q by the the squared coefficient of variation (SCV) or using the Pollaczek–Khintchine (PK) formula. Figure 3.7 shows the relative values for CV, SCV, and the factor associated with the PK formula, $\frac{SCV+1}{2}$ for $W_{q,1}(M/M/c) = 1$. For an exponentially distributed wait, $\sigma = \mu$ and thus $CV = SCV = PK = 1$ whereas for a deterministic distribution $CV = SCV = 0$ and $PK = 0.5$.

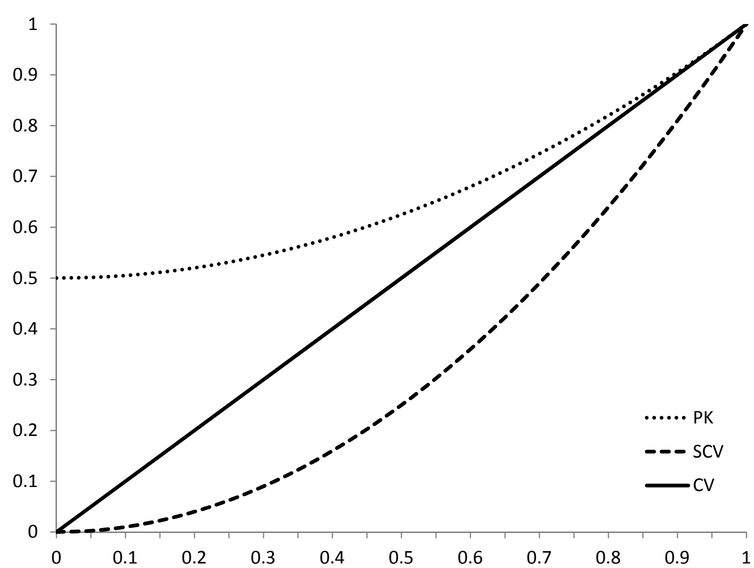


Figure 3.7. Comparison of Variation Factors

3.3.4 Waiting Time Adjustment.

Having obtained $W_{q,1}(ADJ)$, the total processing time can be modified. Adding the service times and the average queue waits for the down-stream nodes and a constant estimate of facility–to–facility travel time, τ, the final equation is

$$T_{tot}(t) = SF \cdot W_{q,1}(ADJ) + \sum_{i=1}^{3} W_{q,i}(M/M/c) + \sum \mu_i + \tau. \tag{3.11}$$

where $W_{q,1}(ADJ)$ is the adjusted wait in queue time at the first node, $W_{q,i}(M/M/c)$ are the analytically computed waits at the remaining queues.

3.4 Identifying Optimal Manning

As demonstrated in Section 3.3.1, reducing the overall utilization of a server results in lower waiting times for customers. In the ideal case (the infinite server system), enough service is available to eliminate any waiting at all. However, this is rarely achievable, or even feasible, due to manning, policy, workspace or financial constraints. Realistically, identifying a specified server utilization that provides an achievable quality of service by reducing wait times to an acceptable level. Utilization can be controlled by a number of means, which can be grouped into one of three methods: controlling arrivals, reducing service time, or adjusting staffing.

Controlling the arrivals is least preferable, since doing so with consistency may not be an option. In general, implementing policies which require passengers to show at various times would be the only manageable option to limit utilization in this way. Doing so may negatively impact customers' perceptions of service, however, since an earlier show may simply cause a longer lobby wait time. Additionally, with multiple large-capacity flights scheduled in close proximity, overcrowding would become an issue as passengers for each flight must wait stagnantly together.

In some cases, reducing service time is a viable option. However, this too can be problematic, as there could exist a lower limit to the speed of a process as imposed by computer/machine capabilities or the number of required steps. Rushing a process may make servers more error prone, thus increasing processing time variability and waiting time thus, inevitably, frustrating passengers and staff alike. Thus a reduction in speed may not produce practically significant results. Adjusting the staffing level is the most feasible option compared. Assuming that rate of service is independent of the capability of an individual server, adding a server will reduce the utilization proportional to the offer load . That is if c is the number of servers, ρ the utilization, λ the rate of arrivals and $1/\mu$ the average service time then. Staffing, is a relative term, since a particular server can be human, machine, or could also pertain to a team of individuals acting as a single entity.

3.5 Other Assumptions and Limitations

Although the equations utilized assume steady state behavior, the system itself never goes to steady state. Once all passengers have been rotated through a facility, that facility is effectively closed. In fact, even though the Markovian property (also called the memoryless property) is assumed for arrivals in the model, the true system exhibits no such behavior in the long run due to the shrinking source of passengers. However, assuming relative stationarity over short intervals still allows for reasonably valid approximations.

Additionally, the model can be extended to include non-Markovian service, but only exponentially-distributed service times are assumed for this research. Service times are also assumed time–independent, though the methodology can be extended to time variant service (i.e., $c(t)$ and $\mu(t)$) as proposed by Mandelbaum and Massey [18]. Since it is the more constrained model, with a high utilization node at the very beginning of the process, this research will focus on CONUS–destined flights. A similar technique, however, can be employed for the passengers to OCONUS locations. The queue adjustment, would then be applied both to the ticket kiosk and PSC check–in counter. The system would only consist of the kiosks, counter and security screening processes, since the Ag Inspection is not required.

Multiple flights will also not be modeled directly, but the technique would be similar, as the simulation would simply have to account for a greater number of passengers. In such cases, it is assumed that flights are coincident. That is they are overlapping, adjacent or separated by a reasonably small margin of time.

IV. Findings and Analysis

4.1 Case Study

The case study deals with describing the capacity of a terminal, given the stochastic nature of passenger arrivals, which are dependent on several factors. The foremost is the schedule of departing flights. Next, the number of seats released by a flight determines the maximum number of passengers that will be processed for the flight. Any remaining never enter the system for the sake of this study. Third, the flight destination determines how passengers are processed, as the USDA inspection is required for only those passengers processing for flights to the US mainland or Guam [34].

4.1.1 Scenario Development.

Only portions of landside operations are of interest, which differ slightly from their civilian counterparts. In particular these are *1*) Roll Call *2*) US Department of Agriculture (USDA) inspection, *3*) ticketing/baggage check-in, and *4*) security screening (x-ray). The following sections discuss the layout and functions of each processing station transited by departing passengers at the 735th AMS. The and passenger flow is depicted in Figure 4.2 as system layout and in Figure 4.1 in simplified flow chart form.

4.1.2 Passenger Characteristics.

The FAA categorizes air travelers into two basic groups with distinct characteristics: business travelers and leisure travelers [2]. Military flights, on the other hand, have different classifications, referred to as Space–Required (or Space–R) and Space–Available (or Space–A) [24].

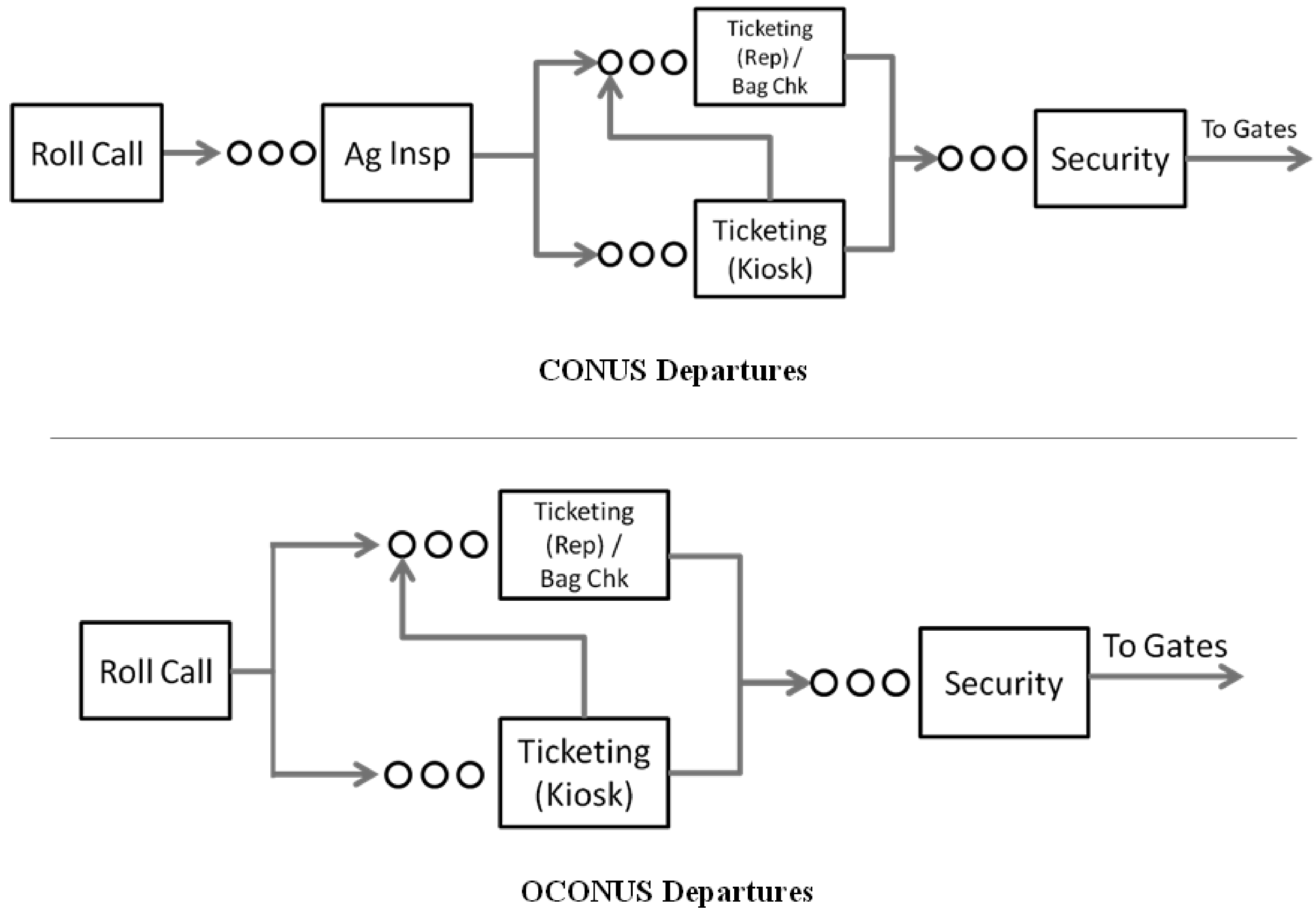


Figure 4.1. Terminal Schematic in Compact Form.

4.1.2.1 Space–R Passengers.

Space–R passengers meet the eligibility criteria to be considered "mission essential" by the DoD as described in Chapter 5 of DoD 4515.13–R, which includes travel for Permanent Change of Station (PCS), travel for temporary duty (TDY) or Temporary Additional Duty (TAD), or for any other authorized travel [24]. Any mission–specific passenger processes temporarily implemented to load Space–R passengers in a manner different than described within this work is beyond the scope of this study. For example, the research presented here examines routine day–to–day operations of the terminal rather than performance during mass troop deployment. However, it should be noted that the methodology, in general, would still hold in that case as well, though arrival patterns may differ.

4.1.2.2 Space–A Passengers.

Those travelers who are not mission-essential, but who meet the criteria in Chapter 6 of the same regulation, are considered Space–A and may fly on DoD aircraft as a privilege and at no cost [24]. Space–A passengers are always stand-by and are allowed to travel if any seats remain for their use. Additionally, Space–A travelers are not served according to their arrival, but are ticketed depending on specific hierarchy criteria. The ordering of passengers according to this hierarchy is conducted automatically when a passenger arrives to the terminal and checks in, which means a passengers time of arrival, then, is only pertinent to other passengers within the same category. Service performance experienced by a specific category of passenger, is beyond the scope of this work. Thus all Space–A passengers are considered for the sake of this study.

4.1.2.3 Have Bags, Will travel.

An over-arching group are those passengers who need to check luggage. Even though kiosks are available for processing passengers, all those possessing baggage other than just carry–on must still enter the line at the ticketing counter to check their bags. Due to the isolated locale of Hickam AFB and sparsity of viable destinations nearer than Travis AFB ($\approx$ 2500 miles and about 5 hours flying away). It is reasonable to assume that an overwhelming majority of passengers will have to process through the counter rather than proceeding to security from the kiosk.

4.1.2.4 Summary.

Since passengers are prioritized prior to entering the queue, there is virtually no concern over the impact of priority within the queue discipline. The vast majority passengers will check luggage, but an allowance can be made for the few who may only require carry–on bags. Thus, modeling passengers as a single class with a routing probability assigned for those entering the system, but not checking bags, is reasonable and parsimonious in the given case.

4.1.3 Passenger Processing.

This section discusses each facility/process that passengers transit from arrival to the terminal until they enter the gate lobby. Figure 4.2 is an annotated architectural layout provided as a visual reference.

4.1.3.1 Passenger Arrival/Roll Call.

All passengers flow for a departing flight comes through roll call. Passengers, who were all assigned a priority upon marking themselves present at arrival, are assigned seats according to their during roll call (counter shown in Figure 4.3b). Any remaining

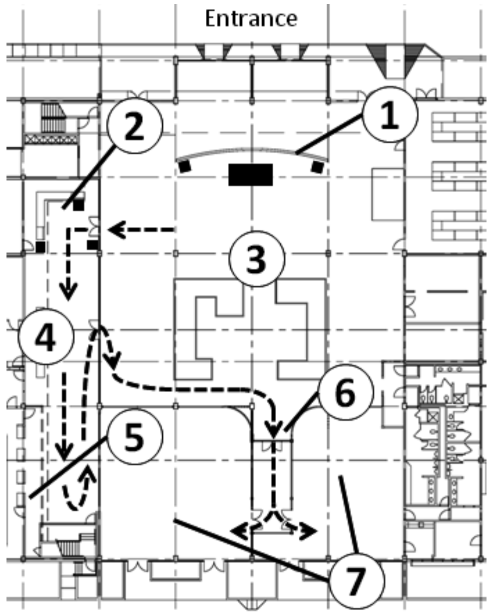


Figure 4.2. 735th AMS Terminal Floor Plan showing pertinent facilities: *1*) roll call counter, *2*) sign–up counter, *3*) main lobby area, *4*) agricultural inspection machine, *5*) check–in counter, *6*) security screening (x–ray), and *7*) outbound gate lobbies. The path through the system from the waiting in the lobby to moving to the gate lounge is shown.

when all seats are filled will await the next flight, which may be several days or weeks away or, frustrated, may remove themselves from the listing (renege). A passenger could conceivably wait quite a while to begin their trip. Passengers are required to arrive at the terminal in accordance with AMC guidelines, which specifies two hours, twenty minutes prior to the departure of a given flight [33], although in practice passengers typically arrive 30 minutes prior. If necessary, such as during peak travel times, managers may adjust required show–times accordingly.

4.1.3.2 The Passenger Service Center.

The Passenger Service Center (PSC) serves as the central hub for passenger processing containing the PSC counter (Area 2 in Figure 4.2) while agriculture inspection station and the, and passenger ticketing/baggage counter. For Space–A passengers,

(a) (b)

Figure 4.3. (a) Main lobby and (b) roll call counter—two of the five available kiosks are on either side of the counter, terminal entrance is just on the opposite side of the curved partition (unseen).

a visit to the PSCsign–up counter initiates their travel. A passenger's eligibility for Space–A travel and their destination are entered into the database, which ranks him/her according to priority category and date of sign-up.

4.1.3.3 US Department of Agriculture (USDA) Inspection [34].

The USDA mandates that all travelers from Hawaii to either the US mainland—which includes the contiguous United States (CONUS) and Alaska—or the US island territory of Guam must undergo an inspection prior to departure. This inspection is intended to scan for agricultural items which may contain pests which can potentially become invasive species deleterious to US agriculture, and as such are restricted from transport from Hawaii to those locations—namely certain fruits, plants and other specified items. No inspection is required for passengers destined to locations outside CONUS (OCONUS) . The USDA inspection is located at area 4 in Figure 4.2.

4.1.3.4 The Passenger Check-in [33].

The check-in process ensures that passengers have all required documents for travel and that travelers are properly manifested for their assigned flight. This in-

(a) (b)

Figure 4.4. (a) Sign–up counter and (b) USDA inspection station

cludes verifying travel documents, issuing boarding passes, assigning seats, checking baggage, collecting applicable charges (e.g., meals, pet fees, excess baggage, etc.), and identifying any potential problems prior to boarding. By policy, additional counters are opened (if available) if waiting times exceed 15 mins. Passengers may use ticket kiosks to begin the check-in process, but any necessary further processing must be completed at the counter. Kiosks, in practice, are under utilized by passengers, which puts the greater load of traffic on the counter. Though, its impact is assumed to be negligible for the purposes of this research, the fact that the kiosks are actually shared resources could add complexity when many travelers are processing. Passengers arriving to the terminal must also use the kiosks to mark themselves present. Thus in the case of multiple departures with dual use kiosks (rather than kiosks dedicated to one process or the other), the utilization of the kiosks would be higher.

4.1.3.5 Security Screening.

The passenger and baggage security screening is conducted in the same manner as at civilian airports per Transportation Security Administration (TSA) guidelines [33:49-51]. Just as in any other terminal, passengers remove outer garments and footwear, empty pockets, place carry–on baggage on the conveyor belt and proceed through an x–ray machine operated by a security team, then proceed to the outbound gates to await transportation to awaiting aircraft. Within the scope of this analysis, once passengers have cleared security they have entered the airside, having departed the landside system. The security area is located in area 6 in Figure 4.2 with outbound gates designated by area 7.

(a) (b)

Figure 4.5. (a) Check–in counter and (b) security station (seen through double doors).

4.1.4 Aircraft Have Finite Size.

The number of Space–R passengers on a flight are effectively random. Sometimes a flight will be completely devoid of duty passengers, whereas some flights are completely oriented to flying a unit of Space–R passengers to a particular location. The number of Space–A passengers who arrive for a flight is random, but the number who are processed depend on the number of seats released minus the number of Space–R passengers ticketed for the flight. In either case, the total number of passengers that are processed for flight is no more than the number of seats released for that particular flight. This depends on a number of factors.

Intuitively, the number of seats released by the aircraft commander will be limited by the size of the aircraft. Furthermore, the number of seats available for passengers will be limited by restrictions imposed by the aircraft's mission. The cargo load, presence of hazardous or restricted cargo, number of through-manifested passengers already aboard, and the size of the aircrew will place limitations on the space available for additional passengers. These concerns are accounted for, however, during roll call. No more passengers will be processed than there is room on the plane. Any remaining will either remain in the lobby for the next flight if one will arrive soon, or leave and return at the next opportunity. Since we are only modeling the processing of passengers who will board the flight, these rejected passengers are not included in this model since they never enter the system.

4.2 Analysis

4.2.1 Steady State OJN Analysis.

Assuming steady state arrival rates for a particular spread of cases provides a system parameters that can be adjusted to approximate the performance of a non-stationary system. Table 4.1 shows the flow rates for chosen arrival rates for which $\rho < 1$. Traffic flows for each node are obtained from Equation 3.1b. Node indices for this and all tables and charts follow the notation *1* = USDA Inspection, *2* = Ticket Kiosks, *3* = PSC Counter, and *4* = Security Screening.

Table 4.1. CONUS steady state arrival rates and effective passenger flows.

γ_1	λ_1	λ_2	λ_3	λ_4
4/hr	4.000	0.200	3.998	4.000
8/hr	8.000	0.400	7.996	8.000
12/hr	12.000	0.600	11.994	12.000
16/hr	16.000	0.800	15.992	16.000
20/hr	20.000	1.000	19.990	20.000
24/hr	24.000	1.200	23.988	24.000
28/hr	28.000	1.400	27.986	28.000
32/hr	32.000	1.600	31.984	32.000

Calculated node-by node utilizations are presented in Table 4.2 for the base case (no superscript), the case where all facilities have one additional server than base (i.e., “One-Up” scenario, $^+$), and the case where each facility has at most one fewer server but at least one sever (i.e., “One-Down” scenario, $^-$) [8]. The impact of an additional server is dramatic, especially for cases with high arrival rates. For example, observe that when $\gamma = 32/\text{hr}$, $\rho_1^+ \approx \frac{1}{2}\rho_1$ while virtually no difference is seen in ρ_1^-. Likewise, the empty probabilities are greatly impacted by service capacity, Table 4.3.

Table 4.2. CONUS steady state average passengers in queue and in process for base number of servers, one added server per process (+), and less one server (−) down to a single server.

γ_1	ρ_1	ρ_2	ρ_3	ρ_4	ρ_1^+	ρ_2^+	ρ_3^+	ρ_4^+	ρ_1^-	ρ_2^-	ρ_3^-	ρ_4^-
4/hr	0.123	0.002	0.061	0.123	0.062	0.002	0.046	0.062	0.123	0.002	0.091	0.123
8/hr	0.247	0.004	0.122	0.247	0.123	0.003	0.091	0.123	0.247	0.005	0.183	0.247
12/hr	0.370	0.005	0.183	0.370	0.185	0.005	0.137	0.185	0.370	0.007	0.274	0.370
16/hr	0.493	0.007	0.243	0.493	0.247	0.006	0.183	0.247	0.493	0.009	0.365	0.493
20/hr	0.617	0.009	0.304	0.617	0.308	0.008	0.228	0.308	0.617	0.011	0.456	0.617
24/hr	0.740	0.011	0.365	0.740	0.370	0.009	0.274	0.370	0.740	0.014	0.548	0.740
28/hr	0.863	0.013	0.426	0.863	0.432	0.011	0.320	0.432	0.863	0.016	0.639	0.863
32/hr	0.987	0.015	0.487	0.987	0.493	0.012	0.365	0.493	0.987	0.018	0.730	0.987

Table 4.3. CONUS steady state average empty node probabilities for base number of servers, one added server per process (+), and less one server (−) down to a single server.

γ_1	$p_{0,1}$	$p_{0,2}$	$p_{0,3}$	$p_{0,4}$	$p_{0,1}^+$	$p_{0,2}^+$	$p_{0,3}^+$	$p_{0,4}^+$	$p_{0,1}^-$	$p_{0,2}^-$	$p_{0,3}^-$	$p_{0,4}^-$
4/hr	0.877	0.991	0.833	0.877	0.884	0.991	0.833	0.884	0.877	0.991	0.833	0.877
8/hr	0.753	0.982	0.694	0.753	0.780	0.982	0.694	0.780	0.753	0.982	0.691	0.753
12/hr	0.630	0.973	0.578	0.630	0.688	0.973	0.578	0.688	0.630	0.973	0.570	0.630
16/hr	0.507	0.964	0.480	0.507	0.604	0.964	0.482	0.604	0.507	0.964	0.465	0.507
20/hr	0.383	0.955	0.398	0.383	0.529	0.955	0.401	0.529	0.383	0.955	0.373	0.383
24/hr	0.260	0.947	0.329	0.260	0.460	0.947	0.334	0.460	0.260	0.947	0.292	0.260
28/hr	0.137	0.938	0.270	0.137	0.397	0.938	0.277	0.397	0.137	0.938	0.220	0.137
32/hr	0.013	0.930	0.220	0.013	0.339	0.930	0.230	0.339	0.013	0.930	0.156	0.013

Thus, the number of servers on their own can greatly contribute to quality of service. In this case we see for a (steady state) system with a passenger arrival rate, say, of 28/hr will incur a mean queue wait at the Ag Inspection of 11.7 min while an additional server there reduces the wait to less than 30 sec on average, Table 4.4. Total process waits and average customers awaiting service are logically similarly and a presented in Tables 4.5–4.7

Table 4.4. **CONUS steady state average waits in queue (minutes).**

γ_1	W_{q1}	W_{q2}	W_{q3}	W_{q4}	W^+_{q1}	W^+_{q2}	W^+_{q3}	W^+_{q4}	W^-_{q1}	W^-_{q2}	W^-_{q3}	W^-_{q4}
4/hr	0.260	2.89E-13	0.001	0.260	0.007	3.66E-16	2.90E-05	0.007	0.260	1.98E-10	0.023	0.260
8/hr	0.606	9.19E-12	0.007	0.606	0.029	2.33E-14	4.27E-04	0.029	0.606	3.15E-09	0.094	0.606
12/hr	1.087	6.94E-11	0.022	1.087	0.066	2.64E-13	0.002	0.066	1.087	1.59E-08	0.222	1.087
16/hr	1.801	2.91E-10	0.050	1.801	0.120	1.47E-12	0.006	0.120	1.801	4.99E-08	0.422	1.801
20/hr	2.976	8.83E-10	0.095	2.976	0.194	5.58E-12	0.013	0.194	2.976	1.21E-07	0.721	2.976
24/hr	5.265	2.18E-09	0.163	5.265	0.293	1.66E-11	0.026	0.293	5.265	2.50E-07	1.174	5.265
28/hr	11.687	4.70E-09	0.261	11.687	0.424	4.15E-11	0.046	0.424	11.687	4.62E-07	1.891	11.687
32/hr	136.900	9.10E-09	0.397	136.900	0.595	9.19E-11	0.074	0.595	136.900	7.85E-07	3.132	136.900

Table 4.5. **CONUS steady state average process time (minutes).**

γ_1	W_1	W_2	W_3	W_4	W^+_1	W^+_2	W^+_3	W^+_4	W^-_1	W^-_2	W^-_3	W^-_4
4/hr	2.110	2.740	2.741	2.110	1.857	2.740	2.740	1.857	2.110	2.740	2.763	2.110
8/hr	2.456	2.740	2.747	2.456	1.879	2.740	2.740	1.879	2.456	2.740	2.834	2.456
12/hr	2.937	2.740	2.762	2.937	1.916	2.740	2.742	1.916	2.937	2.740	2.962	2.937
16/hr	3.651	2.740	2.790	3.651	1.970	2.740	2.746	1.970	3.651	2.740	3.162	3.651
20/hr	4.826	2.740	2.835	4.826	2.044	2.740	2.753	2.044	4.826	2.740	3.461	4.826
24/hr	7.115	2.740	2.903	7.115	2.143	2.740	2.766	2.143	7.115	2.740	3.914	7.115
28/hr	13.537	2.740	3.001	13.537	2.274	2.740	2.786	2.274	13.537	2.740	4.631	13.537
32/hr	138.750	2.740	3.137	138.750	2.445	2.740	2.814	2.445	138.750	2.740	5.872	138.750

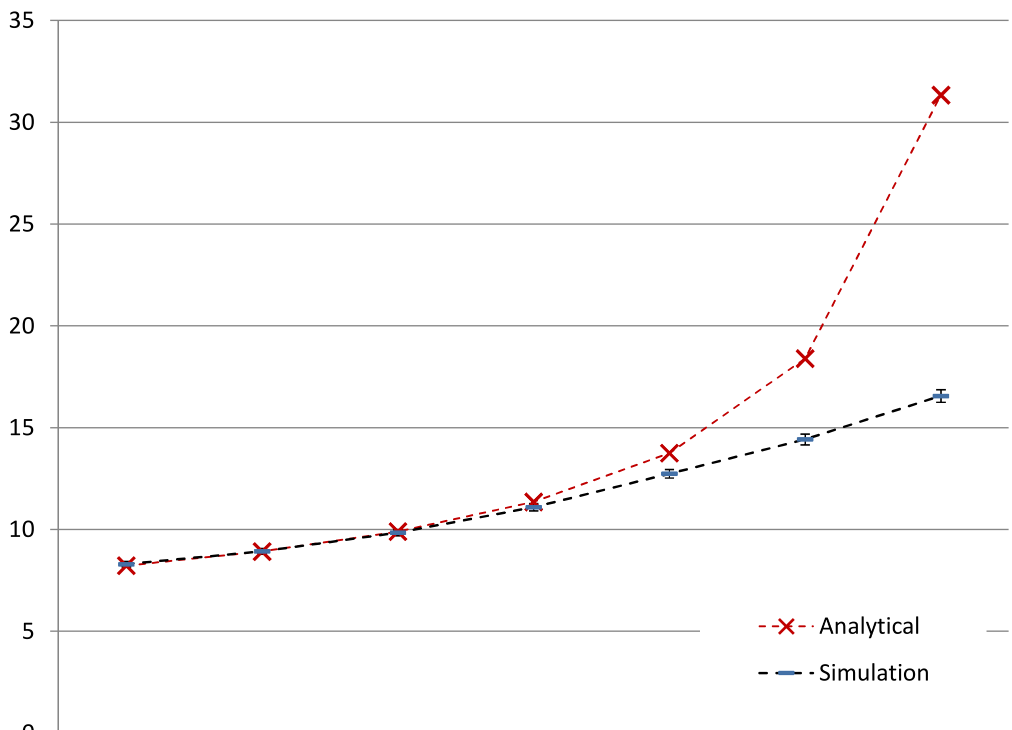
Table 4.6. **CONUS steady state average passengers in queue for base number of servers, one added server per process (+), and less one server (−) down to a single server.**

γ_1	L_{q1}	L_{q2}	L_{q3}	L_{q4}	L^+_{q1}	L^+_{q2}	L^+_{q3}	L^+_{q4}	L^-_{q1}	L^-_{q2}	L^-_{q3}	L^-_{q4}
4/hr	0.017	0.000	0.000	0.017	0.000	0.000	0.000	0.000	0.017	0.000	0.002	0.017
8/hr	0.081	0.000	0.001	0.081	0.004	0.000	0.000	0.004	0.081	0.000	0.013	0.081
12/hr	0.217	0.000	0.004	0.217	0.013	0.000	0.000	0.013	0.217	0.000	0.044	0.217
16/hr	0.480	0.000	0.013	0.480	0.032	0.000	0.002	0.032	0.480	0.000	0.112	0.480
20/hr	0.992	0.000	0.032	0.992	0.065	0.000	0.004	0.065	0.992	0.000	0.240	0.992
24/hr	2.106	0.000	0.065	2.106	0.117	0.000	0.010	0.117	2.106	0.000	0.469	2.106
28/hr	5.454	0.000	0.122	5.454	0.198	0.000	0.021	0.198	5.454	0.000	0.882	5.454
32/hr	73.013	0.000	0.212	73.013	0.317	0.000	0.040	0.317	73.013	0.000	1.669	73.013

Table 4.7. **CONUS steady state average passengers in process for base number of servers, one added server per process (+), and less one server (−) down to a single server.**

γ_1	L_1	L_2	L_3	L_4	L^+_1	L^+_2	L^+_3	L^+_4	L^-_1	L^-_2	L^-_3	L^-_4
4/hr	0.141	0.009	0.183	0.141	0.124	0.009	0.183	0.124	0.141	0.009	0.184	0.141
8/hr	0.327	0.018	0.366	0.327	0.250	0.018	0.365	0.250	0.327	0.018	0.378	0.327
12/hr	0.587	0.027	0.552	0.587	0.383	0.027	0.548	0.383	0.587	0.027	0.592	0.587
16/hr	0.974	0.037	0.744	0.974	0.525	0.037	0.732	0.525	0.974	0.037	0.843	0.974
20/hr	1.609	0.046	0.945	1.609	0.681	0.046	0.917	0.681	1.609	0.046	1.153	1.609
24/hr	2.846	0.055	1.161	2.846	0.857	0.055	1.106	0.857	2.846	0.055	1.565	2.846
28/hr	6.317	0.064	1.400	6.317	1.061	0.064	1.299	1.061	6.317	0.064	2.160	6.317
32/hr	74.000	0.073	1.672	74.000	1.304	0.073	1.500	1.304	74.000	0.073	3.130	74.000

Results were compared to a simulation which closely represents the passenger flow of a single, moderate capacity, CONUS-bound flight at the 735th AMS passenger terminal. The simulation was run for a 40–passenger plane–load with 100 replications (4000 data points in all), using the service rates from Section 3.2.2 and arrival rates from Table 4.1 assuming passengers arrive equally spaced. This amounts to a terminating $D/M/c$–like system. These results compare favorably with a simulated system for low utilizations, Figure 4.6. Utilizations diverge for high arrival rates due to the termination of passenger flow for the simulated system.



	4/hr	8/hr	12/hr	16/hr	20/hr	24/hr	28/hr
Analytical	8.222	8.919	9.895	11.353	13.748	18.395	31.334
Simulation	8.295	8.927	9.846	11.090	12.737	14.427	16.556

Figure 4.6. Results: $M/M/c$ average waiting time vs. simulation

4.2.2 First Queue Adjustment Results.

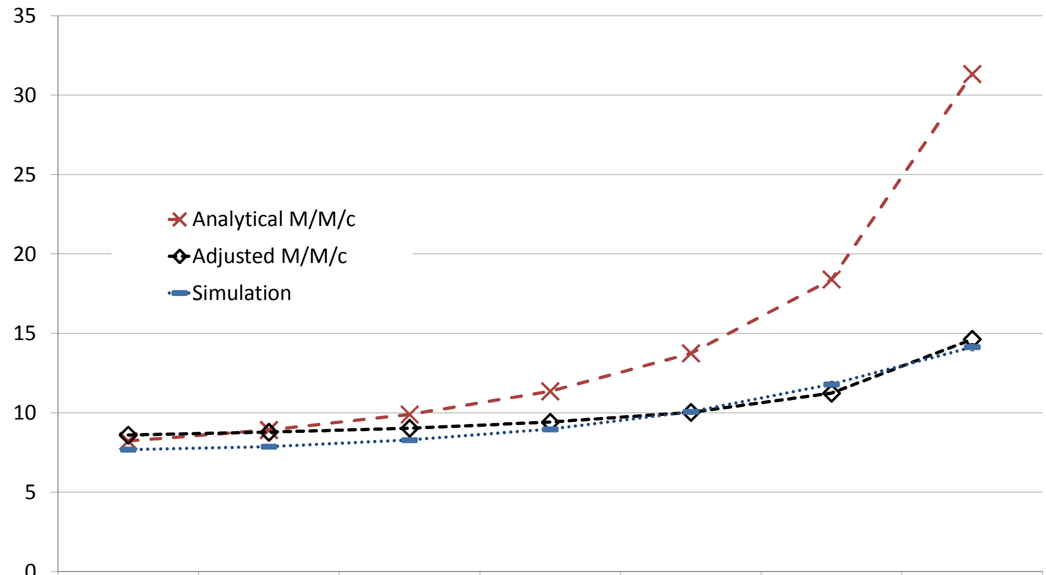
The coefficient of variance adjustment, $CV \approx 0.52$, to adjust the first queue waiting time produces a more accurate approximation than the steady state system. Figure 4.7 shows mean total process times (in minutes) for all three models. The adjusted model, practically comparable or better estimates. Table 4.8 provides the relative error for each model as well as 95% confidence intervals about the simulated means and CV values associated with each arrival rate to the first queue.

Table 4.8. Simulation total wait time statistics, relative approximation errors for adjusted and unadjusted analytical models and, CV's

γ	$\bar{x}_{Sim}$	$\hat{\sigma}_{Sim}$	+95% CI	−95% CI	Rel Err Adj	Rel Err Anl	CV
4/hr	7.681	4.032	7.806	7.556	13%	7%	0.525
8/hr	7.870	4.088	7.996	7.743	14%	13%	0.520
12/hr	8.286	4.258	8.418	8.154	12%	19%	0.514
16/hr	8.964	4.606	9.107	8.821	9%	27%	0.514
20/hr	10.066	5.182	10.227	9.905	6%	37%	0.515
24/hr	11.793	6.163	11.984	11.602	3%	56%	0.523
28/hr	14.136	7.482	14.368	13.904	16%	122%	0.529
32/hr	16.908	8.924	17.184	16.631	475%	1561%	0.528

4.2.3 Waiting Time Distribution.

Finally, the waiting time distribution, Figure 4.8, is approximated using a simulation of the full model. The resulting distribution is skew-right owning to the boundary at zero-waiting time on the left. Utilizing the central limit theorem, the postulated distribution for the right-hand tail, is approximately normal. Thus, with the $CV = 0.52$ (which is the ratio of the standard deviation and the mean), we have $T_{tot}^{ADJ}(t) \sim Norm(T, 0.52T)$, which is a reasonable fit to the simulated data. For instance, the 90th percentile, assuming normal is 16.7, which compares to 16.99, from the empirical quartiles in Figure 4.8.

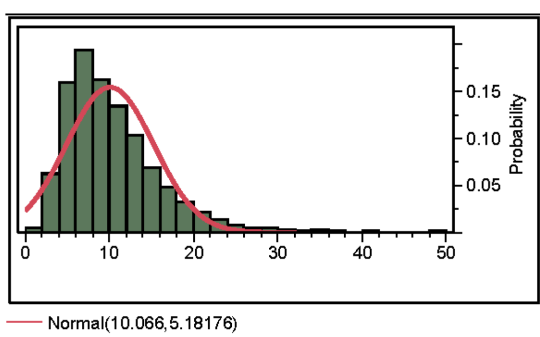


	4/hr	8/hr	12/hr	16/hr	20/hr	24/hr	28/hr
Analytical M/M/c	8.222	8.919	9.895	11.353	13.748	18.395	31.334
Adjusted M/M/c	8.592	8.775	9.029	9.407	10.028	11.237	14.629
Simulation	7.681	7.870	8.286	8.964	10.066	11.793	14.136

Figure 4.7. Results: Adjusted average waiting time vs. simulation

4.3 Conclusion

The USDA inspection station is limited by the scanning machine itself regardless of the number of agents available to place parcels on the conveyor belt. The same is true of the Security station. The kiosks are individual machines operated by the customer aside for when staff assistance is necessary as when the customer has a question or



Quantiles		
100.0%	maximum	48.5798
99.5%		29.8197
97.5%		22.4784
90.0%		16.9912
75.0%	quartile	12.7616
50.0%	median	9.05558
25.0%	quartile	6.25921
10.0%		4.51699
2.5%		3.00938
0.5%		2.18145
0.0%	minimum	1.42634

Moments	
Mean	10.066034
Std Dev	5.1817595
Std Err Mean	0.0819308
Upper 95% Mean	10.226664
Lower 95% Mean	9.9054042
N	4000

Figure 4.8. Results: Waiting Time Distribution

a computer error occurs. The counter is operated by human staff members. The server number is only limited by the number of workstations available for processing. In terms of standards found in the literature, Table 2.2, the Hickam terminal is currently operating at very high (A - B) level of service.

V. Summary and Conclusions

5.1 Conclusions

This research has provided an approach to estimate the performance measures of an airport terminal's landside processing facilities. Using a hybrid simulation-analytical methodology, a reasonable waiting time estimates for non-stationary queuing networks with generally distributed arrivals were calculated. This approximation required adjusting the waiting times by a factor equal to coefficient of variance of the departure distribution from the first queue. Simulating the arrivals to the system, can provide an adequate SF value. Using Open Jackson Networks, the remaining performance measures were found. In this manner, a system can be effectively modeled with limited information about a system, and without more data intensive requirements of a full process simulation.

5.2 Limitations and Areas for Additional Research

Despite the usefulness of the methodology presented, some areas of study remain. Expanded research to more accurate, generalized multi-flight research is required to fully characterize the impacts of multiple-departures, particularly when passenger arrivals do not overlap or coincide. More robust research could be conducted with observations from multiple terminals. Also generalizing the service distributions and studying impacts of time-varying, or state-dependent service may provide more complete insight into quality of service performance.

Regarding the sign-up and roll-call processes, queueing analysis using balking or retrial elements, would provide decision makers with valuable information regarding how those policies ultimately impact customer service. Also, specifically studying flows through the lobby itself in order to characterize congestion and passenger comfort issues would enhance design considerations for future terminals.

Lastly, the methodology developed here, could be easily incorporated into a decision support tool for planners a and aerial port managers. considerably more analysis must be conducted regarding the CV's, among other elements in order to properly generalize these methods and support decision making. Study the case as a regenerating process for unequally spaced flights.

5.3 Recommendations

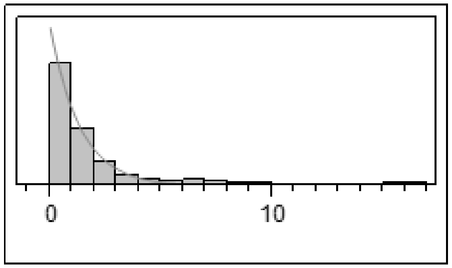
The major recommendation from this study is to explore policy options which would alleviate congestion for CONUS-bound passengers caused by the Ag Inspection and Security Screening. A second station of each roughly halves the waiting time for passengers at each of those facilities.

Appendix A. M(t)/G/∞ Approximation Simulation Figures

The appendix contains large figures, which were presented in Section 3.3.1. The histograms figures are organized with the arrival distributions on top and departure distributions at the bottom. Figures A.1 through A.6 are output for $M(t)/M/1$ models, while Figures A.7 through A.14 show output for the $D/M/1$ simulations. Mean, standard deviation and goodness–of–fit information are provided in all but Models 6 and 7. Oneway ANOVA outputs illustrate the evolution of the departure process towards mirroring the arrival process as the server utilization decreases. The ANOVA for Model 7 deceptively concludes that the arrival and departure distributions are different. However, there is no practical difference. Note that in Figure A.14 the difference between means is only 2.0×10^{-7}. The respective standard deviations (2.4×10^{-16} and 4.3×10^{-7}) are similarly negligible. The obvious conclusion is that the distributions are truly indistinguishable.

Distributions Type=Ag Arrivals

Value



Exponential(1.35116)

Moments

Mean	1.3511629
Std Dev	1.8317299
Std Err Mean	0.0927532
Upper 95% Mean	1.5335234
Lower 95% Mean	1.1688025
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	1.3511629	1.2254816	1.4946342

-2log(Likelihood) = 1014.75321730998

Goodness-of-Fit Test

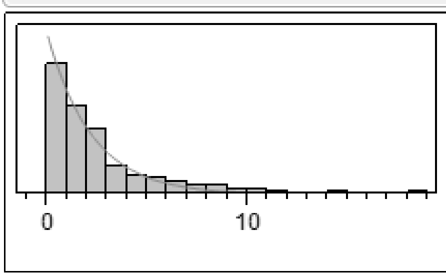
Kolmogorov's D

D		Prob>D
0.066123	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Distributions Type=Ag Departures

Value



Exponential(2.23789)

Moments

Mean	2.2378922
Std Dev	2.3897172
Std Err Mean	0.121008
Upper 95% Mean	2.4758038
Lower 95% Mean	1.9999806
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	2.2378922	2.0297297	2.4755194

-2log(Likelihood) = 1408.31685035805

Goodness-of-Fit Test

Kolmogorov's D

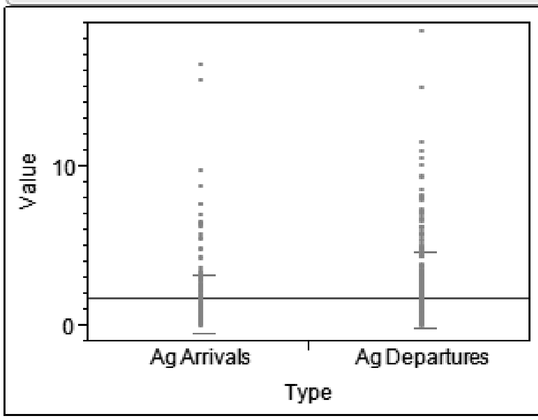
D		Prob>D
0.034642	>	0.1500

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Figure A.1. Sim 1 Distribution Results: $M(t)/M/1$ Simulation, $\hat{\rho}_1 = 0.8325$

Figure A.2. Sim 1 Oneway ANOVA: $M(t)/M/1$ **Simulation,** $\hat{\rho}_1 = 0.8325$

Oneway Analysis of Value By Type

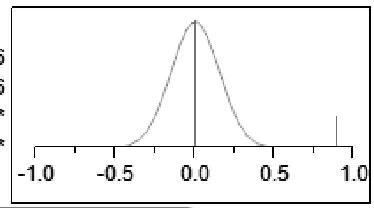


Excluded Rows 20

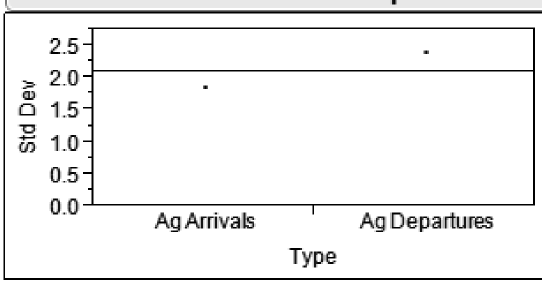
t Test

Ag Departures-Ag Arrivals
Assuming unequal variances

Difference	0.88673	t Ratio	5.815886
Std Err Dif	0.15247	DF	728.8016
Upper CL Dif	1.18606	Prob > |t|	<.0001*
Lower CL Dif	0.58740	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	390	1.831730	1.108419	1.010751
Ag Departures	390	2.389717	1.675261	1.564779

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	3.5001	1	778	0.0617
Brown-Forsythe	18.8911	1	778	<.0001*
Levene	24.9598	1	778	<.0001*
Bartlett	27.1533	1	.	<.0001*
F Test 2-sided	1.7020	389	389	<.0001*

Welch's Test

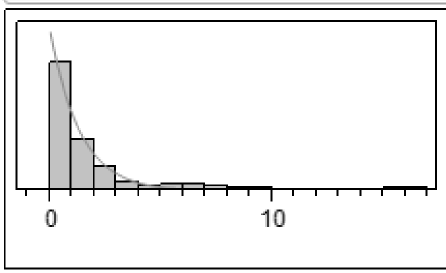
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
33.8245	1	728.8	<.0001*

t Test
5.8159

Distributions Type=Ag Arrivals

Value



Exponential(1.34677)

Moments

Mean	1.3467711
Std Dev	1.8487384
Std Err Mean	0.0924369
Upper 95% Mean	1.5284954
Lower 95% Mean	1.1650468
N	400

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	1.3467711	1.2229752	1.4878546

-2log(Likelihood) = 1038.16795984247

Goodness-of-Fit Test

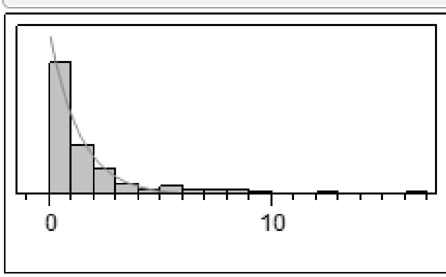
Kolmogorov's D

D		Prob>D
0.068977	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Distributions Type=Ag Departures

Value



Exponential(1.38029)

Moments

Mean	1.380286
Std Dev	1.8515136
Std Err Mean	0.0925757
Upper 95% Mean	1.562283
Lower 95% Mean	1.1982889
N	400

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	1.380286	1.2534093	1.5248804

-2log(Likelihood) = 1057.83256331996

Goodness-of-Fit Test

Kolmogorov's D

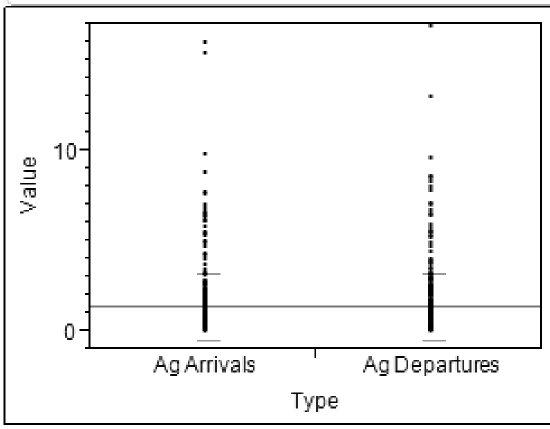
D		Prob>D
0.074383	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Figure A.3. Sim 2 Distribution Results: $M(t)/M/1$ Simulation, $\hat{\rho}_2 = 0.4641$

Figure A.4. Sim 2 Oneway ANOVA: $M(t)/M/1$ **Simulation,** $\hat{\rho}_2 = 0.4614$

Oneway Analysis of Value By Type

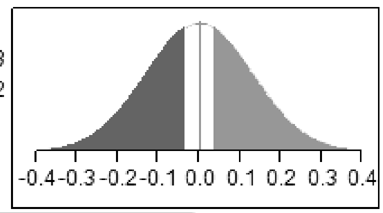


t Test

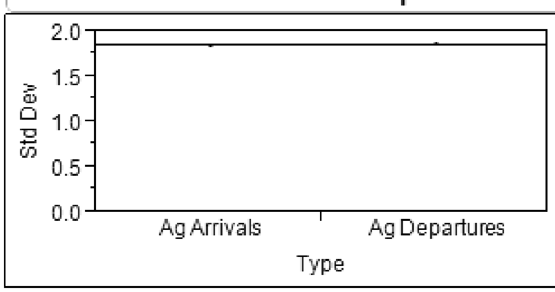
Ag Departures-Ag Arrivals

Assuming unequal variances

Difference	0.03351	t Ratio	0.256183
Std Err Dif	0.13082	DF	797.9982
Upper CL Dif	0.29031	Prob > |t|	0.7979
Lower CL Dif	-0.22328	Prob > t	0.3989
Confidence	0.95	Prob < t	0.6011



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	400	1.848738	1.138239	1.027845
Ag Departures	400	1.851514	1.163290	1.044688

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	0.0001	1	798	0.9927
Brown-Forsythe	0.0214	1	798	0.8837
Levene	0.0599	1	798	0.8067
Bartlett	0.0009	1	.	0.9761
F Test 2-sided	1.0030	399	399	0.9761

Welch's Test

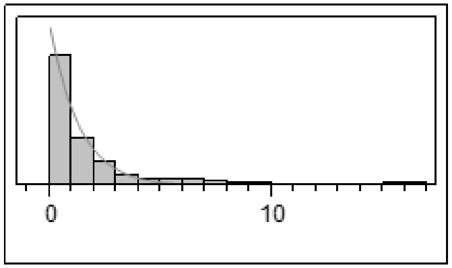
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0656	1	798	0.7979

t Test
0.2562

Distributions Type=Ag Arrivals

Value



Exponential(1.33631)

Moments

Mean	1.3363063
Std Dev	1.8736191
Std Err Mean	0.093681
Upper 95% Mean	1.5204763
Lower 95% Mean	1.1521364
N	400

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	1.3363063	1.2134723	1.4762936

-2log(Likelihood) = 1031.92747618979

Goodness-of-Fit Test

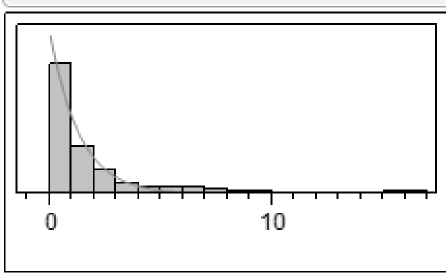
Kolmogorov's D

D		Prob>D
0.101490	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Distributions Type=Ag Departures

Value



Exponential(1.33631)

Moments

Mean	1.3363072
Std Dev	1.8734224
Std Err Mean	0.0936711
Upper 95% Mean	1.5204578
Lower 95% Mean	1.1521566
N	400

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	1.3363072	1.2134731	1.4762945

-2log(Likelihood) = 1031.9279685917

Goodness-of-Fit Test

Kolmogorov's D

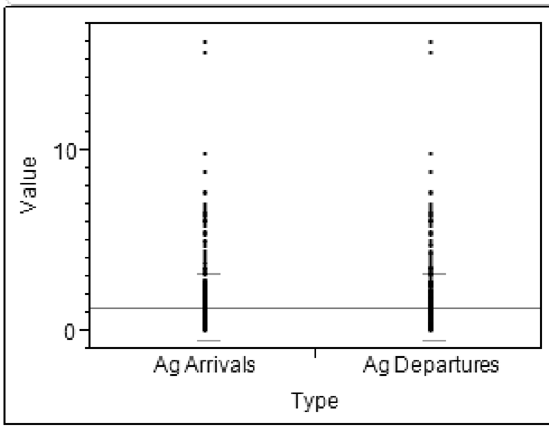
D		Prob>D
0.101640	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Figure A.5. Sim 3 Distribution Results: $M(t)/M/1$ **Simulation,** $\hat{\rho}_3 = 0.0014$

Figure A.6. Sim 3 Oneway ANOVA: $M(t)/M/1$ Simulation, $\hat{\rho}_3 = 0.0014$

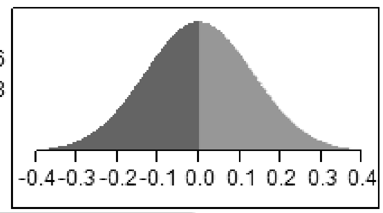
Oneway Analysis of Value By Type



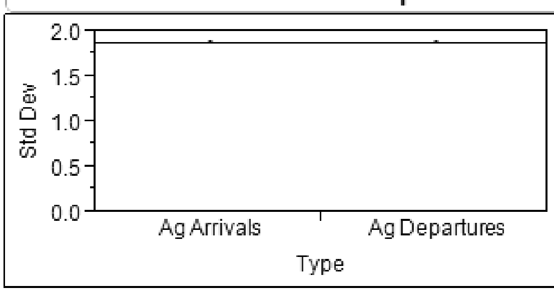
t Test

Ag Departures-Ag Arrivals
Assuming unequal variances

Difference	8.225e-7	t Ratio	6.209e-6
Std Err Dif	0.13248	DF	798
Upper CL Dif	0.26005	Prob > |t|	1.0000
Lower CL Dif	-0.26005	Prob > t	0.5000
Confidence	0.95	Prob < t	0.5000



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	400	1.873619	1.173547	1.046694
Ag Departures	400	1.873422	1.173429	1.046475

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	0.0000	1	798	0.9995
Brown-Forsythe	0.0000	1	798	0.9985
Levene	0.0000	1	798	0.9991
Bartlett	0.0000	1	.	0.9983
F Test 2-sided	1.0002	399	399	0.9983

Welch's Test

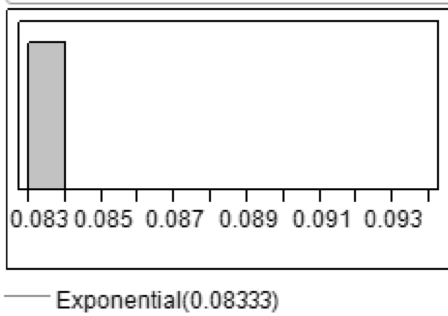
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0000	1	798	1.0000

t Test
0.0000

Distributions Type=Ag Arrivals

Value



Moments

Mean	0.083333
Std Dev	0
Std Err Mean	0
Upper 95% Mean	0.083333
Lower 95% Mean	0.083333
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	0.083333	0.0755816	0.0921816

-2log(Likelihood) = -1158.23030684088

Goodness-of-Fit Test

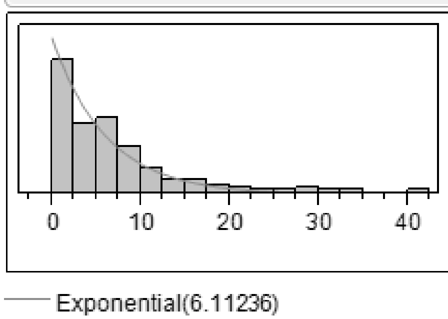
Kolmogorov's D

D		Prob>D
0.632121	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Distributions Type=Ag Departures

Value



Moments

Mean	6.1123563
Std Dev	6.1566702
Std Err Mean	0.3117551
Upper 95% Mean	6.7252921
Lower 95% Mean	5.4994204
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	6.1123563	5.5438021	6.7613876

-2log(Likelihood) = 2192.04362607925

Goodness-of-Fit Test

Kolmogorov's D

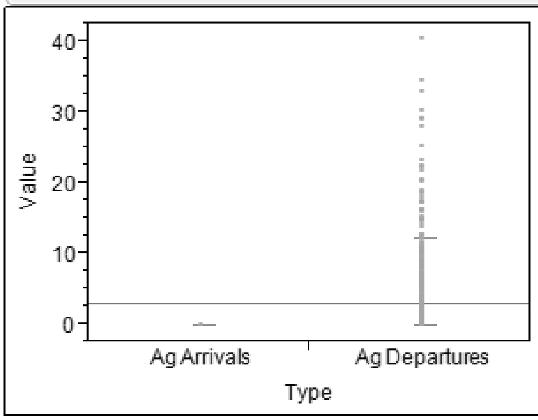
D	Prob>D
0.064497	0.0121*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Figure A.7. Sim 4 Distribution Results: $D/M/1$ Simulation, $\hat{\rho}_4 = 0.8624$

Figure A.8. Sim 4 Oneway ANOVA: $D/M/1$ **Simulation,** $\hat{\rho}_4 = 0.8624$

Oneway Analysis of Value By Type

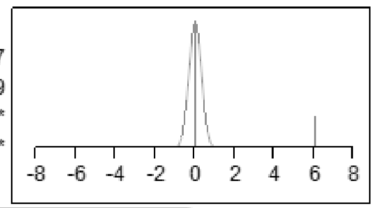


Excluded Rows 20

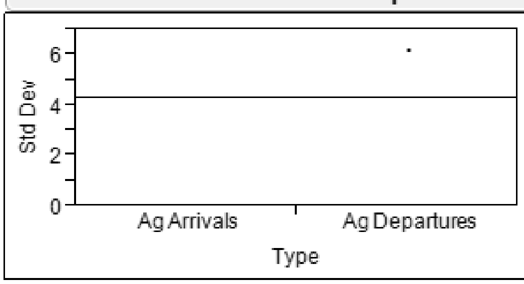
t Test

Ag Departures-Ag Arrivals
Assuming unequal variances

Difference	6.02902	t Ratio	19.33897
Std Err Dif	0.31176	DF	389
Upper CL Dif	6.64196	Prob > |t|	<.0001*
Lower CL Dif	5.41609	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	390	2.362e-16	2.359e-16	0.000000
Ag Departures	390	6.156670	4.354039	4.246559

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	49.1911	1	778	<.0001*
Brown-Forsythe	324.8684	1	778	<.0001*
Levene	391.2269	1	778	<.0001*
Bartlett	28831.514	1	.	<.0001*
F Test 2-sided	6.793e+32	389	389	<.0001*

Welch's Test

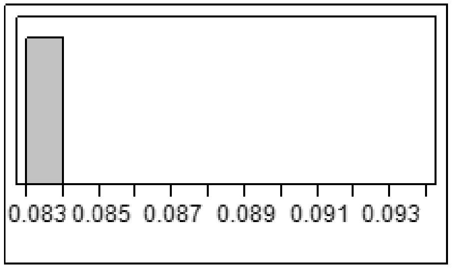
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
373.9958	1	389	<.0001*

t Test
19.3390

Distributions Type=Ag Arrivals

Value



Exponential(0.08333)

Moments

Mean	0.083333
Std Dev	0
Std Err Mean	0
Upper 95% Mean	0.083333
Lower 95% Mean	0.083333
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	0.083333	0.0755816	0.0921816

-2log(Likelihood) = -1158.23030684088

Goodness-of-Fit Test

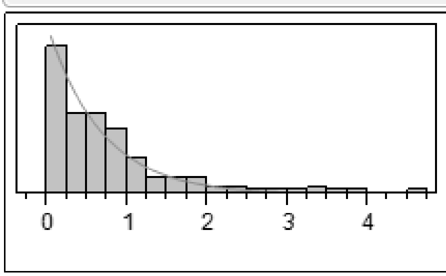
Kolmogorov's D

D		Prob>D
0.632121	<	0.0100*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Distributions Type=Ag Departures

Value



Exponential(0.67956)

Moments

Mean	0.6795613
Std Dev	0.6841646
Std Err Mean	0.034644
Upper 95% Mean	0.7476742
Lower 95% Mean	0.6114483
N	390

Fitted Exponential

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	σ	0.6795613	0.6163504	0.7517194

-2log(Likelihood) = 478.679837834897

Goodness-of-Fit Test

Kolmogorov's D

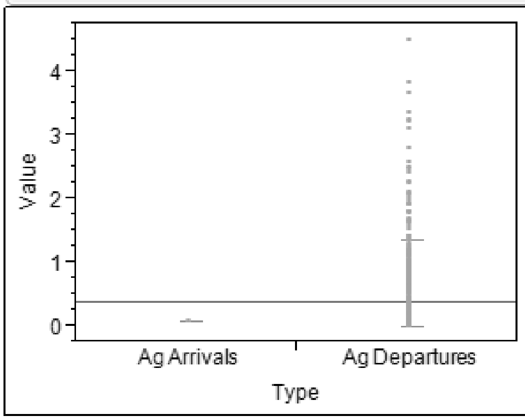
D	Prob>D
0.064274	0.0127*

Note: Ho = The data is from the Exponential distribution. Small p-values reject Ho.

Figure A.9. Sim 5 Distribution Results: $D/M/1$ Simulation, $\hat{\rho}_5 = 0.6708$

Figure A.10. Sim 5 Oneway ANOVA: $D/M/1$ Simulation, $\hat{\rho}_5 = 0.6708$

Oneway Analysis of Value By Type

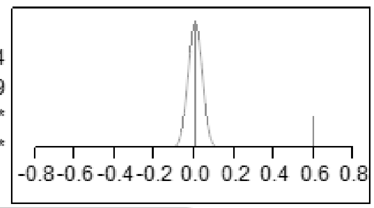


Excluded Rows 20

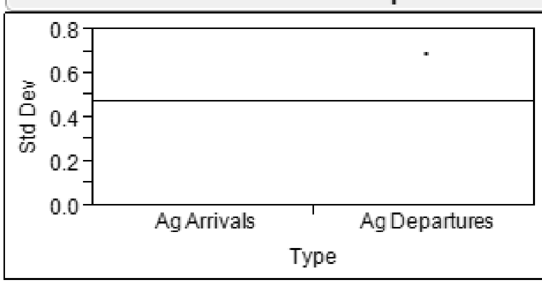
t Test

Ag Departures-Ag Arrivals
Assuming unequal variances

Difference	0.596228	t Ratio	17.21014
Std Err Dif	0.034644	DF	389
Upper CL Dif	0.664341	Prob > |t|	<.0001*
Lower CL Dif	0.528115	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	390	2.362e-16	2.359e-16	0.0000000
Ag Departures	390	0.6841646	0.4838611	0.4718431

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	49.2466	1	778	<.0001*
Brown-Forsythe	324.5769	1	778	<.0001*
Levene	391.2764	1	778	<.0001*
Bartlett	27124.370	1	.	<.0001*
F Test 2-sided	8.388e+30	389	389	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

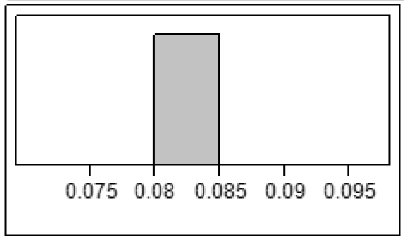
F Ratio	DFNum	DFDen	Prob > F
296.1888	1	389	<.0001*

t Test
17.2101

Figure A.11. Sim 6 Distribution Results: $D/M/1$ Simulation, $\hat{\rho}_5 = 0.6708$

Distributions Type=Ag Arrivals

Value

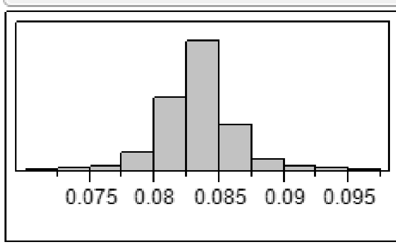


Moments

Mean	0.083333
Std Dev	0
Std Err Mean	0
Upper 95% Mean	0.083333
Lower 95% Mean	0.083333
N	390

Distributions Type=Ag Departures

Value



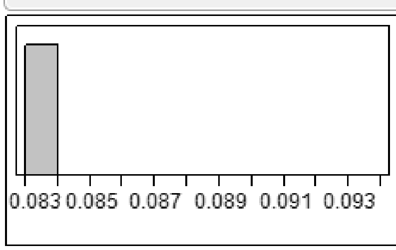
Moments

Mean	0.0833519
Std Dev	0.0027793
Std Err Mean	0.0001407
Upper 95% Mean	0.0836286
Lower 95% Mean	0.0830752
N	390

Figure A.12. Sim 7 Distribution Results: $D/M/1$ Simulation, $\hat{\rho}_7 = .0000$

Distributions Type=Ag Arrivals

Value

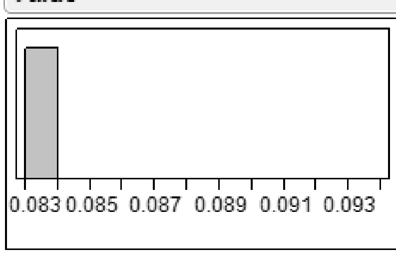


Moments

Mean	0.083333
Std Dev	0
Std Err Mean	0
Upper 95% Mean	0.083333
Lower 95% Mean	0.083333
N	390

Distributions Type=Ag Departures

Value

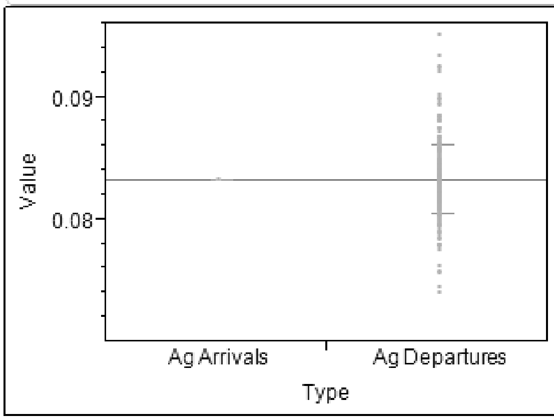


Moments

Mean	0.0833332
Std Dev	4.3494e-7
Std Err Mean	2.2024e-8
Upper 95% Mean	0.0833332
Lower 95% Mean	0.0833332
N	390

Figure A.13. Sim 6 Oneway ANOVA: $D/M/1$ Simulation, $\hat{\rho}_5 = 0.6708$

Oneway Analysis of Value By Type



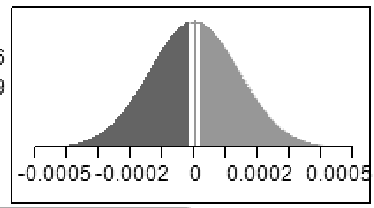
Excluded Rows 20

t Test

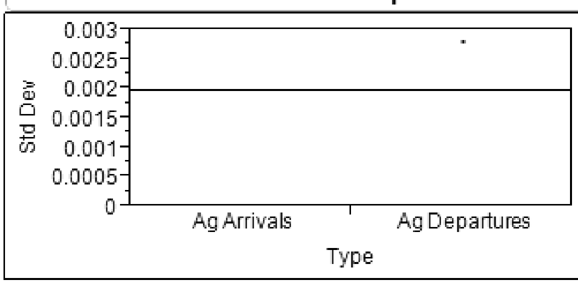
Ag Departures-Ag Arrivals

Assuming unequal variances

Difference	1.887e-5	t Ratio	0.134096
Std Err Dif	0.00014	DF	389
Upper CL Dif	0.00030	Prob > |t|	0.8934
Lower CL Dif	-0.00026	Prob > t	0.4467
Confidence	0.95	Prob < t	0.5533



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	390	2.362e-16	2.359e-16	0.0000000
Ag Departures	390	0.0027793	0.0019394	0.0019393

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	71.2221	1	778	<.0001*
Brown-Forsythe	370.9063	1	778	<.0001*
Levene	371.0664	1	778	<.0001*
Bartlett	22846.191	1	.	<.0001*
F Test 2-sided	1.384e+26	389	389	<.0001*

Welch's Test

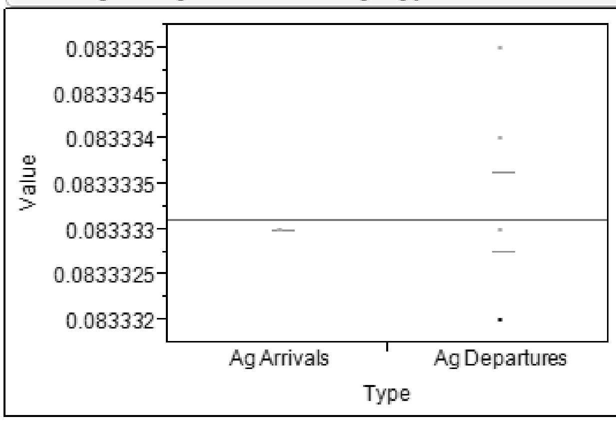
Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.0180	1	389	0.8934

t Test
0.1341

Figure A.14. Sim 7 Oneway ANOVA: $D/M/1$ Simulation, $\hat{\rho}_7 = .0000$

Oneway Analysis of Value By Type



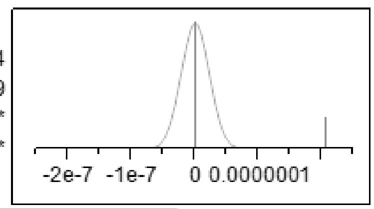
Excluded Rows 20

t Test

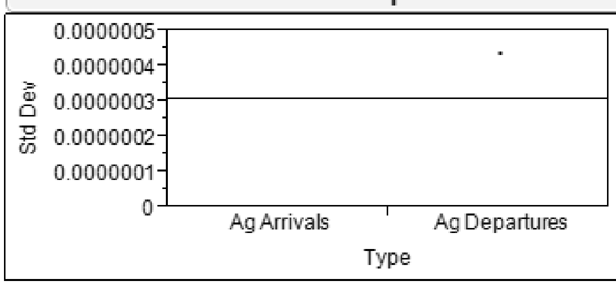
Ag Departures-Ag Arrivals

Assuming unequal variances

Difference	2.0513e-7	t Ratio	9.313734
Std Err Dif	2.2024e-8	DF	389
Upper CL Dif	2.4843e-7	Prob > |t|	<.0001*
Lower CL Dif	1.6183e-7	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Ag Arrivals	390	2.362e-16	2.359e-16	0
Ag Departures	390	4.3494e-7	3.4346e-7	2.2564e-7

Test	F Ratio	DFNum	DFDen	p-Value
O'Brien[.5]	141.0366	1	778	<.0001*
Brown-Forsythe	110.1190	1	778	<.0001*
Levene	648.7922	1	778	<.0001*
Bartlett	16037.734	1	.	<.0001*
F Test 2-sided	3.39e+18	389	389	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
86.7456	1	389	<.0001*

t Test
9.3137

Appendix B. Results Summary Sent to 735th AMS

This is briefly summary of my findings. The main idea is that the performance of the system is greatly dependent on the utilization of the servers (inspection stations, counter agents, etc.). This information provided here is based on service time estimates from the Passenger Services Survey collect in Sept 2010. The findings assume that flights are boarded one at a time and that passengers "enter the system" when their names are called at roll call. For now, I've only included the estimates for flights leaving for CONUS locations.

The key to the analysis is the utilization value for each server which is simply

$$\text{Utilization} = \frac{\text{Ave Flow In} * \text{Ave Service Time}}{\# \text{ Servers}}$$

For instance if 30 passengers arrive per hour (0.5 per min) and it takes a counter agent 1 min to process them and 2 counter agents are available, then the utilization of the counter is 50In the table below have the utilization of each process, the average observed system size and the average time processing time per passenger. This table assumes

- 1x ag inspection station with average service time of 1.85 min/per pax
- 5x available kiosks with average service time of 2.74 min/per pax
- 3x counter agents with average service time of 2.74 min/per pax
- 1x Security station with average service time of 1.85 min/per pax

I also assume here that very few passengers use the kiosks to begin processing (only 5% of passengers) and that only 1% of passengers are able to use the kiosk and then proceed to security without checking bags. Lastly, I built in about 2 min of travel time from station to station for each passenger. So the total processing time is

$$\text{Ave Total Time} = \text{Total Ave Wait} + \text{Total Ave Service} + \text{Travel Time}$$

The total number of passengers in the system (average system size) is then

$$\text{Ave Sys Size} = \text{Ave Arrival Rate} * (\text{Ave Total Wait} + \text{Ave Total Service})$$

Obviously those passengers who go through first will have shorter than average processing times, whereas, those later will observe longer times as the line builds. The target utilization for any system is usually around 75%, since above this, process quickly lose the ability to handle the variance in arrival and service times very well. Observe in Table B.1 that 86% utilization at the agriculture inspection station results in an average total passenger processing time of over 30 minutes.

Table B.1. Results: Base Case

Pax Load/Hr	Ag Insp Utilization	Kiosk Utilization	Check-in Counter Utilization	Security Utilization	Average Sys Size	Average Processing Time
4.0	12.3%	0.2%	6.1%	12.4%	0.716	10.741
8.0	24.7%	0.4%	12.2%	24.8%	1.510	11.326
12.0	37.0%	0.5%	18.3%	37.2%	2.429	12.147
16.0	49.3%	0.7%	24.3%	49.6%	3.567	13.376
20.0	61.7%	0.9%	30.4%	61.9%	5.133	15.400
24.0	74.0%	1.1%	36.5%	74.3%	7.738	19.344
28.0	86.3%	1.3%	42.6%	86.7%	14.213	30.457

Considering a loss of a server at each station (aside from security and ag) we have the results in Table B.2. Adding a server at each station, Table B.3 on the other hand can drastically reduce service times.

The previous two charts illustrate the "integer effect." That is, a ± 1 change in the number of servers can dramatically change the complexion of a system. Notice how much one additional ag station can affect utilization of the process. My overall impression is that more flexibility with the Ag Station could greatly improve the

Table B.2. Results: -1 Server Per Station

Pax Load/Hr	Ag Insp Utilization	Kiosk Utilization	Check-in Counter Utilization	Security Utilization	Average Sys Size	Average Processing Time
4.0	12.3%	0.2%	9.1%	12.4%	0.648	9.725
8.0	24.7%	0.5%	18.3%	24.8%	1.399	10.490
12.0	37.0%	0.7%	27.4%	37.2%	2.317	11.583
16.0	49.3%	0.9%	36.5%	49.6%	3.525	13.220
20.0	61.7%	1.1%	45.6%	61.9%	5.296	15.888
24.0	74.0%	1.4%	54.8%	74.3%	8.391	20.977
28.0	86.3%	1.6%	63.9%	86.7%	16.259	34.840

Table B.3. Results: +1 Server Per Station

Pax Load/Hr	Ag Insp Utilization	Kiosk Utilization	Check-in Counter Utilization	Security Utilization	Average Sys Size	Average Processing Time
4.0	6.2%	0.2%	4.6%	6.2%	0.613	9.194
8.0	12.3%	0.3%	9.1%	12.4%	1.232	9.238
12.0	18.5%	0.5%	13.7%	18.6%	1.863	9.314
16.0	24.7%	0.6%	18.3%	24.8%	2.514	9.427
20.0	30.8%	0.8%	22.8%	31.0%	3.195	9.584
24.0	37.0%	0.9%	27.4%	37.2%	3.918	9.796
28.0	43.2%	1.1%	32.0%	43.4%	4.703	10.078

process, but I am unsure of the amount of control your organization has over that. Increasing Kiosk utilization may benefit the middle part of the process, since passengers will spend less time in line there, but that traffic will still impact the security check. Similarly to the ag station, the ability to add service there for large flights will also increase the level of service the terminal can provide.

Appendix C. Process Flow Data and Service Distributions

Table C.1. Security Service Times

Date	Customer	Service Time	Date	Customer	Service Time
1-Sep-10	1	1	6-Sep-10	1	1
1-Sep-10	2	2	6-Sep-10	2	2
1-Sep-10	3	1	6-Sep-10	3	2
1-Sep-10	4	1	6-Sep-10	4	2
1-Sep-10	5	1	6-Sep-10	5	1
1-Sep-10	6	1	6-Sep-10	6	1
1-Sep-10	7	1	6-Sep-10	7	1
1-Sep-10	8	1	6-Sep-10	8	2
1-Sep-10	9	2	6-Sep-10	9	2
1-Sep-10	10	3	6-Sep-10	10	2
2-Sep-10	1	2	7-Sep-10	1	2
2-Sep-10	2	2	7-Sep-10	2	1
2-Sep-10	3	3	7-Sep-10	3	1
2-Sep-10	4	2	7-Sep-10	4	1
2-Sep-10	5	2	7-Sep-10	5	2
2-Sep-10	6	3	7-Sep-10	6	2
2-Sep-10	7	3	7-Sep-10	7	3
2-Sep-10	8	2	7-Sep-10	8	2
2-Sep-10	9	4	7-Sep-10	9	2
2-Sep-10	10	2	7-Sep-10	10	2
3-Sep-10	1	1	8-Sep-10	1	2
3-Sep-10	2	2	8-Sep-10	2	1
3-Sep-10	3	2	8-Sep-10	3	3
3-Sep-10	4	1	8-Sep-10	4	2
3-Sep-10	5	2	8-Sep-10	5	2
3-Sep-10	6	2	8-Sep-10	6	2
3-Sep-10	7	3	8-Sep-10	7	3
3-Sep-10	8	1	8-Sep-10	8	2
3-Sep-10	9	3	8-Sep-10	9	2
3-Sep-10	10	2	8-Sep-10	10	2
4-Sep-10	1	1	9-Sep-10	1	3
4-Sep-10	2	1	9-Sep-10	2	2
4-Sep-10	3	1	9-Sep-10	3	2
4-Sep-10	4	1	9-Sep-10	4	2
4-Sep-10	5	2	9-Sep-10	5	1
4-Sep-10	6	1	9-Sep-10	6	4
4-Sep-10	7	1	9-Sep-10	7	1
4-Sep-10	8	2	9-Sep-10	8	1
4-Sep-10	9	1	9-Sep-10	9	1
4-Sep-10	10	3	9-Sep-10	10	2
5-Sep-10	1	3	10-Sep-10	1	2
5-Sep-10	2	1	10-Sep-10	2	3
5-Sep-10	3	2	10-Sep-10	3	1
5-Sep-10	4	1	10-Sep-10	4	1
5-Sep-10	5	2	10-Sep-10	5	2
5-Sep-10	6	1	10-Sep-10	6	3
5-Sep-10	7	1	10-Sep-10	7	3
5-Sep-10	8	2	10-Sep-10	8	2
5-Sep-10	9	1	10-Sep-10	9	3
5-Sep-10	10	3	10-Sep-10	10	2

Table C.2. Check-in Service Times

Date	Customer	Service Time	Date	Customer	Service Time
1-Sep-10	1	2	6-Sep-10	1	2
1-Sep-10	2	5	6-Sep-10	2	2
1-Sep-10	3	1	6-Sep-10	3	2
1-Sep-10	4	3	6-Sep-10	4	5
1-Sep-10	5	2	6-Sep-10	5	8
1-Sep-10	6	5	6-Sep-10	6	2
1-Sep-10	7	3	6-Sep-10	7	3
1-Sep-10	8	2	6-Sep-10	8	3
1-Sep-10	9	1	6-Sep-10	9	5
1-Sep-10	10	3	6-Sep-10	10	3
2-Sep-10	1	3	7-Sep-10	1	3
2-Sep-10	2	2	7-Sep-10	2	4
2-Sep-10	3	2	7-Sep-10	3	3
2-Sep-10	4	3	7-Sep-10	4	3
2-Sep-10	5	4	7-Sep-10	5	5
2-Sep-10	6	3	7-Sep-10	6	2
2-Sep-10	7	3	7-Sep-10	7	3
2-Sep-10	8	2	7-Sep-10	8	3
2-Sep-10	9	3	7-Sep-10	9	2
2-Sep-10	10	4	7-Sep-10	10	3
3-Sep-10	1	3	8-Sep-10	1	3
3-Sep-10	2	2	8-Sep-10	2	6
3-Sep-10	3	2	8-Sep-10	3	3
3-Sep-10	4	3	8-Sep-10	4	2
3-Sep-10	5	3	8-Sep-10	5	3
3-Sep-10	6	2	8-Sep-10	6	2
3-Sep-10	7	3	8-Sep-10	7	3
3-Sep-10	8	2	8-Sep-10	8	3
3-Sep-10	9	3	8-Sep-10	9	2
3-Sep-10	10	2	8-Sep-10	10	3
4-Sep-10	1	3	9-Sep-10	1	3
4-Sep-10	2	2	9-Sep-10	2	2
4-Sep-10	3	2	9-Sep-10	3	3
4-Sep-10	4	3	9-Sep-10	4	3
4-Sep-10	5	2	9-Sep-10	5	3
4-Sep-10	6	2	9-Sep-10	6	2
4-Sep-10	7	2	9-Sep-10	7	4
4-Sep-10	8	3	9-Sep-10	8	1
4-Sep-10	9	2	9-Sep-10	9	1
4-Sep-10	10	1	9-Sep-10	10	3
5-Sep-10	1	3	10-Sep-10	1	2
5-Sep-10	2	2	10-Sep-10	2	2
5-Sep-10	3	1	10-Sep-10	3	4
5-Sep-10	4	3	10-Sep-10	4	2
5-Sep-10	5	2	10-Sep-10	5	3
5-Sep-10	6	2	10-Sep-10	6	2
5-Sep-10	7	1	10-Sep-10	7	5
5-Sep-10	8	3	10-Sep-10	8	5
5-Sep-10	9	2	10-Sep-10	9	3
5-Sep-10	10	1	10-Sep-10	10	2

Process:	Location: Hickam Passenger Terminal										Date: 1 Sep 10			Observer: XXXXXXX
Elements of Operation		Time Observation Results												
Step No.	Operation Description	Example	1	2	3	4	5	6	7	8	9	10	Avg	Boundaries of Observation
The following data will illustrate passenger cycle (touch) times. Identify a random passenger and time the process.														
1	Space A Sign-up	3	4	2	2	3	2	2	2	3	4	2	2.6	Start: Passenger presents at counter Stop: Passenger is signed up
2	Space A Roll Call	4	4	1	1	1	1	1	1	1	2	1	1.4	Start: Passenger name is called Stop: Passenger proceeds to check-in
3	Passenger Check-in	6*	2	5	1	3	2	5	3	2	1	3	2.7	Start: Passenger presents at counter Stop: Passenger receives boarding pass
4	Anti-hijacking (X-Ray)	5	1	2	1	1	1	1	1	1	2	3	1.4	Start: Passenger presents at screening Stop: Passenger enters gate
The following data will illustrate passenger wait times. Identify one passenger (mid group) and follow them through the process.														
1	Space A Roll Call	12	1	1	1	2	2	3	5	5	3	1	2.4	Start: Roll call begins Stop: Passenger is called forward
2	Passenger Check-in	11	1	4	6	3	2	1	1	3	4	1	2.6	Start: Passenger enters line for check-in Stop: Passenger arrives at counter
3	Anti-hijacking (X-Ray)	13	2	1	1	1	1	1	1	1	2	2	1.3	Start: Passenger enters line for x-ray Stop: Passenger places baggage on belt
The following data will capture show times for Space Required and Space Available Passengers.														
1	Space Required	150	180	180	180	180	180	180	180	180	180	180	180	Enter time in minutes from required passenger show at terminal to estimated aircraft departure
1	Space Available	240	140	140	140	140	140	140	140	140	140	140	140	Enter time in minutes from required passenger show at terminal to estimated aircraft departure

Figure C.1. AFSO21 Process Flow Form Sample

Appendix D. Quad Chart

The Quad Chart for this research is found below.

Using Hybrid Simulation / Analytical Queueing Networks to Capacitate USAF Air Mobility Command Passenger Terminals

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RESEARCH QUESTIONS

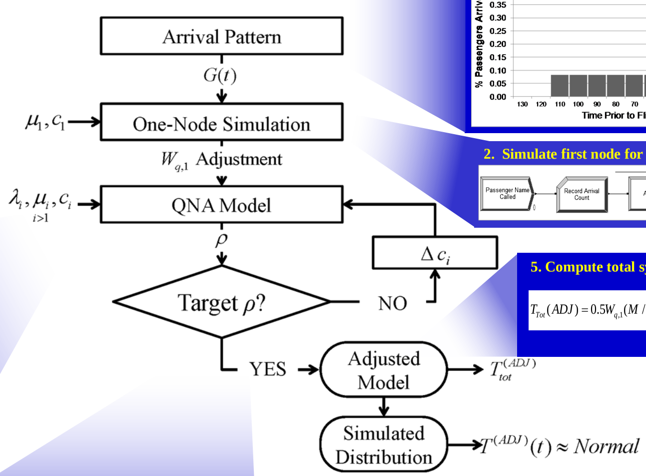
- How can the performance of any Air Mobility Command (AMC) terminal be quantified?
- How can bottlenecks in the process be fixed?

RESEARCH OBJECTIVES

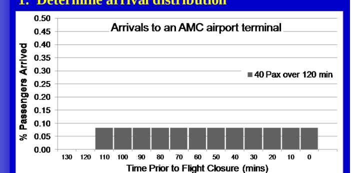
- Develop a “simple” and portable method which can
  - o Model operations at an airport passenger terminal
  - o Estimate individual station and overall performance
  - o Determine the optimal number of servers at each station
- Apply method to passenger processing at Hickam terminal

METHODOLOGY

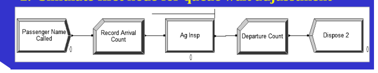
- Develop a “simple” and portable method which can
  - o Model operations at an airport passenger terminal
  - o Estimate individual station and overall performance
  - o Determine the optimal number of servers at each station
- Apply method to Hickam AFB terminal



1. Determine arrival distribution



2. Simulate first node for queue wait adjustment



3. Compute downstream waits using queueing network analysis (QNA)

Traffic Equations:

$$\lambda_i = \gamma_i + \sum_{i}^{k} \lambda_i r_{ii}$$

λ_i = total mean flow into node i
μ_i = mean service rate at node i

Empty queue probability:

$$p_{0,i} = \left(\sum_{n=0}^{c_i-1} \frac{r_i^n}{n!} + \frac{r_i^{c_i}}{c_i!(1-\rho_i)} \right)^{-1} \quad \text{where } \rho_i = \frac{\lambda_i}{c_i \mu_i} \text{ and } r_i = \frac{\lambda_i}{\mu_i}$$

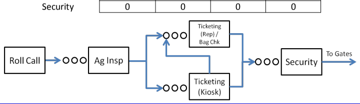
We are interested in the average waiting time in queue:

$$W_{q,i} = \frac{L_{q,i}}{\lambda_i} \quad \text{where } L_{q,i} = \left(\frac{r_i^{c_i} \rho_i}{c_i!(1-\rho_i)^2} \right) p_{0,i}$$

Routing matrix and network schematic:

CONUS-bound

From \ To	Ag Insp	Ticket Kiosk	Counter	Security
Ag Insp	0	0.05	0.95	0
Ticket Kiosk	0	0	0.99	0.01
Counter	0	0	0	1
Security	0	0	0	0



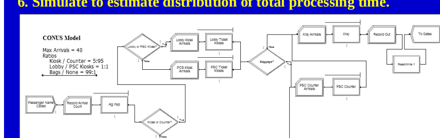
4. Determine number of servers based on target utilization, ρ

Facility	Pax/hr	$1/\mu$ (min)	c	ρ	W_q (min)
Ag Inspection	20	1.85	**1**	**0.617**	**2.98**
			2	0.308	0.19
Kiosk	1	2.74	1	0.046	0.13
			2	0.023	0.00
			3	0.015	0.00
			4	0.011	0.00
			5	**0.009**	**0.00**
Counter	19.99	2.74	1	0.913	28.71
			2	0.456	0.72
			3	**0.304**	**0.10**
Security	20	1.85	**1**	**0.617**	**2.98**
			2	0.308	0.19

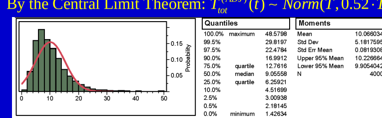
5. Compute total system time.

$$T_{tot}(ADJ) = 0.5 W_{q,1}(M/M/C) + \sum_{i=1}^{3} W_{q,i}(M/M/C) + \sum_{i=1}^{4} \frac{1}{\mu_i} + \tau$$

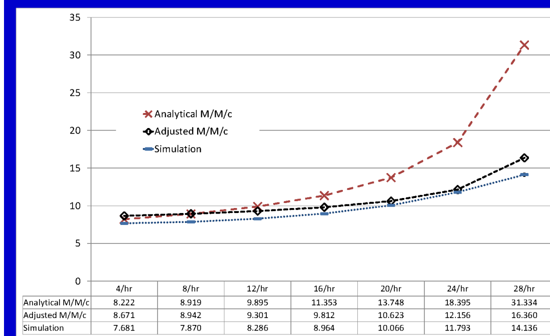
6. Simulate to estimate distribution of total processing time.



By the Central Limit Theorem: $T_{tot}^{(ADJ)}(t) \sim Norm(T, 0.52 \cdot T)$



RESULTS



	4/hr	8/hr	12/hr	16/hr	20/hr	24/hr	28/hr
Analytical M/M/c	8.222	8.919	9.895	11.353	13.748	18.395	31.334
Adjusted M/M/c	8.671	8.942	9.301	9.812	10.623	12.156	16.360
Simulation	7.681	7.870	8.286	8.964	10.066	11.793	14.136

From the first node analysis, It was determined that the first node's analytical queue waiting should be multiplied by a factor of 0.5. Having done so, the adjusted model estimates mean total waiting time within ±1 standard deviation of results obtained by simulating the entire system.

For moderate passenger loads, a single station each for USDA inspection and for Security and just 2 counter agents will still produce acceptable processing times.

CONCLUSION

- A hybrid approach to utilizing simulation to handle time dependent complications and QNA to analyze flows through a network process produces reasonable estimates comparable to simulation alone.
- Controlling arrival time to the input queue has very little improvement over the queue performance since the only the arrival rate matters (not the input distribution)

RECOMMENDATIONS

Explore options to alleviate congestion for CONUS-bound passengers caused by the USDA inspection and security screening.

FUTURE RESEARCH

- Develop generalized multi-departure model.
- Study the affects of queue-adjustments at down-stream queues
- Collect precise service time data. Study impact of non-exponentially distributed service (e.g., Erlang-k, etc.)
- Study performance of additional AMC terminals.
- Analyze sign-up and roll-call processes to examine passenger balking or retrial patterns
- Study flows through the lobby itself in order to characterize congestion and passenger comfort
- Incorporate methodology into a decision support tool for planners a and aerial port managers.

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Vita

Captain Meredithe A. Jessup II graduated high school from the Baltimore Polytechnic Institute in 1998. He accomplished his undergraduate studies at the United States Air Force Academy, completing in 2003 with a Bachelor of Science degree in Mathematics and receiving his commission as an Air Force officer.

Capt Jessup's first assignment as an operations research analyst was to the 36th Electronic Warfare Squadron, 53d Electronic Warfare Group, 53 Wing at Eglin AFB, Florida. As an Operations Analyst in the 36th, Meredithe developed, conducted, and analyzed operational tests for various Combat Air Force electronic warfare systems. Also, as the Group Executive Officer, Meredithe supervised the Group Command Section's daily operations and suspenses, recommended actions to the Group Commander, and coordinated incoming correspondence.

In 2008, Meredithe was assigned to 13th Air Force at Hickam AFB, Hawaii. At 13 AF, he reported capability risk assessments to Component Numbered Air Force Pacific Air Forces leadership. He also supported deliberate, contingency, and crisis planning as well as conducting various other studies and assessments. While at Hickam, Meredithe also conducted duties in the 613th Air Operations Center's Strategy Division as part of and leading the Operational Assessment Team. On the OAT, Meredithe provided operational analysis to the Joint Forces Air Component Commander, built operational planning teams, and led assessment working groups.

In August 2010, Meredithe entered the Air Force Institute of Technology's Graduate School of Engineering and Management at Wright-Patterson AFB, Ohio. At AFIT, he focused his studies on Probabilistic Operations Research. Upon graduation, he will be assigned to the Space and Missile Systems Center at Los Angeles, California.

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14. ABSTRACT
The objective of this study is to model operations at an airport passenger terminal to determine the optimal service capacities at each station given estimated passenger flow patterns and service rates. The central formulation is an open Jackson queueing network useful to any USAF AMC terminal regardless of passenger type mix and flow data. A complete methodology for analyzing passenger flows and queue performance of a single flight is produced appropriate to be embedded in a framework to analyze the same for multiple departing flights. Queueing network analysis (QNA) is used, as compared to discrete-event computer simulation (DES), because no special software license or methodological training is required, results are obtained in a spreadsheet model with computational response times that are instantaneous, and data requirements are substantially reduced. However, because of the assumptions of QNA, additional research contributions were required. First, arrivals of passengers are time-dependent, not steady-state. Theoretical results for time-dependent queue networks in the literature are limited, so a method for using DES to adjust for arrival time-dependency in QNA is developed. Second, beyond quality of service in the network, a key performance measure is the percentage of passengers who do not clear the system by a fixed time. To populate the QNA mean value system sojourn time, DES is used to develop a generic sojourn time probability distribution. All DES computations have been pre-calculated off-line in this thesis and complete a hybrid DES/QNA analytical model. The model is exercised and validated through analysis of the facility at Hickam AFB which is currently undergoing redesign. For larger flights, adding a server at the high-utilization queues, namely the USDA inspection and security screening stations, halve system congestion and dramatically increase throughput. The policy of forcing arrival in advance with controlled release to the input queue has very little improvement over the policy of allowing passengers to arrive freely as in a civilian airport.

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