# Designing Internal Logistics Processes for a New Manufacturing Site

By

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B.S. Chemical Engineering, University of Notre Dame, 2012

Submitted to the MIT Sloan School of Management and the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degrees of

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## Abstract

The Boeing Company is the world's largest aerospace company and is constantly evaluating improvement opportunities to the production system. It is of ongoing interest to the company to have to tools to assess new manufacturing sites. Among the required tasks for such an effort, engineers must identify the processes and capabilities that will be needed. A critical element of this study is the system of internal logistics processes that could manage the flow of parts and material throughout a site. Planning the capacity of these processes is difficult when many of the parameters are uncertain and yet to be determined.

This thesis proposes a method for estimating capacity requirements of internal logistics processes by employing the concepts of queuing theory and Little's Law. Using this methodology, a process model was developed and validated by discrete event simulation to provide process planners with an understanding of the relationship and importance of numerous parameters. This understanding allows planners and management to assess the capacity requirements of the processes in terms of projected costs and performance.

Values of wait times predicted by the proposed model were in strong agreement with values observed from simulation (R-squared of 96.4%; MAPE of 14.9%) suggesting that the proposed methodology represents an *easy-to-use* and *accurate* representation of process parameters. In order to improve the applicability of capacity recommendations for Boeing, further refinement is needed of underlying process parameters as well as cost modeling of threshold parameters ($k$ and $\rho^n\_max$).

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# 1 Introduction

## 1.1 Thesis Overview

The Boeing Company is the world's largest aerospace company and a leading manufacturer of commercial jetliners, defense, space and security systems and provider of aftermarket support services. The company is constantly undergoing continuous improvement efforts to produce the highest quality aircraft by the most effective and efficient means possible. Recently, leadership has embarked on a multi-year effort to explore improvements to its production system design, including how to best manage the on-site logistics processes (i.e. "internal logistics") and determine the best approach to establishing new manufacturing facilities. In order to control upfront investment costs and recurring costs of regular operations, Boeing leadership must understand how much capacity will be required to support these internal logistics processes and what impact various risk factors may have on system performance.

In order to provide a better understanding of capacity requirements and the importance of associated process parameters, this thesis will present the output of research conducted alongside Boeing leadership and operations planners. The goal of this research was to understand capacity planning in the context of the Boeing production system design, to recognize the challenges faced by process designers, and to develop and validate a methodology to provide designers the tools needed to recommend sufficient capacity in future processes. This research effort determined that process designers would benefit from more robust tools at their disposal to ensure that internal logistics processes are capable of meeting expected demand and variation of regular production. Previous capacity estimation efforts occasionally relied on parametric models which perversely ensured that any inefficiencies of the previous system appropriately scaled with the new system. To counteract this problem, this thesis will recommend an analytical approach to capacity planning – based on academic research and verified by discrete event simulation – that was developed with special consideration of the demands of Boeing internal logistics processes.

In chapter one, this thesis will introduce Boeing, ongoing improvement efforts to the Boeing production system, and the specific processes known as "internal logistics." Chapter two will introduce the technical content relevant to capacity planning including queuing theory, Little's Law, and discrete event simulation. Chapter three will present how issues related to capacity planning manifest themselves in system performance and the motivation for solving these issues. Chapter four will provide an overview of the analytical approach that was developed for internal logistics capacity planners using the principles of queuing theory and Little's Law. Chapter five will apply this capacity planning methodology to the anticipated system parameters to demonstrate the impact and relationship of several key variables on system performance. Chapter six will present a discussion of this analysis to provide additional understanding around process variability, validation methods, and supporting assumptions. This thesis will conclude with chapter seven which will provide a summary of key findings and recommendations and opportunities for further study.

## 1.2 Problem Introduction

This thesis will attempt to solve the problems exemplified by the experience of Ashley[1], a Boeing engineering manager responsible for designing the logistics processes for new manufacturing sites. Ashley leads a small team of former supply chain analysts and logistics

[1] Name changed to protect privacy.

operators who have been assigned to the project. The following is an example of a typical work interaction for Ashley:[2]

*Ashley opens the email she just received from her senior manager. Estimates for the proposed warehouse are due by next Friday. He assures her that these estimates do not need to be exact figures but does also remind her of the importance of presenting a design that fits within budgeted upfront and recurring costs. Ashley is not surprised by this request but still feels her blood pressure rising.*

*About six months ago, another engineer had worked on this problem. He took the dimensions of five other warehouses in the manufacturing network, averaged the square footage, and rounded up a little bit to provide some "wiggle room." He had moved on to another project working on a software development effort but had left Ashley the results of his "analysis."*

*But now leadership wanted to understand expected design costs. Ashley had no idea if her former colleague had scaled up his estimate for square footage correctly. She also had some serious doubts about his cost numbers. She was just now starting to receive projections from other teams on the number of parts that would be stored in the warehouse – but she was still waiting on a few stragglers. Ashley thought to herself, "There's no way he knew back in April how many parts would be in the warehouse... nobody can tell me that number today!"*

*Ashley looked back at the process flow diagram she had been working on. The first box on her slide said "Receiving."*

*She mused to herself: "I know we need a big receiving area but how many dock doors will we need? And once those parts are off the truck, how can I possibly know how many put-away people I'll need?" She changed her attention to the next box labeled "Put-away:"*

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[2] This account is representative of several real-life exchanges experienced by Ashley.

*"We're going to change how we stow parts and material for this warehouse anyway. There's nowhere in Boeing doing things this way today. How am I supposed to know how much daily costs will be 10 years from now?"*

*Just then, her phone rings. It's the supply chain analyst on her team. He wants to know if Ashley likes the electric tug supplier he found. The electric tugs would be critical to the kit delivery process. Ashley tells him she will take a look and call him right back.*

*"That's another thing," she thinks to herself, "how many tugs will we need? And how often will they go back-and-forth from the warehouse to the factory?"*

*Ashley wishes she had the answers. She's missing the data she needs and worried her design will just keep getting squeezed by cost-conscious leadership.*

Ashley's experience is not unique to Boeing – many firms could benefit from more well-defined processes for designing and evaluating systems. However, Ashley's problem is both a lack of *tools* and *data*. Not only is she unsure how to approach the problem at hand, she does not have much of the information she needs to provide a reliable recommendation.

If Ashley cannot tell her boss how much the internal logistics system will cost 10 years from now, then maybe she could tell him instead *what that cost would depend on.* For a system as complex as the one Ashley is designing, that recurring cost estimate depends on dozens, if not hundreds, of variables. Just picking a variable to scrutinize first may feel overwhelming.

In the absence of well-defined data (in this case, yet to be defined process parameters), this thesis will use principles of capacity planning, along with a comprehensive process model, to provide an understanding of how the system variables are interconnected. This problem statement will be expanded on in further detail in chapter three.

## 1.3 Internal Logistics Processes

Historically, the majority of Boeing manufacturing operations occurred in factories near Seattle, WA. Manufacturing operations included the fabrication of (mostly aluminum) components, assembly of sub-assemblies, final assembly, paint, and systems tests. Over time, Boeing expanded its supply base across the United States and international geographies. To manage the complexity of an international supply chain, Boeing has made significant investments in its logistics capabilities.

Within Boeing, there is a supply chain division that manages a significant variety of logistics activities including material ordering, transportation, on-site receiving, storage of material, and conveyance of material from warehouses to production workers on the factory floor. *External logistics* encompasses all movement and management of material while that material is not located on a Boeing site. This includes material ordering, transportation, the estimation and tracking of shipping rates, among other activities. Therefore, *internal logistics* includes all logistics activities that occur while material is located on a Boeing site. Internal logistics includes a wide variety of processes that fall under the umbrella of processes traditionally known as "materials management." Internal logistics within the context of this thesis will be divided into nine sub-processes:

1. Receiving
2. Quality Check
3. Put-away
4. Pick, Kit, and Integrate
5. Kit Staging
6. Delivery

7. Tug Unloading
8. Consumed Kit Processing
9. Shipping

Additional process details of the internal logistics system will be provided in chapter five.

## 1.4 Process Improvement Efforts and Capacity Planning

In order to ensure that Boeing is competitive in current and future t markets, leadership is regularly managing studies to identify and implement improvements to the production system. Following broader trends in the aerospace industry, Boeing has pushed for increased design-for-manufacturing and model-based systems engineering. Ongoing efforts include creating the tools and processes necessary to define the production system needs of a "greenfield" manufacturing environment. Ashley's team – focused on the internal logistics processes – is one of many teams working on this project.

At the core of Ashley's problem is the question of process capacity. To determine the number of truck unloading bays in the receiving area or the number of semi-automated put-away stations required, she will need to understand the capacity of these processes. She will also need some criteria at her disposal for selecting the *right amount* of capacity to recommend. How much capacity will be enough? Is it better to have too much capacity than not enough? Which variables should be optimized and which are inconsequential to her design?

# 2 Technical Content Review

This section will provide an overview of the technical content underlying the capacity planning methodology developed over the course of this thesis project. The concepts introduced in this chapter – queuing theory, Little's Law, and discrete event simulation (DES) – will be combined into a detailed methodology for identifying capacity requirements within the context of Ashley's internal logistics planning effort.

## 2.1 Queuing Theory

Queuing theory relates to the study of systems by which requests (or customers, or products) arrive to a system and are serviced according to some pre-determined discipline. Congestion occurs when there are more service requests than available servers which causes a queue to develop. Queuing theory is a well-established subject with applications across a variety of fields, including call service centers, supermarket checkout lines, gas stations, and IT systems. A. K. Erlang is widely regarded as one of the original founders of queuing theory for his work studying telephone exchange systems in the early 1900s [1].

The M/M/c queue, or Erlang-C model, is a commonly used multi-server queuing model relevant for systems with more than one server. Arrivals of service requests are *probabilistic* with inter-arrival times following a Poisson distribution. The processing time of each server is assumed to be exponentially distributed and independent of other servers. This model assumes no maximum queue length, allowing for infinite queue size. It also assumes no queue abandonment will occur (such as an impatient customer service caller hanging up while still on hold) [2].

The Erlang-C model is defined by:

$$C(n,x) = n \times B(n,x) / \big(n - x \times (1 - B(n,x))\big) \tag{1}$$

Where:

- $n = number\ of\ servers$
- $x = \frac{\lambda}{\mu}$
  - $\lambda = arrival\ rate$
  - $\mu = service\ rate$
- $B(n,x) = (x^n/n!)/(1 + x + x^2/2! + x^3/3! + \cdots + x^n/n!)$
  - This is the *Erlang-B function* which accounts for the probability of service requests arriving to a system with no available servers.

The average queue length, $L_q$, is given by the following equation [3]:

$$L_q = \frac{x}{n-x} \times C(n,x) \qquad (2)$$

An approximation of this model is useful for simplifying this equation for systems of known standard deviations of inter-arrival and service times [4]:

$$L_q = \frac{\rho^{\sqrt{2(n+1)}}}{1-\rho} \times \frac{C_A^2 + C_S^2}{2} \qquad (3)$$

Where:

- $\rho = capacity\ utilization = \frac{\lambda}{n\mu}$
- $C_A = coefficient\ of\ variation, inter\_arrival\ times$
- $C_S = coefficient\ of\ variation, service\ times$

This simplified model is known as the G/G/N model. Like the Erlang-C model, it may only be used for stable systems where $\rho<1$, otherwise the queue length would continue to grow to infinity as additional requests arrive [3], [4].

The models presented thus far all assume that service requests are processed according to the principle of *first-in/first-out* (FIFO). That is, all requests are prioritized equally and are serviced in the order in which they arrive. However, in certain situations it may be desirable for system managers to prioritize some requests over others.

*Non-preemptive priority* queues describe systems under the following conditions:

- Processing of the request(s) currently being served is completed even if requests of higher priority arrive;
- Each priority class has a separate queue;
- When a server becomes free, the request from the head of the highest priority queue is processed by the available server [5].

For non-preemptive priority queues, *Kleinrock's conservation theorem* is applicable [5]

$$\sum_{k=1}^{K} \rho_k \overline{W}_k = \frac{\rho}{1-\rho} \times \bar{R} \quad (4)$$

Where:

- $K = number\ of\ priority\ classes, k = 1, \dots, K$
- $\overline{W}_k = mean\ wait\ time\ of\ class_k\ service\ requests$
- $\bar{R} = mean\ residual\ service\ time\ upon\ arrival$

This theorem provides operations managers with two powerful conclusions that guide their understanding of the behavior of systems of non-preemptive priority queues:

- The weighted average of wait times is constant no matter the queuing discipline employed.
- Any attempt to modify the queuing discipline so as to reduce some value of $\overline{W}_k$ will force an increase in the value of some other $\overline{W}_k$ [5].

This concept will prove useful when analyzing whether or not to prioritize emergent (non-scheduled) kit requests.

## 2.2 Little's Law

Little's Law states that the long-term average number, $L$, of customers (or products, or service requests…) in a system is equal to the long-term average arrival rate, $\lambda$, multiplied by the average time, $W$, a customer spends in the system. Simply put:

$$L = \lambda \times W \quad (5)$$

This theorem holds true for stable systems, which excludes situations such as startup or shutdown. It was first published in 1954 [6]. In 1961, Little published a proof of *Little's Law*, showing no such situation existed in which it did not hold true [7].

This theorem is useful for studying queuing systems because it relates expected queue lengths to expected wait times in an intuitive manner: the average number of "customers" in the queue divided by the rate of arrival will be used to calculate expected queue wait times.

## 2.3 Discrete Event Simulation and Monte Carlo

Discrete event simulation (DES) is a widely used operations management technique for assessing the performance of a physical system in a virtual setting. System events are modeled according to discrete time intervals. Random number generation is used to model probabilistic behavior related to random variables (such as arrival and service rates). DES can be useful for diagnosing a variety of process issues and can be tied to any number of performance indicators such as worker utilization, on-time delivery rate, scrap rate, etc.

In the context of analyzing queue behavior, a simple DES model can simulate service requests entering a queue, waiting for an available server, undergoing processing, and exiting the system. Such an analysis will be useful for testing the validity of analytical models presented in previous sections. Additionally, DES can provide an estimate of *maximum queue length* which is not easily obtained from available analytical models [8].

Running consecutive DES models produces a data set of estimated performance indicators, $\theta$, similar to established Monte Carlo analytical techniques. For $N$ consecutively executed model runs, the standard error (SE) of $\theta$ is the standard deviation of the sampling distribution from $N$ samples [9].

$$s_\theta = \frac{\sigma_\theta}{\sqrt{N}} \tag{6}$$

# 3 Capacity Planning Problem

In chapter one of this thesis, an introduction was provided covering the ongoing improvement efforts focused on assessing and redesigning internal logistics processes supporting the production system. Chapter three will expand on the ongoing process improvement efforts by providing a more thorough understanding of the issues affecting internal logistics process performance and why capacity planning was selected as the central problem under consideration for this thesis.

## 3.1 Factors Affecting System Performance

Leadership has an extensive selection of metrics at their disposal for measuring the performance of internal logistics processes. In general, managers will concern themselves with the *effectiveness* and *efficiency* of their operations. Considering the effectiveness and efficiency of Boeing internal logistics processes, this thesis proposes that leadership pay close attention to the following three factors: *time-in-system, variability,* and *cost.*

### 3.1.1 Time-in-System

The total time that parts and material spend in the production system has a significant impact on operating expenses. By the principles of Little's Law (introduced in the previous chapter), the longer that parts and material remain in the factory *on average*, the more parts and material there will be in the factory at any given time. Therefore, slow inventory turnover can lead to numerous other issues impacting system effectiveness and efficiency:

**Floor Space**

Excessive raw material and work in process (WIP) inventory leads to the need for additional floor space throughout the production system. Acquiring additional floor space in a manufacturing context can add significant operating and capital expenses. When operating areas are no longer able to support necessary inventory levels, firms must invest in additional storage facilities, which can be either temporary (i.e. renting warehouse space from a third party) or permanent (i.e. capital expenditures on facility expansion).

**Materials Management**

Managing excessive inventory places additional strain on limited materials management resources, including warehouse staff and inventory control processes.

**Capital Opportunity Costs**

Excessive material inventories tie up a firm's working capital. This can lead to limited investment in necessary capital expense projects or other more attractive investment opportunities.

**Poor Quality**

In many cases, excessive inventory can lead to challenges with maintaining product quality. With more parts on the floor, it's more difficult for firms to ensure the quality of every part as it makes its way through production. With more time spent in system, parts are exposed to the risk of product damage for longer time intervals. Poor quality means higher raw materials costs, higher labor costs, and possibly missed sales or damage to reputation.

### 3.1.2 Variability

In an operations setting, variability can manifest itself in any number of ways. In the context of queuing theory, as detailed in chapter two, variability in arrival and service times translates into increased average queue sizes. Increased queue sizes directly relates to increased time-in-system. In highly variable systems, firms may be forced to invest in extra capacity to avoid excessive non-value-added time of parts and material waiting in queues.

Variability can also be understood in terms of process quality. A tightly controlled "six sigma" process will produce few defects and require little rework. By contrast, a poorly controlled process will produce excessive defects, leading to increased raw material costs, decreased labor and equipment efficiency, and increased demands on system capacity. It is imperative that operations managers understand the relevant sources of variability, the impact on system performance, and how they can manage and limit variability within the system design.

### 3.1.3 Cost

In general, both time-in-system and variability contribute to the cost of operating the internal logistics system. While cost efficiency may be a shared goal across firms, the extent to which firms dedicate their time and resources to cost avoidance certainly varies. In designing logistics processes, costs associated with the system should be categorized by what is either recurring or nonrecurring.

**Nonrecurring Costs**

All one-time costs associated with setting up the system are nonrecurring costs. These include capital expenses associated with purchasing (or refurbishing) equipment and facilities.

**Recurring Costs**

All regular operating expenses associated with running the system can be thought of as recurring costs. This includes labor, overhead such as electricity, raw materials, and facility/equipment maintenance.

## 3.2 Process Design

At this point it is useful to return to the questions plaguing Ashley, the process engineer introduced in chapter one:

*How much capacity should be acquired to support internal logistics processes at a new manufacturing site? Which processes should be transferred from existing operations and which processes require improvements? How much space will be required to support these processes? How much will it cost to implement these processes in a new manufacturing space?*

A common thread underlying these questions is the concept of *capacity*. When process capacity is significantly in excess of demand, the firm's cost efficiency is negatively impacted. Resources allocated to acquiring the excessive capacity are unproductive. When capacity is too low, the firm's effectiveness and efficiency are both negatively affected. Customer service could be impacted resulting in brand damage and missed sales. Striking the right balance between *too much* and *not enough* capacity allows firms to meet customer demand in an efficient manner.

For these reasons, this thesis will focus on capacity planning in the context of Boeing's on-going internal logistics improvement efforts. Specifically, how much capacity should be acquired to support internal logistics operations at a new manufacturing site? The answer to this question will depend on many of the factors already mentioned. What do these new processes look like? How well will they perform? How will performance variability, such as the amount of rework required, affect capacity demands?

To answer these questions, a methodology for identifying the number of servers needed at each process step will be proposed based on principles of queuing theory and Little's Law. A similar methodology will be developed for identifying the amount of equipment needed to support operations. Additionally, a number of assumptions will be presented around system parameters and operating discipline, especially related to the handling of emergent requests otherwise known as "rework."

An understanding of the current state of internal logistics processes and areas of improvement will be developed. Then the proposed methodology will be applied to the envisioned processes to determine how much capacity is required and the behavior of various factors' effect on this determination.

# 4 Methodology Overview

This chapter will explain the methodology that will be used to determine capacity requirements of proposed internal logistics operations for a manufacturing site currently under assessment. First, the supporting assumptions need to be established around key parameters of these proposed processes. Second, an approach for determining the number of servers needed for each process will be presented. Following that, another approach for determining the number of pieces of equipment needed will be presented. Chapter four will conclude with a third approach for calculating expected wait times of emergent part requests, which can be understood as non-standard operations, and the effect prioritization of certain requests may have on standard operations.

## 4.1 Process Assumptions

In planning the design of a future production system, the exact numerical values of certain process parameters are mostly unknown. This analysis will address this issue by making reasonable assumptions of parameter values based on discussions with operations leadership and from observation of existing processes. A sensitivity analysis will be provided for certain selections of these parameters. Additionally, modeling efforts will anticipate the needs of planners who will gain access to more mature parameter estimates over time, so the manipulation of these values in the model will be relatively user-friendly.

Other exact values relevant to ongoing Boeing planning conversations were obfuscated for the sake of confidentiality. The remainder of this section will present the significance of each process parameter and will then provide the assumed value used for capacity planning analysis, where appropriate.

### Production Rate

Production rate refers to the number of shipsets (ss) to be produced per month. One shipset is the equivalent of one commercial jetliner. For capacity planning purposes, it is helpful to design operations to support production at 100% of projected rate. Therefore, values used in this analysis for production rate range from 10 to 15 ss/month.

While an understanding of capacity requirements at rates less than 100% of full production will be useful for planners concerned with initial start-up stages of operation, partial rate analysis and/or rate ramp-up analysis were excluded from the scope of this thesis.

### Parts per Shipset

Parts per shipset is equal to the number of individual parts that will be processed by internal logistics for each shipset. A bill of materials (BoM) for an aircraft may include hundreds of thousands of parts [10]. For this context, "parts" also include materials that will not be installed on a shipset (such as hand tools), because these materials will still be needed by manufacturing personnel to complete their required work. The parts per shipset value will consist of all parts and materials that a production worker needs to do their work, including supplier-provided "hard parts," fasteners, consumables, tools, and hazardous material. This analysis assumes a value of 100,000 parts/ss.

### Number of Point-of-Use Locations

Point-of-use (POU) locations are the areas within the factory where integrated kits (i-kits) are delivered by logistics personnel to be consumed by production workers. I-kits contain all the parts that a production worker needs to complete their scheduled "job" including all "hard parts," fasteners, consumables, tools, and hazardous material. Production workers may complete one to four jobs (or more) per shift. Production workers at POU locations can be thought of as the "customers" of the internal logistics system. As the number of POU locations increases within the system, the complexity of operations for internal logistics processes also increases. For the proposed production system under consideration the number of POU locations was assumed to be equal to 140.

**Integrated Kit (i-kit) Delivery Demand**

I-kit delivery demand is related to the number of total i-kits that must be delivered to all POU locations over a set period of time (usually per shift). In order to estimate this parameter, assumptions were made regarding the frequency of delivery to each POU location. The delivery frequency is dependent on the lengths of jobs to be completed at that POU location, where one i-kit corresponds to one job. Based on these factors, baseline demand for i-kits was determined to be ~422 i-kits/shift.

*Baseline* demand is different from *total* demand in that baseline demand ignores the *emergent* kit deliveries that will be requested periodically throughout a shift to account for missing parts, incomplete kits, product damage, or operator mistakes. Logistics planners anticipate that a certain number of emergent kits (e-kits) will need to be prepared and delivered on an *ad hoc* basis by internal logistics processes to support less-than-perfect system quality.

**Delivery On-time-in-full (OTIF) Percentage**

The first parameter addressing system quality is the percent of deliveries made on-time and in-full (OTIF%). If a delivery arrives late (or not at all) or is missing some number of parts, planners assumed a process will be in place for production workers to request a replacement delivery. These e-kit requests are assumed to be solely caused by quality issues associated with processes upstream from production operations (i.e. internal logistics). Baseline OTIF% was assumed to be equal to 99.5% or approximately five quality defects per 1,000 deliveries.

## Production Quality Percentage

The second parameter addressing system quality is the production quality percentage (PQ%). This parameter is related to the number of e-kits that must be delivered due to issues stemming from manufacturing operations, such as product damage. Baseline PQ% was assumed to be equal to 99.0% or approximately 10 quality defects per 1,000 production jobs.

## Truck Arrivals per Shift

A number of other more granular assumptions were also made in relation to each individual process within the internal logistics system. One example of these more granular assumptions is the average number of truck arrivals to receiving per shift. This value was assumed to be approximately 30 trucks/shift. For calculating the number of servers needed for unloading trucks, this assumption guides planners' understanding of how many trucks must be unloaded during each shift.

A complete list of assumed parameter values is compiled in Table 1.

**Table 1: List of Assumed Parameter Values**

| Parameter | Value | Units of Measure |
|---|---|---|
| Production rate | 10-15 | ss/month |
| Operating days per month | 20-24 | days/month |
| Hours per operating day | 21 | hr/day |
| Shifts per day | 3 | shifts/day |
| Parts per shipset | 100,000 | parts/ss |
| Number POU locations | 140 | |
| i-kit Delivery Demand | 422 | i-kits/shift |
| i-kit Delivery OTIF % | 99.5% | |
| Production Quality % | 99.0% | |
| Truck arrivals per shift | 30 | trucks/shift |

## 4.2 Capacity Planning: Servers

To make a determination of the number of servers required to support a process, this analysis will use the principles detailed in chapter two related to queuing theory and Little's Law. First, assumptions related to process parameters will be clearly defined. Second, a sensitivity of expected utilization and queue length will be analyzed with respect to the number of process servers. Finally, the expected wait time will be calculated and normalized with respect to the process cycle time. These ratios will be useful because they are directly related to the non-value-added time experienced by inventory during manufacturing. As detailed in chapter three, efforts to control and reduce time-in-system provides numerous benefits related to the effectiveness and the efficiency of the manufacturing process.

To illustrate this methodology, an example will be provided for the truck receiving process which represents the first process of the internal logistics system.

As already mentioned, the average truck arrival rate is estimated to be 30 trucks/shift.

$$\lambda = 30 \text{ trucks/shift}$$

$$\lambda = 0.07 \text{ trucks/min}$$

The coefficient of variation of truck arrivals needs to be assumed (the exact value is unknown, but could be estimated more precisely by conducting time studies of current receiving operations). For this example, this value was assumed to be 100%.

$$C_A = 100\%$$

Next, the average and coefficient of variation for truck unloading cycle times must also be assumed. The following values were determined to be reasonable starting points:

$$Cycle\ time, unloading = 120\ min/truck$$

$$\mu = \frac{1}{120\ min/truck} = 0.0083\ trucks/min$$

$$C_S = 50\%$$

A reasonable range of $n$ values is now necessary to conduct a sensitivity analysis. After some brief trial and error, a range from 7 to 13 is found as reasonable.

$$n = \{7,8,9, \dots ,13\}$$

For each value of $n$, the time available is determined by the shift length of that process. All shifts are assumed to be 7 hours in length (21 operating hours per day / 3 shifts per day).

$$Available\ time\ (min/shift) = \{2940, 3360, 3780, \dots, 5460\}$$

The maximum service rate is then also calculated for each value of $n$.

$$Maxmum\ service\ rate\ (trucks/shift) = \frac{Available\ time}{\mu} = \{24.5, 28.0, 31.5, \dots, 45.5\}$$

The expected utilization is then calculated for each value of $n$.

$$\rho = \frac{E[A]}{Maximum\ service\ rate} = \{1.224, 1.071, 0.952, \dots, 0.659\}$$

Note that this calculation matches the equation for capacity utilization presented in chapter two:

$$\rho = \frac{\lambda}{n\mu}$$

$$\rho_{n=7} = \frac{(0.07\ trucks/min)}{(7 \times 0.0083\ trucks/min)} = 1.224$$

Table 2 displays the results of the sensitivity analysis thus far:

**Table 2: Projected Utilization of Varying Number of Servers, N**

| $n$ | $Available\ time\ (min/shift)$ | $Maximum\ service\ rate\ (trucks/shift)$ | $\rho$ |
|---|---|---|---|
| 7 | 2940 | 24.5 | 122.4% |
| 8 | 3360 | 28.0 | 107.1% |
| 9 | 3780 | 31.5 | 95.2% |
| 10 | 4200 | 35.0 | 85.7% |
| 11 | 4620 | 38.5 | 77.9% |
| 12 | 5040 | 42.0 | 71.4% |
| 13 | 5460 | 45.5 | 65.9% |

The G/G/N queuing model can now be applied to calculate the average number of trucks waiting in queue for each value of $n$, so long as the value of $\rho_n < 100\%$.

$$L_{n=9} = \frac{\rho_{n=9}{}^{\sqrt{2(n+1)}}}{1-\rho_{n=9}} \times \frac{C_A^2 + C_S^2}{2} = 10.6\ trucks$$

Little's Law can then be applied to determine the expected time each truck spends in queue, on average, for each value of $n$.

$$L = \lambda \times W$$

$$W_{n=9} = \frac{L_{n=9}}{\lambda} = \frac{10.6\ trucks}{30\ trucks/shift} \times \frac{7\ hours}{1\ shift} \times \frac{60\ min}{1\ hour} = 147.7\ min$$

Table 3 displays the updated sensitivity analysis complete with expected wait times.

**Table 3: Expected Wait Times of Varying Number of Servers, N**

| $n$ | $\rho$ | $L_q$ | $W$ $(minutes)$ |
|---|---|---|---|
| 7 | 122.4% | - | - |
| 8 | 107.1% | - | - |
| 9 | 95.2% | 10.6 | 147.7 |
| 10 | 85.7% | 2.1 | 29.7 |
| 11 | 77.9% | 0.8 | 11.7 |
| 12 | 71.4% | 0.4 | 5.5 |
| 13 | 65.9% | 0.2 | 2.8 |

From the perspective of a designer wishing to select a value of $n$, there are two competing forces related to the system efficiency that must be balanced:

- ***Utilization, ρ.*** The utilization of the system is tied to the process efficiency. Utilization at 100% means that the system is meeting demand with the minimum required resources. Utilization less than 100% means that there is additional unused capacity within the system. In general, utilization should be maximized, with some additional capacity reserved to handle typical process variability.

- ***Queue wait time, W.*** The time-in-system, another measure of process efficiency, is directly related to the time material waits to be processed. As wait times increase, additional costs are incurred related to working capital costs, facilities cost, materials management expenses, and potential quality issues. In general, wait times should be minimized.

This thesis proposes that system designers relate these competing variables by using the following ratio:

$$\frac{VA}{NVA} = \frac{Cycle\ time}{Wait\ time} \tag{7}$$

Where:

- VA = Value-added time or the productive processing time
- NVA = Non-value-added time or the non-productive time material spends in the system

*Value-added time* in this context can be defined as the *productive time* or the processing time that directly adds value to the customer. Value-added time is estimated by the cycle time of the process, which is a significant simplifying assumption. *Non-value-added time* is all non-productive time and can be estimated by the wait times experienced within the process. As needed, non-value-added time will also be estimated by subtracting value-added time from *all available time.* Using these simplified definitions and the ratio in Equation 7 allows the process designer to select the value of *n* that satisfies the following objective function:

$$\max \rho \ \forall \ \frac{VA}{NVA} \geq k \tag{8}$$

This objective function provides the designer with a heuristic approach to select a reasonable value for *n.* Table 4 shows the updated sensitivity analysis with calculated values of *VA/NVA*.

**Table 4: Expected Values of VA/NVA of Varying Number of Servers, N**

| $n$ | $\rho$ | $L_q$ | $W$ (minutes) | $VA/NVA$ |
|---|---|---|---|---|
| 7 | 122.4% | - | - | - |
| 8 | 107.1% | - | - | - |
| 9 | 95.2% | 10.6 | 147.7 | 0.8 |
| **10** | **85.7%** | **2.1** | **29.7** | **4.0** |
| 11 | 77.9% | 0.8 | 11.7 | 10.3 |
| 12 | 71.4% | 0.4 | 5.5 | 21.8 |
| 13 | 65.9% | 0.2 | 2.8 | 42.3 |

**According to the proposed design rule, for $k = 3$,[3] the designer would select $n = 10$.**

This value of $n$ corresponds to the maximum rate of utilization for which $VA/NVA \geq k$. For the example provided, this means that 10 truck bays should be built to unload trucks in a receiving area matching these process parameters.

## 4.3 Capacity Planning: Equipment

It will also be incumbent on system designers to use these principles for similarly selecting the amount of equipment needed to support internal logistics processes. A good example of how this methodology can be applied is the case of selecting the number of electric tugs to be deployed in the system. These electric tugs will be manually operated and used for moving material to and from the production floor.

First the demand for tugs must be determined. This demand will be equal to the rate of tug deliveries that must be completed to support full production. Deliveries of material can be categorized by one of two types of deliveries: *standard* or *emergent*.

- **Standard deliveries** will be made according to a daily schedule that pulls from a ready-to-be-used buffer of i-kits (in the kit staging area) to deliver material "just-in-time" to the

[3] A VA/NVA ratio of 3:1 is considered "world-class" by industry experts. However, the metric of VA/NVA used in this thesis assumes that all process cycle time is value-added, which is almost certainly not the case. Therefore, considerable tuning would be worthwhile to identify the right value of $k$. Tuning this heuristic did not fall within the scope of this project, but would make for an interesting opportunity for additional study. This topic will be discussed in further detail in chapters six and seven.

production floor. Because tugs can deliver more than one i-kit per departure, the average number of i-kits that will be delivered for each trip should be equal to the maximum tugging capacity of each tug. A reasonable starting assumption is that each tug will be able to deliver four i-kits per delivery. If assumed *i-kit delivery demand = 422 i-kits/shift*, then the expected number of standard deliveries will be 106 deliveries/shift.

- **Emergent deliveries** will be made as demand for emergent kits arises throughout standard operations. Emergent demand could be due to improperly prepared i-kits, miss-delivered i-kits, or production quality issues. Using assumed values of delivery *OTIF% = 99.5%* and *PQ% = 99.0%,* the expected number of emergent deliveries will be six deliveries/shift.

Therefore, the total rate of tug deliveries will be expected to be 112 deliveries/shift.

Next, the estimated time-in-system (per delivery) must be calculated. This time will be heavily dependent on assumed values for cycle times of each process step as well as expected tug downtime due to equipment failures or regular battery recharging. Additionally, at certain high-traffic steps throughout the delivery process, the tug may be waiting in queue to be loaded or unloaded. These wait times were also calculated using G/G/N and Little's Law as described in the previous section. Table 5 details the assumptions of the underlying values needed to calculate tug time-in-system (per delivery):

**Table 5: Lifecycle of an Electric Tug (per delivery)**

| Description | Time (min/delivery) | VA or NVA | Explanation |
|---|---|---|---|
| Cycle time, tug loading | 5.0 | VA | Time to load tug at warehouse staging area |
| Cycle time, tug convey (from warehouse to factory) | 12.0 | VA | Time for tug to drive from warehouse to each POU delivery location |
| Cycle time, receipt at POU | 5.0 | VA | Total time for tug to deliver i-kits to each POU location |
| Cycle time, tug convey (from factory to warehouse) | 12.0 | VA | Time for tug to drive back to warehouse from factory |
| Cycle time, tug unloading | 10.0 | VA | Time to unload tug at kit return area |
| *Total VA time-in-system* | *44.0 min/delivery* | | |
| Waiting, tug loading | 5.6 | NVA | Wait time for tug to be loaded at warehouse staging area |
| Waiting, tug unloading | 1.9 | NVA | Wait time for tug to be unloaded at kit return area |
| Downtime, average per delivery | 0.4 | NVA | Average tug downtime, assuming 2 hours downtime per day |
| *Total NVA time-in-system* | *7.9 min/delivery* | | |
| **Total time-in-system** | **51.9 min/delivery** | | |

Next, Little's Law can be used to determine the number of tugs, *L*, required to meet this delivery demand at 100% capacity utilization.

$$\lambda = 112\, deliveries/shift = 16.0\ deliveries/hr$$

$$W = 51.9\, min/delivery = 0.87\ hr/delivery$$

$$L = \lambda \times W$$

$$L = \left(16.0\frac{deliveries}{hr}\right) \times \left(0.87\frac{hr}{delivery}\right) = 13.8$$

This approach suggests that 13.8 tugs, on average, will be needed to satisfy expected delivery demand at 100% utilization.

Similar to the previous analysis for server capacity, a sensitivity analysis can now be used to calculate expected utilization for increasing values of *n*, the number of tugs to be acquired for this system. After brief trial-and-error, a range from 14 to 19 is found as reasonable.

$$n = \{14, 15, 16, \ldots, 19\}$$

The capacity utilization calculation is straightforward:

$$\rho_{n=14} = \frac{n_{\rho=100\%}}{n} = \frac{13.8}{14} = 98.8\%$$

The *VA/NVA* ratio can also be calculated. First, *value-added time* is related to the rate of tug-deliveries and the total VA time per delivery. A modified version of Little's Law can be used:

$$VA_{n=14} = \lambda \times W_{VA} = \left(16.0 \frac{deliveries}{hr}\right) \times \left(44.0 \frac{min}{delivery}\right) = 704\ min/hr$$

This equation suggests that value-added time is constant with respect to *n*. Upon further reflection, this appears to be reasonable. The total value-added time experienced by the deployed tugs in the system should not change depending on the number of tugs. Value-added time, in this case, is a function of the work that must be completed and the percentage of time workers spend performing that work out of all available worker time.

Therefore, *non-value-added time* with respect to *n* should be determined by first calculating the total amount of available time as a function of *n* and then subtracting value-added time.

$$NVA_{n=14} = (Available\ time)_{n=14} - VA_{n=14}$$

$$NVA_{n=14} = \left(14 * 60\ \frac{min}{hr}\right) - 704 \frac{min}{hr} = 136\ min/hr$$

From this equation, it is clear that *non-value-added time* will increase with the value of *n*. Table 6 shows the sensitivity analysis for the range of *n* values with *VA/NVA* ratios calculated:

**Table 6: Expected Values of VA/NVA of Varying Number of Equipment, N**

| $n$ | $\rho$ | $VA\ (\frac{min}{hr})$ | $NVA\ (\frac{min}{hr})$ | $VA/NVA$ |
|---|---|---|---|---|
| 14 | 98.8% | 704 | 136 | 5.1 |
| 15 | 92.2% | 704 | 196 | 3.6 |
| 16 | 86.4% | 704 | 256 | 2.7 |
| 17 | 81.3% | 704 | 317 | 2.2 |
| 18 | 76.8% | 704 | 377 | 1.9 |
| 19 | 72.8% | 704 | 437 | 1.6 |

Observation of these results yields an interesting discovery. Unlike the previous method for analyzing servers, the value of *VA/NVA decreases* with respect to the amount of equipment in use (tugs deployed, in this example). This leaves a system designer with two options:

- Select the value of *n* which maximizes both utilization and *VA/NVA* (in this case, *n = 14);*
- Or, determine another efficiency metric that can be used to provide sufficient capacity buffer.

This methodology proposes that the *probability of no available equipment* is a worthwhile efficiency metric to examine further. If a binomial distribution is applied to the condition of equipment availability (equipment is either *available* or it is *not available*), then the *probability of no available equipment* can be calculated by the following simple relationship:

$$P(no\ equip.available) = \rho^n \tag{9}$$

This metric is added to the sensitivity analysis shown in Table 7.

**Table 7: Expected Values of $\rho^n$ of Varying Number of Equipment, N**

| $n$ | $\rho$ | $VA\ (\frac{min}{hr})$ | $NVA\ (\frac{min}{hr})$ | $VA/NVA$ | $\rho^n$ |
|---|---|---|---|---|---|
| 14 | 98.8% | 704 | 136 | 5.1 | 84.2% |
| 15 | 92.2% | 704 | 196 | 3.6 | 29.6% |
| 16 | 86.4% | 704 | 256 | 2.7 | 9.7% |
| 17 | 81.3% | 704 | 317 | 2.2 | 3.0% |
| 18 | 76.8% | 704 | 377 | 1.9 | 0.9% |
| 19 | 72.8% | 704 | 437 | 1.6 | 0.2% |

What this methodology is now in need of is an understanding of what is a good value of $\rho^n$. The probability of no available equipment is only a useful metric in that it tells the designer the likelihood of a worker in the system waiting for a piece of equipment to become available at any given time. Framed this way, a probability of 80-100% seems unacceptably high, due to the likelihood of additional waiting injected throughout the system.

This analysis can be progressed by making an assumption regarding expected wait time. If a worker in the system finds that no equipment is available, then the next piece of equipment to come available must be in the process of finishing its delivery cycle, up to that point in the cycle. A uniform distribution can be applied to the random chance a worker finds herself waiting for a piece of equipment to come available. It is as equally likely that the delivery cycle just started, as it is to being a split-second from completion, as it is to being somewhere in the middle. Therefore, given that no equipment is available, the expected wait time for the next available piece of equipment can be calculated by dividing the average process cycle time by two:

$$E[wait\ time\ for\ next\ available\ equip., given\ no\ avail. equip.] = \frac{1}{2} \times \frac{total\ cycle\ time}{n} \quad (10)$$

From this value, the expected average wait time for any worker in the system is equal to the *probability of no available equipment* multiplied by the *expected wait time when no equipment is available.*

$$E[wait\ time\ for\ next\ available\ equip.] = \frac{\rho^n}{2} \times \frac{total\ cycle\ time}{n} \quad (11)$$

These metrics are also added to the sensitivity analysis (with *VA*, *NVA*, and *VA/NVA* removed) as shown in Table 8.

**Table 8: Expected Wait Times of Varying Number of Equipment, N**

| $n$ | $\rho$ | $\rho^n$ | *E[wait, given no avail. equip.] (min)* | *E[wait] (min)* |
|---|---|---|---|---|
| 14 | 98.8% | 84.2% | 1.9 | 1.6 |
| 15 | 92.2% | 29.6% | 1.7 | 0.5 |
| 16 | 86.4% | 9.7% | 1.6 | 0.2 |
| **17** | **81.3%** | **3.0%** | **1.5** | **<0.1** |
| 18 | 76.8% | 0.9% | 1.4 | <0.1 |
| 19 | 72.8% | 0.2% | 1.4 | <0.1 |

It is reasonable to assume that factory workers (as well as management) would want the expected wait time for equipment to be roughly zero. Setting the constraint that $\rho^n \leq 5\%$ provides expected equipment wait times roughly equal to zero (E[wait] < 6 seconds). **This suggests the system designer should select *n* = *17* because this is the value of *n* for which utilization is maximized and $\rho^n \leq 5\%$.**[4]

## 4.4 Calculating Expected Wait Times of Emergent Requests

As previously discussed, the impact of managing emergent kit requests must also be considered. The scope of this analysis will include two different management methods for processing emergent kit requests alongside standard operations: (1) First-in/first-out (FIFO) and (2) Emergent Request Prioritization.

### 4.4.1 Method 1: First-in/first-out (FIFO)

Kit requests will be processed on a first-come, first-serve basis. This approach minimizes the impact that emergent kit requests have on standard i-kit preparation, staging, and delivery. For example, say there is one i-kit in the queue and one i-kit being processed in the kit staging area, at any given time, on average. If an emergent kit request arrives to the queue, the worker(s) in that area would process the i-kit already in the queue before beginning to process the emergent kit request.

Because e-kits are processed with the same priority as standard i-kits, calculating the expected wait time for e-kits under this approach is identical to calculating the expected wait

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[4] Note that $\rho^n\_max$ is similar to the design variable of $k$ introduced in the previous section. The relationship between these design variables – and how the selection of threshold values impact design outcomes – will be discussed in further detail in chapters six and seven.

time of *any* standard i-kit. Therefore, the expected e-kit wait time is equal to the average wait time of all i-kits through that process:

$$E[e\_kit\ wait\ time] = E[i\_kit\ wait\ time] = \bar{W} \quad (12)$$

### 4.4.2 Method 2: Emergent Request Prioritization

The reasonable alternative approach is to prioritize emergent kit requests as soon as they arrive. Workers will finish whatever is already in process, then begin working on the emergent request before working on any other i-kits already in the queue. This approach provides the benefit of minimizing the amount of wait time experienced by e-kits, but should also introduce a corresponding increase in the average wait time experienced by standard (regularly scheduled) i-kits.

This management approach can be modeled as a *non-preferential priority queue* (as introduced in chapter two). Calculating the expected wait times of e-kits requires the system designer to understand the expected wait time of only the first item in the queue. There is some probability that an e-kit arrives to find an empty queue and at least one available server. In this case it will immediately begin to be processed by an available server. The probability that all servers are occupied (busy) when arriving to the process area is equal to $\rho^n$.[5]

$$P(no\ servers\ available) = \rho^n$$

If no e-kits are already waiting in the queue, the e-kit arriving to find no servers available will immediately go the front of the queue. Given that no servers are available, the expected wait time of the first request in the queue can be modeled as the average cycle time of the process

[5] This concept is equivalent to equation 9 introduced in the previous section regarding equipment capacity planning.

(assuming uniform random probability of arriving in the queue at the beginning, middle, or end of the cycle).

$$E[wait\ time, given\ no\ avail.servers] = \frac{1}{2} \times \frac{total\ cycle\ time}{n}$$

This equation can be modified by recognizing that if the system has no available servers, it is operating at a higher rate than the average cycle time. A system at 100% capacity will have a temporary service rate equal to its maximum service rate. The expected wait time for e-kits arriving to a full system can be rewritten as such:

$$E[wait\ time, given\ no\ avail.servers] = \frac{1}{2} \times \frac{1}{Maximum\ Service\ Rate}$$

Therefore, assuming e-kits arriving to an empty queue with at least one available server experience zero wait time, the expected wait time of e-kit requests can be written as such:

$$E[e\_kit\ wait\ time] = P(no\ servers\ available) \times E[wait\ time, given\ no\ avail.servers]$$

$$E[e\_kit\ wait\ time] = \frac{\rho^n}{2} \times \frac{1}{Maximum\ Service\ Rate}$$

The astute reader will recognize that the expected e-kit wait time will increase if the e-kit cannot go directly to the front of the queue upon arrival due to one or more e-kits already waiting in the queue. Therefore, a principal underlying assumption supporting the remainder of this analysis is that the probability of an e-kit request arriving to a queue that already contains at least one e-kit request is negligible. The validity of this assumption is supported by the relatively low number of emergent deliveries compared to the number of regularly scheduled requests (at assumed levels of quality, only sixout of 112 total deliveries per shift will be due to emergent requests (5.4%)).

To calculate the impact this approach has on the expected wait time of *non-prioritized* i-kits, *Kleinrock's conservation theorem* is applicable (as introduced in chapter two) [5]:

$$\sum_{k=1}^{K} \rho_k \bar{W}_k = \frac{\rho}{1-\rho} \times \bar{R}$$

Because the weighted average of wait times is constant no matter the queuing discipline employed, this theorem can be rewritten as such:

$$\bar{W} = x \times E[e\_kit\ wait\ time] + (1-x) \times E[i\_kit\ wait\ time] \quad (13)$$

Where $x$ is the percent of total requests attributable to emergent kit requests.

# 5 Capacity Planning Analysis

Chapter five will present the data extracted from implementing the methodology detailed in the previous chapter. First, a review of the proposed internal logistics processes will be provided. Second, the data from the capacity planning analysis for servers will be presented for different levels of system variability. Following that, the data from the capacity planning analysis for equipment will be presented. Next, fulfillment capability data will be presented resulting from the analysis of expected wait times of emergent part requests. Chapter five will conclude with data from a sensitivity analysis of expected levels of quality.

## 5.1 Process Overview

The internal logistics system is composed of nine separate processes that combine to process parts and material from arrival onsite into integrated kits delivered to production operations. Figure 1 is a system diagram of the proposed internal logistics processes:

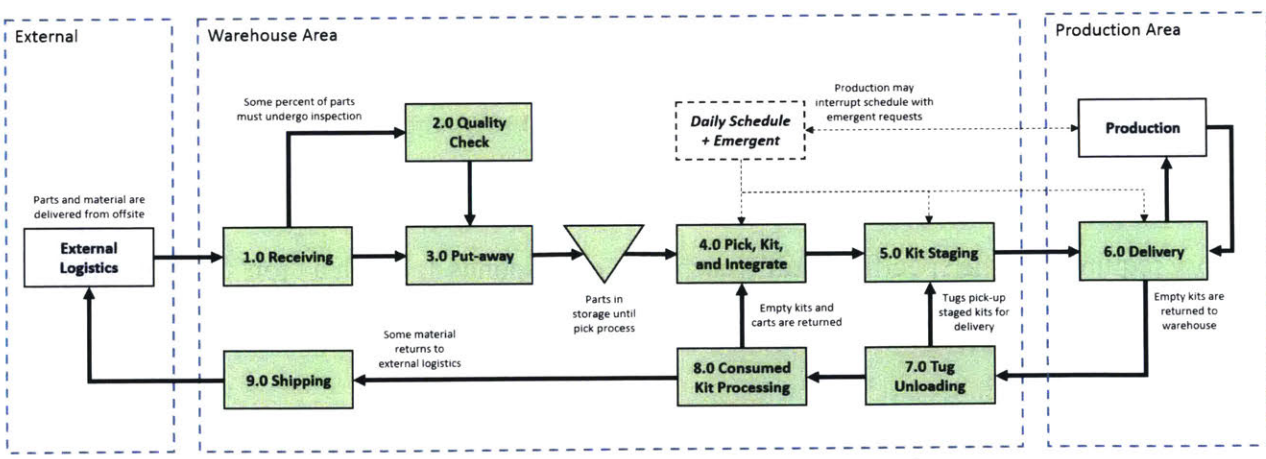


**Figure 1: Process Flow Diagram of Internal Logistics System**

Following are additional details of each internal logistics sub process:

### 1.0 Receiving

Trucks arrive with deliveries from external consolidation centers. Trucks wait in queue until a truck bay is available. Once a bay is available, the truck will be unloaded by logistics personnel. Logistics personnel will document that the delivery was received. Some percentage of parts and material will be inspected for quality while the rest will go directly to put-away.

**2.0 Quality Check**

Due to regulatory requirements, some parts must undergo quality inspection. A number of quality check servers will be available to conduct the inspection, as required. Parts will wait in queue until a server is available. This process assumes 100% recovery of parts, meaning that all parts leaving quality check go into storage via put-away.

**3.0 Put-away**

Parts arrive to the put-away process in containers (aka "totes") that allow for direct placement into storage. A number of servers are available to load totes onto automated storage racks. Totes wait in queue until a server is available.

**4.0 Pick, Kit, and Integrate**

The pick, kit, and integrate process works to a schedule that is set in advance with reasonable leadtime. Servers at process work stations will build i-kits according to schedule (with the exception of emergent kit requests). Parts are automatically picked from storage and loaded into categorized kits (tools, hard parts, standards, etc.). This is repeated for each kit category required for the specified "job" (each i-kit corresponds 1:1 with a "job" in production) until the i-kit is completed. I-kits are loaded onto carts (aka "daughter carts") that are then sent to kit staging.

**5.0 Kit Staging**

The kit staging process receives i-kits from "pick, kit, and integrate" and organizes i-kits by the area of the factory where they will be delivered. The kit staging area will be divided according to the three different areas of the factory: building 1, building 2, and building 3.

Within each dedicated area, batches of i-kits are grouped so that they can be delivered together (assuming tugs will deliver a maximum of four i-kits per delivery). Logistics personnel load i-kit deliveries onto tugs that will then convey the material to production. Emergent kit requests will not be grouped with other i-kits and will be loaded onto the first available tug.

**6.0 Delivery**

Electric tugs, operated manually by tug drivers, will pick up i-kit deliveries from kit staging and drive the i-kits from the warehouse to the factory floor. I-kits will be delivered just-in-time so that production operations has the material to complete the next job before completing their current "job." Tug drivers will unload full i-kits at the corresponding point-of-use locations and load empty kits to be returned to the warehouse.

**7.0 Tug Unloading**

Tugs will return to the warehouse from production with empty kits. Logistics personnel at the warehouse will assist with unloading empty kits from the tugs. Tug drivers will then return to kit staging to pick up more i-kits for delivery. Empty i-kits (with daughter carts) will be sent to "consumed kit processing."

**8.0 Consumed Kit Processing**

Consumed (empty) kits returned from production must be broken down and returned to logistics operations. Empty kit containers and carts will be returned to "pick, kit, and integrate." Some material will need to return to external logistics via the shipping process. As consumed kits arrive to this area, they will wait in queue until a server becomes available.

**9.0 Shipping**

Some material will need to be returned to external logistics. Trucks will be loaded with shipments by logistics personnel working in the shipping area.

**Process Data**

Each internal logistics process has unique requirements in terms of the amount of capacity needed. For example, a single "server" at quality check looks a lot different than a server in shipping. Each process also experiences differences in the time between arrivals of parts and corresponding service times. The ratio of inter-arrival rate to cycle time (E[A]/c_t) is useful for comparing processes with significantly different magnitudes of inter-arrival times or cycle times. Table 9 presents information related to the unique process units and "servers" of each process along with assumed E[A]/c_t ratios:

**Table 9: Ratios of E[A]/c_t for Internal Logistics Processes**

| Process Name | Process Units | "Server" Description | E[A]/c_t[6] |
|---|---|---|---|
| 1.0 Receiving | Trucks | Truck bays | 12% |
| 2.0 Quality Check | Totes | Inspection stations | 65% |
| 3.0 Put-away | Totes | Put-away stations | 19% |
| 4.0 P., K., and I. | Requests (i-kit or e-kit) | Pick stations | 7% |
| 5.0 Kit Staging (building 2)[7] | Deliveries (batches of i-kits or single e-kits) | Loading stations | 155% |
| 6.0 Delivery[8] | Deliveries | Electric tugs | N/A |
| 7.0 Tug Unloading | Deliveries | Unloading stations | 38% |
| 8.0 Consumed Kit Processing | Requests | Processing stations | 10% |
| 9.0 Shipping | Trucks | Truck bays | 23% |

## 5.2 Capacity Planning: Servers

Using the methodology presented in chapter four, the number of servers required for each process was analytically determined for differing levels of variation. Three different variation levels were assessed:

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[6] Take 1.0 Receiving, for example. The assumed inter-arrival time of truck shipments is equal to 14 minutes (i.e. one truck arrives every 14 minutes, on average). The assumed cycle time of a single "server" is 120 minutes. Therefore, the ratio of E[A]/c_t = 14/120 = 11.67%.

[7] Because 5.0 Kit Staging is divided into three different areas, this analysis will just focus on the area of greatest demand. Building 2 will require the greatest rate of kit deliveries. Therefore, the capacity required by building 2 will be more than sufficient for the areas serving building 1 and building 3.

[8] The number of tugs required for 6.0 Delivery will be calculated by the capacity planning method for equipment instead of "servers."

- Low: $COV_{arrivals} = COV_{service} = 25\%$
- Medium: $COV_{arrivals} = COV_{service} = 75\%$
- High: $COV_{arrivals} = COV_{service} = 125\%$

The results of this analysis are presented in Table 10.

**Table 10: Results of Capacity Planning Analysis: Servers Required**

| Process Name | E[A]/c_t | Variable | Low_COVs | Med_COVs | High_COVs |
|---|---|---|---|---|---|
| 1.0 Receiving | 12% | N | 9.0 | 10.0 | 11.0 |
| | | $\rho$ | 95.2% | 85.7% | 77.9% |
| | | L (trucks) | 1.1 | 1.9 | 2.1 |
| | | W (min) | 14.8 | 26.8 | 29.2 |
| | | VA/NVA | 8.1 | 4.5 | 4.1 |
| 2.0 Quality Check | 65% | N | 2.0 | 3.0 | 3.0 |
| | | $\rho$ | 77.1% | 51.4% | 51.4% |
| | | L (totes) | 0.1 | 0.2 | 0.5 |
| | | W (min) | 2.8 | 3.4 | 9.5 |
| | | VA/NVA | 10.7 | 8.7 | 3.1 |
| 3.0 Put-away | 19% | N | 6.0 | 7.0 | 8.0 |
| | | $\rho$ | 85.7% | 73.5% | 64.3% |
| | | L (totes) | 0.2 | 0.6 | 0.7 |
| | | W (min) | 0.0 | 0.1 | 0.1 |
| | | VA/NVA | 20.9 | 8.3 | 7.7 |
| 4.0 Pick, Kit, and Integrate | 7% | N | 16.0 | 17.0 | 18.0 |
| | | $\rho$ | 95.6% | 90.0% | 85.0% |
| | | L (requests) | 1.1 | 3.0 | 3.8 |
| | | W (min) | 1.1 | 2.9 | 3.7 |
| | | VA/NVA | 14.0 | 5.1 | 4.0 |
| 5.0 Kit Staging (building 2 only) | 155% | N | 1.0 | 2.0 | 2.0 |
| | | $\rho$ | 64.4% | 32.2% | 32.2% |
| | | L (deliveries) | 0.1 | 0.1 | 0.1 |
| | | W (min) | 0.6 | 0.4 | 1.1 |
| | | VA/NVA | 8.9 | 12.5 | 4.5 |
| 6.0 Convey Deliveries | **N/A** | **N/A** | **N/A** | **N/A** | **N/A** |
| 7.0 Tug Unloading | 38% | N | 3.0 | 4.0 | 5.0 |
| | | $\rho$ | 88.8% | 66.6% | 53.3% |
| | | L (deliveries) | 0.4 | 0.5 | 0.4 |
| | | W (min) | 1.5 | 1.7 | 1.4 |
| | | VA/NVA | 6.7 | 5.7 | 7.1 |
| 8.0 Consumed Kit Processing | 10% | N | 11.0 | 12.0 | 13.0 |
| | | $\rho$ | 93.4% | 85.6% | 79.0% |
| | | L (i-kits) | 0.7 | 1.8 | 2.1 |
| | | W (min) | 0.7 | 1.7 | 2.1 |
| | | VA/NVA | 15.2 | 5.8 | 4.8 |
| 9.0 Shipping | 23% | N | 5.0 | 6.0 | 7.0 |
| | 23% | $\rho$ | 85.7% | 71.4% | 61.2% |
| | 23% | L (trucks) | 0.3 | 0.6 | 0.6 |
| | 23% | W (min) | 7.2 | 15.7 | 15.9 |
| | 23% | VA/NVA | 16.7 | 7.7 | 7.6 |

Figure 2 displays the number of servers required as a function of E[A]/c_t:

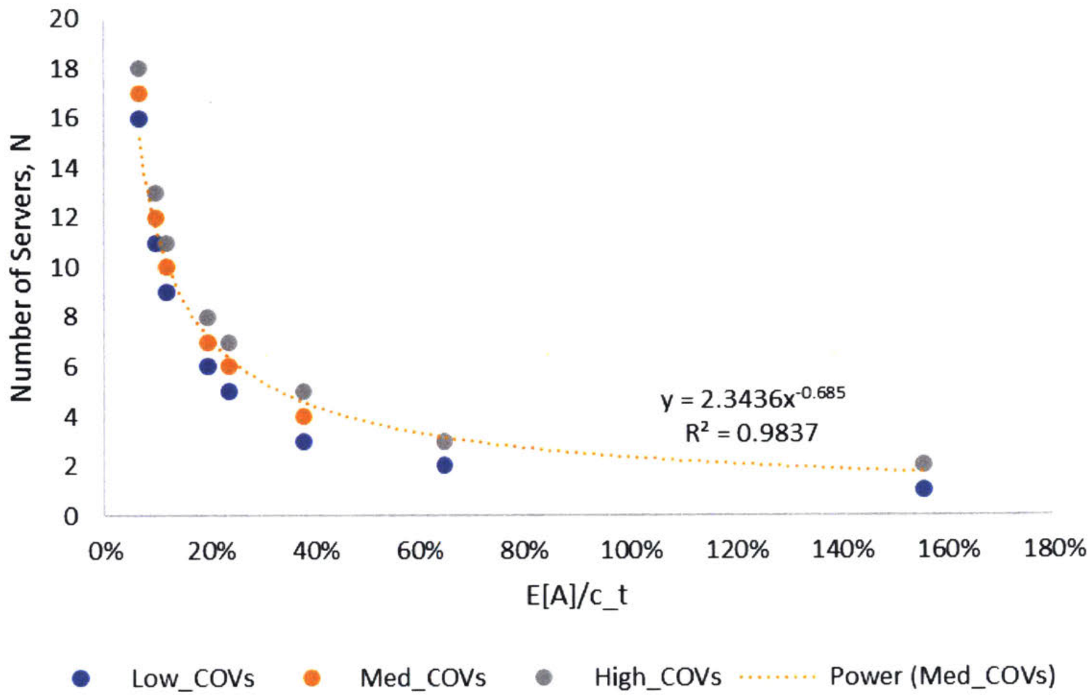


**Figure 2: Number of Servers Required versus E[A]/c_t Ratio**

The number of servers required consistently increases with the level of process variation. Additionally, as the ratio of inter-arrival times to cycle times decreases, the number of servers required increases exponentially. The trend line for medium COV processes indicates a strong correlation of the power-relationship between these variables (R-squared = 98.37%).

Additionally, a substantial correlation is also found between E[A]/c_t and utilization, $\rho$, as shown in Figure 3.

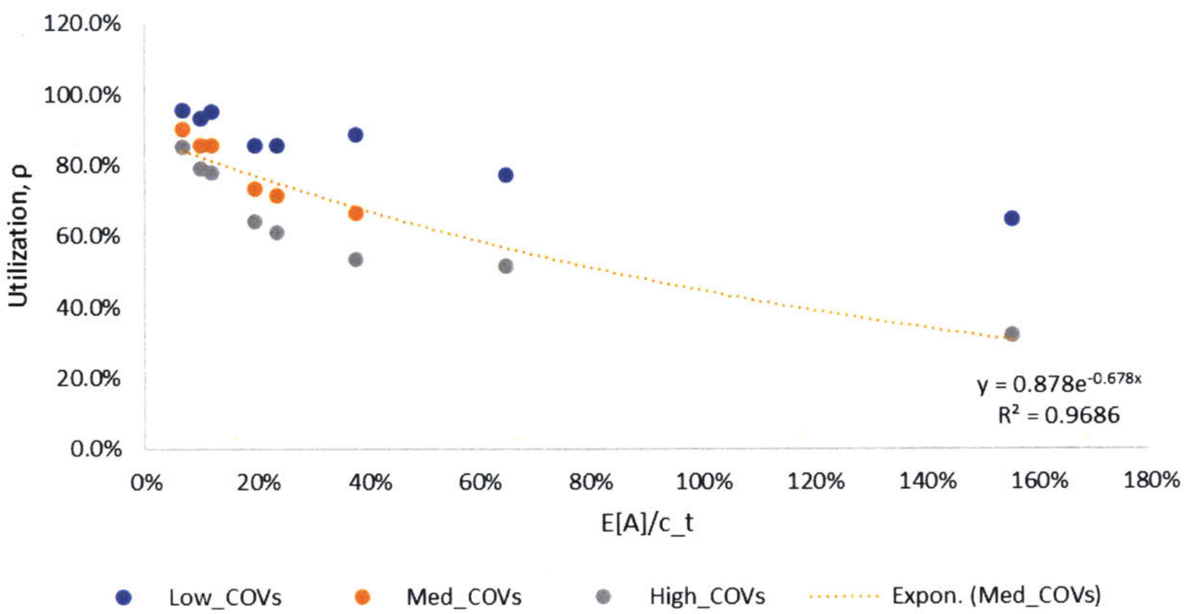


**Figure 3: Process Utilization versus E[A]/c_t Ratio**

For the medium variation processes, the exponential correlation between utilization and E[A]/c_t is strong (R-squared = 96.86%). This suggests that processes with a greater number of servers and lower ratios of inter-arrival time to cycle time can operate at utilization factors closer to 100%. Also note that the amount of utilization expected for each process tends to decrease with increased system variation, likely due to the increased capacity required, *N*.

To validate this data, DES trials were conducted in MATLAB to observe the mean and standard deviations of queue lengths and wait times experienced for each process. Results of DES experimentation revealed that some process inputs were not perfectly replicated by random log-normal distributed variables utilized by DES. Therefore, predicted wait time values were recalculated using the actual arrival rates, service rates, and COVs expressed by random variables used in simulation trials. Figure 4 shows the wait times obtained via DES (plotted on the x-axis) against the predicted wait times from the queuing analysis methodology (on the y-axis).

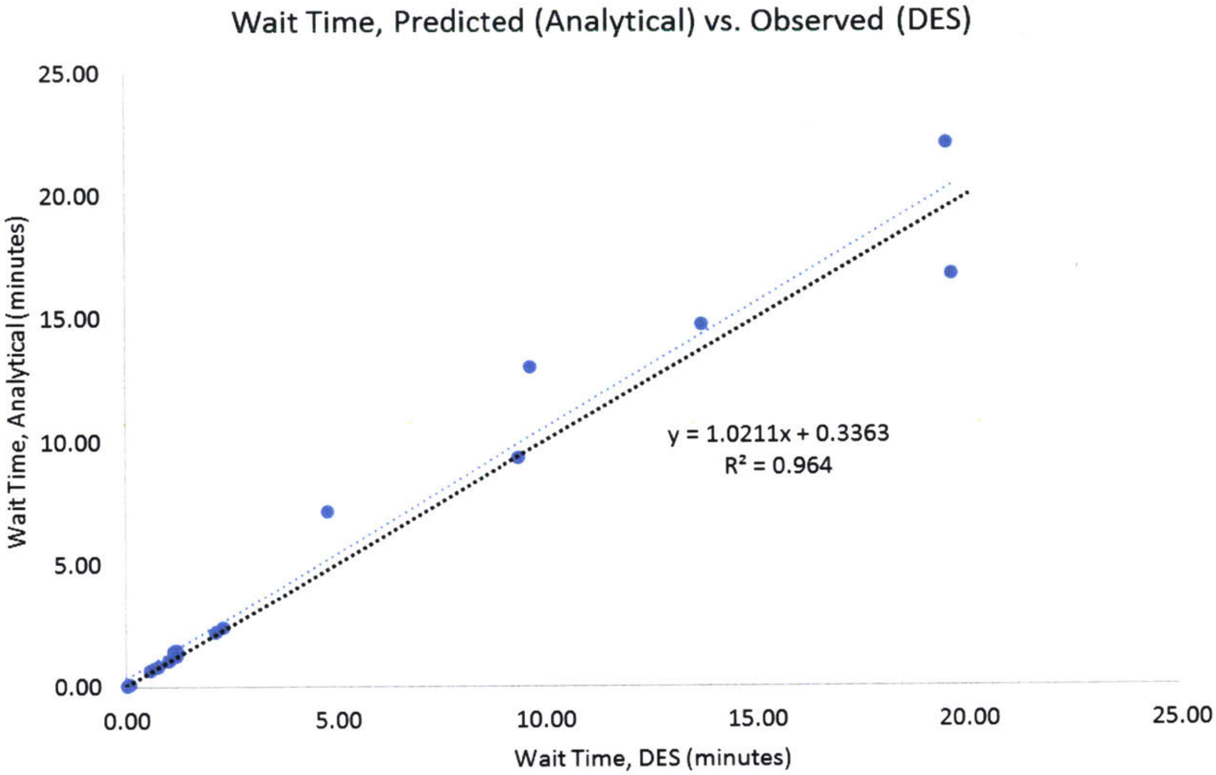


**Figure 4: Predicted Wait Times versus Simulated Values**

The blue trend line shows the linear relationship between the predicted wait times and the wait times observed via simulation. A strong, positive linear correlation is expressed by this trend line (R-squared = 96.4%) which validates the predictive model. However, a slight bias is displayed in this relationship, as the predicted wait times are consistently greater than the simulated values of each process (a perfectly congruent relationship would track with the black trend line). This slight bias is captured by the slope of the blue trend line (1.0211 > 1). Mean average percent error of the predicted values is 14.9%, suggesting strong predictive power of the analytical methodology.

Segmenting by process variability displays the (non-intuitive) result of decreased errors for processes of greater underlying variability, as shown in Figure 5:

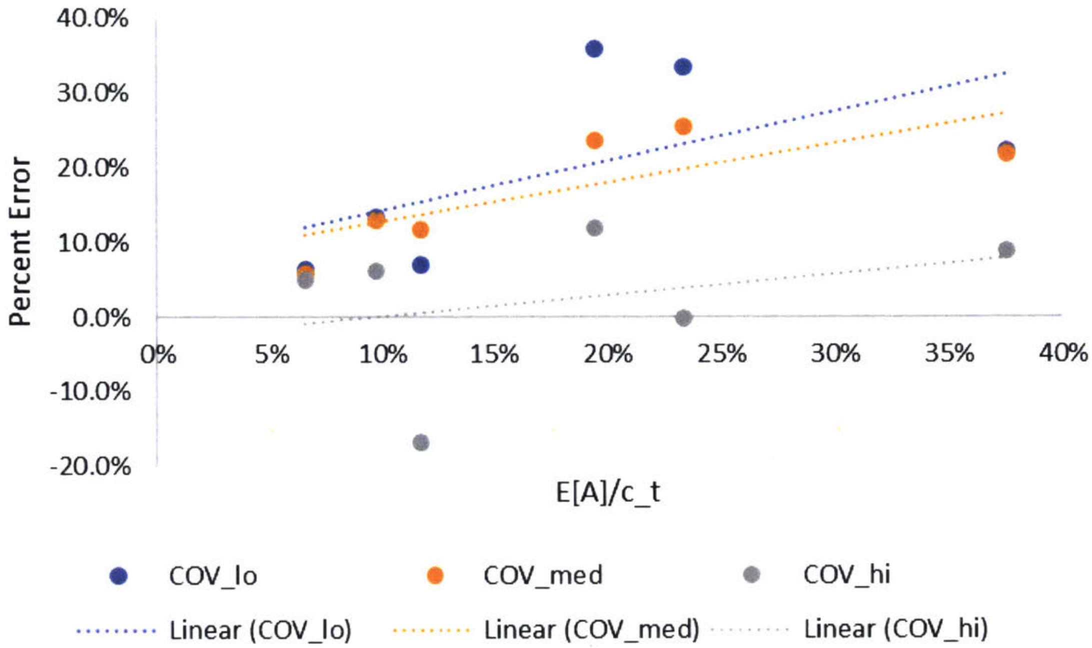


**Figure 5: Percent Error of Predicted Values versus E[A]/c_t Ratio**

Table 11 displays MAPE values for each level of process variation:

**Table 11: MAPE of Predicted Wait Time Values by Level of Process Variation**

| | |
|---|---|
| MAPE (COV_low) | 19.7% |
| MAPE (COV_med) | 16.9% |
| **MAPE (average)** | **14.9%** |
| MAPE (COV_high) | 8.1% |

For most of the simulated processes, the predicted wait time values are greater than values observed by DES. Predicted values for wait time fall outside the 95% confidence interval for 21 out of 24 simulated processes (87.5%). However, for each process, a clear relationship can be seen between predicted and simulated wait times, suggesting some predictive value. Figure 6 shows comparisons of predicted and simulated wait time values for 1.0 Receiving, 3.0 Put-away, and 4.0 Pick, Kit, and Integrate.

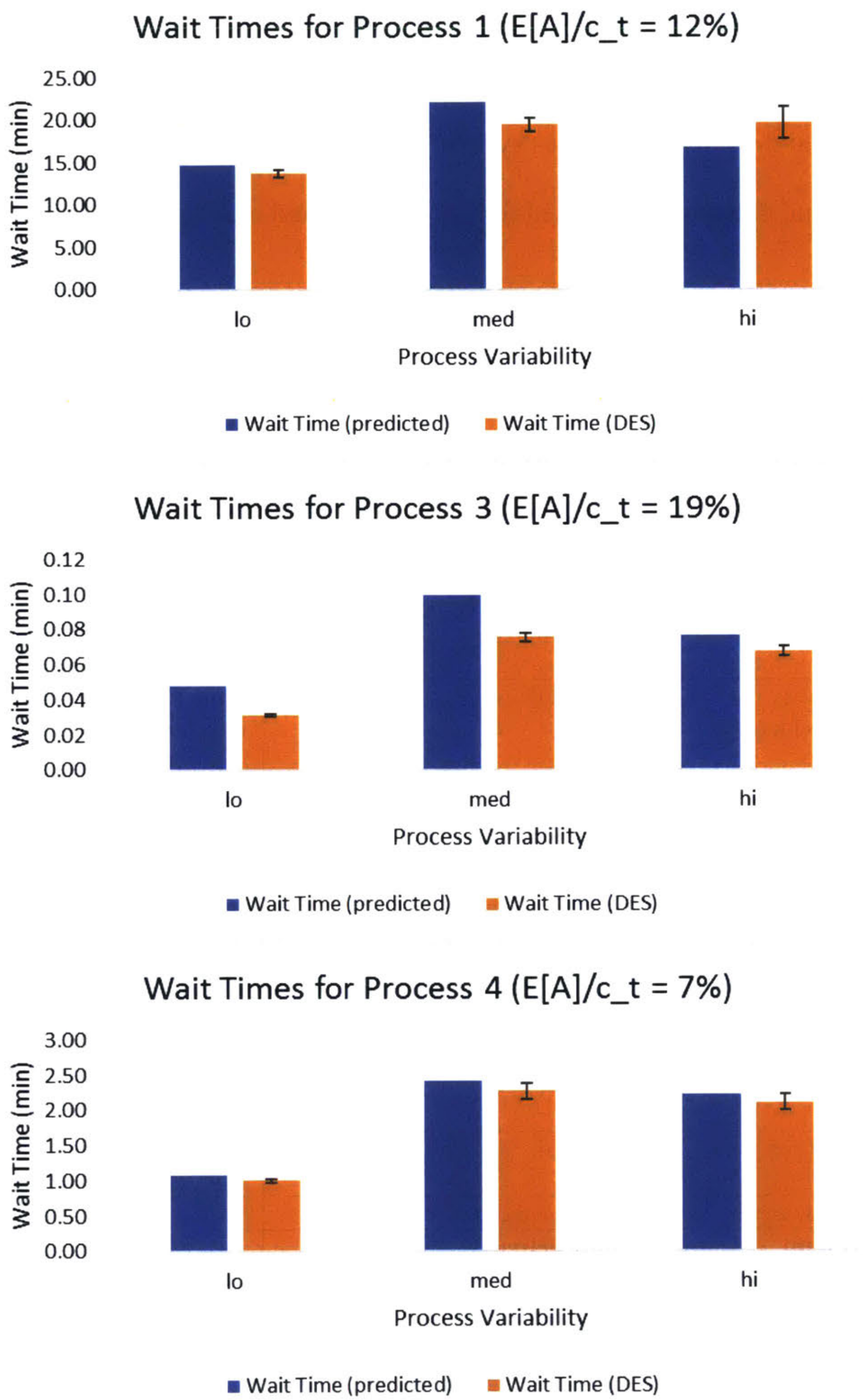


**Figure 6: Predicted and Simulated Wait Times of Processes 1, 3, and 4**

Results for the remaining processes displayed similar agreement between predicted and simulated wait time values.

### 5.3 Capacity Planning: Equipment

The capacity planning analysis for equipment was applied for two different pieces of equipment critical to the internal logistics system: electric tugs (used for conveying kits to and from the factory) and daughter carts (used for easy loading and unloading of kitted parts and material).

#### 5.3.1 Electric Tugs

The "life cycle" of one tug delivery is captured by Table 12 (adapted from Table 5).

**Table 12: Lifecycle of an Electric Tug (per delivery) with Unknown Wait Times**

| **Description** | **Time (min/delivery)** | **VA or NVA** | **Explanation** |
|---|---|---|---|
| Cycle time, tug loading | 5.0 | VA | Time to load tug at warehouse staging area |
| Cycle time, tug convey (from warehouse to factory) | 12.0 | VA | Time for tug to drive from warehouse to each POU delivery location |
| Cycle time, receipt at POU | 5.0 | VA | Total time for tug to deliver i-kits to each POU location |
| Cycle time, tug convey (from factory to warehouse) | 12.0 | VA | Time for tug to drive back to warehouse from factory |
| Cycle time, tug unloading | 10.0 | VA | Time to unload tug at kit return area |
| *Total VA time-in-system* | *44.0 min/delivery* | | |
| Waiting, tug loading | ? | NVA | Wait time for tug to be loaded at warehouse staging area |
| Waiting, tug unloading | ? | NVA | Wait time for tug to be unloaded at kit return area |
| Downtime, average per delivery | 0.4 | NVA | Average tug downtime, assuming 2 hours downtime per day |
| *Total NVA time-in-system* | *? min/delivery* | | |
| **Total time-in-system** | **? min/delivery** | | |

Assumed values for average cycle time and downtime remain constant for this analysis. With that understanding, the undefined variables impacting total time-in-system are wait times associated with tug loading and unloading. For low, medium, and high process variability, wait times predicted for 5.0 Kit Staging (tug loading) and 7.0 Tug Unloading are shown in Table 13:

**Table 13: Results of Capacity Planning Analysis of Processes 5 and 7**

| Process Name | E[A]/c_t | Variable | Low_COVs | Med_COVs | High_COVs |
|---|---|---|---|---|---|
| 5.0 Kit Staging (building 2 only)[9] | 155% | N | 1.0 | 2.0 | 2.0 |
| | | $\rho$ | 64.4% | 32.2% | 32.2% |
| | | L (deliveries) | 0.1 | 0.1 | 0.1 |
| | | **W (min)** | **0.6** | **0.4** | **1.1** |
| 7.0 Tug Unloading | 38% | N | 3.0 | 4.0 | 5.0 |
| | | $\rho$ | 88.8% | 66.6% | 53.3% |
| | | L (deliveries) | 0.4 | 0.5 | 0.4 |
| | | **W (min)** | **1.5** | **1.7** | **1.4** |

The expected time-in-system for electric tugs can now be updated with these expected values of wait time. Table 14 shows updated equipment lifecycles of tugs for each level of process variability.

**Table 14: Lifecycle of an Electric Tug for Different Levels of Process Variability**

| **Description** | **Time, Low_COVs (min/delivery)** | **Time, Med_COVs (min/delivery)** | **Time, High_COVs (min/delivery)** |
|---|---|---|---|
| *Total VA time-in-system* | *44.0 min/delivery* | *44.0 min/delivery* | *44.0 min/delivery* |
| Waiting, tug loading | 0.6 | 0.4 | 1.1 |
| Waiting, tug unloading | 1.5 | 1.7 | 1.4 |
| Downtime, average per delivery | 0.4 | 0.4 | 0.4 |
| *Total NVA time-in-system* | *2.5 min/delivery* | *2.5 min/delivery* | *2.9 min/delivery* |
| **Total time-in-system** | **46.5 min/delivery** | **46.5 min/delivery** | **46.9 min/delivery** |

The resulting sensitivity analyses for each level of variability are shown in Tables 15, 16, and 17.

[9] The expected wait times for the building 2 staging area will be greater than for staging areas for building 1 and building 3 because these areas will be given the same capacity but will experience less average demand. Using the expected wait time for building 2 staging for all staging areas is a conservative assumption but is reasonable for the sake of simplicity.

Table 15: Expected Wait Times of Varying Number of Electric Tugs with Low Process Variability

| Number tugs in service | Utilization | P(no tugs available) | *given tugs avail = 0,* Wait time, 1st delivery in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 12 | 103.0% | N/A | N/A | N/A |
| 13 | 95.1% | 51.7% | 1.8 | 0.9 |
| 14 | 88.3% | 17.4% | 1.7 | 0.3 |
| 15 | 82.4% | 5.5% | 1.5 | 0.1 |
| **16** | **77.2%** | **1.6%** | **1.5** | **0.0** |
| 17 | 72.7% | 0.4% | 1.4 | 0.0 |
| 18 | 68.7% | 0.1% | 1.3 | 0.0 |
| 19 | 65.0% | 0.0% | 1.2 | 0.0 |

Table 16: Expected Wait Times of Varying Number of Electric Tugs with Medium Process Variability

| Number tugs in service | Utilization | P(no tugs available) | *given tugs avail = 0,* Wait time, 1st delivery in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 12 | 103.2% | N/A | N/A | N/A |
| 13 | 95.2% | 53.1% | 1.8 | 0.9 |
| 14 | 88.4% | 17.9% | 1.7 | 0.3 |
| 15 | 82.5% | 5.6% | 1.6 | 0.1 |
| **16** | **77.4%** | **1.7%** | **1.5** | **0.0** |
| 17 | 72.8% | 0.5% | 1.4 | 0.0 |
| 18 | 68.8% | 0.1% | 1.3 | 0.0 |
| 19 | 65.2% | 0.0% | 1.2 | 0.0 |

Table 17: Expected Wait Times of Varying Number of Electric Tugs with High Process Variability

| Number tugs in service | Utilization | P(no tugs available) | *given tugs avail = 0,* Wait time, 1st delivery in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 12 | 104.0% | N/A | N/A | N/A |
| 13 | 96.0% | 59.1% | 1.8 | 1.1 |
| 14 | 89.2% | 20.1% | 1.7 | 0.3 |
| 15 | 83.2% | 6.4% | 1.6 | 0.1 |
| **16** | **78.0%** | **1.9%** | **1.5** | **0.0** |
| 17 | 73.4% | 0.5% | 1.4 | 0.0 |
| 18 | 69.4% | 0.1% | 1.3 | 0.0 |
| 19 | 65.7% | 0.0% | 1.2 | 0.0 |

This analysis suggests that 16 tugs are necessary to support operations of these assumed process parameters. This capacity recommendation is consistent for varying levels of underlying coefficients of variation.

### 5.3.2 Daughter Carts

The "life cycle" of one daughter cart (aka "kit cart") as it moves through various internal logistics processes is captured by Table 18.

**Table 18: Lifecycle of a Daughter Cart (per delivery) with Unknown Wait Times**

| **Description** | **Time (min/delivery)** | **VA or NVA** | **Explanation** |
|---|---|---|---|
| Cycle time, Pick, Kit, and Integrate | 15.0 | VA | Time to build i-kit and load onto kit cart |
| Cycle time, Kit Staging | 5.0 | VA | Time to stage cart in-tow of electric tug |
| Cycle time, Delivery (from warehouse to factory) | 7.5 | VA | Time for tug to deliver one i-kit to one work location |
| Cycle time, receive delivery at work location | 1.3 | VA | Time to unload i-kit at work location |
| Time in-use by production | 120.0 | VA | Time for production operations to complete "job" |
| Cycle time, Delivery return (from factory to warehouse) | 7.5 | VA | Time for tug to deliver one i-kit back to warehouse |
| Cycle time, Tug Unloading | 10.0 | VA | Time to unload tug at warehouse |
| Cycle time, Consumed Kit Processing | 10.0 | VA | Time to process empty kit carts |
| *Total VA time-in-system* | *176.3 min/delivery* | | |
| Time in empty buffer (before Pick, Kit, and Integrate) | 30.0 | NVA | Empty buffer before Pick, Kit, and Integrate provides slack for the system |
| Waiting, Kit Staging | ? | NVA | Wait time for tug to be loaded at warehouse staging area |
| Time in staging buffer | 420.0 | NVA | Kits are prepared up to one to two shifts ahead of when they are needed in the factory |
| Time waiting for "job" at production location | 90.0 | NVA | Time between kit delivery and production beginning "job" |
| Time waiting for pick-up after "job" completion | 30.0 | NVA | Time waiting for return to warehouse |
| Waiting, Tug Unloading | ? | NVA | Wait time for tug to be unloaded at kit return area |
| Waiting, Consumed Kit Processing | ? | NVA | Wait time in queue for processing empty kit carts |
| *Total NVA time-in-system* | *? min/delivery* | | |
| **Total time-in-system** | **? min/delivery** | | |

Compared to the electric tugs, the kit cart life cycle is more greatly impacted by assumed buffer times (in empty buffer and at kit staging area). Relevant wait times impacting the time-in-system for kit carts now include 8.0 Consumed Kit Processing, as shown in Table 19.

**Table 19: Results of Capacity Planning Analysis of Processes 5, 7, and 8**

| Process Name | E[A]/c_t | Variable | Low_COVs | Med_COVs | High_COVs |
|---|---|---|---|---|---|
| 5.0 Kit Staging (building 2 only) | 155% | N | 1.0 | 2.0 | 2.0 |
| | | $\rho$ | 64.4% | 32.2% | 32.2% |
| | | L (deliveries) | 0.1 | 0.1 | 0.1 |
| | | **W (min)** | **0.6** | **0.4** | **1.1** |
| 7.0 Tug Unloading | 38% | N | 3.0 | 4.0 | 5.0 |
| | | $\rho$ | 88.8% | 66.6% | 53.3% |
| | | L (deliveries) | 0.4 | 0.5 | 0.4 |
| | | **W (min)** | **1.5** | **1.7** | **1.4** |
| 8.0 Consumed Kit Processing | 10% | N | 11.0 | 12.0 | 13.0 |
| | | $\rho$ | 93.4% | 85.6% | 79.0% |
| | | L (i-kits) | 0.7 | 1.8 | 2.1 |
| | | **W (min)** | **0.7** | **1.7** | **2.1** |

Expected time-in-system values are updated and shown in Table 20.

**Table 20: Lifecycle of a Daughter Cart for Different Levels of Process Variability**

| **Description** | **Time, Low_COVs (min/delivery)** | **Time, Med_COVs (min/delivery)** | **Time, High_COVs (min/delivery)** |
|---|---|---|---|
| *Total VA time-in-system* | *176.3 min/delivery* | *176.3 min/delivery* | *176.3 min/delivery* |
| Waiting, tug loading | 0.6 | 0.4 | 1.1 |
| Waiting, tug unloading | 1.5 | 1.7 | 1.4 |
| Waiting, consumed kit processing | 0.7 | 1.7 | 2.1 |
| Other NVA time | 570.0 | 570.0 | 570.0 |
| *Total NVA time-in-system* | *572.8 min/delivery* | *573.8 min/delivery* | *574.6 min/delivery* |
| **Total time-in-system[10]** | **749.1 min/delivery** | **750.1 min/delivery** | **750.9 min/delivery** |

Sensitivity analyses of each level of variability are shown in Tables 21, 22, and 23.

[10] On average, 61.2 kit carts will be delivered per hour. 61.2 deliveries/hr x 749.1 min/delivery x (1/60) = 763.9 kit carts. Rounding down to the nearest integer value (763) will provide the starting point for the sensitivity analysis for the low COV scenario.

Table 21: Expected Wait Times of Varying Number of Daughter Carts with Low Process Variability

| Number i-kit carts in service | Utilization | P(no carts available)* | *given carts avail = 0* Wait time, 1st i-kit in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 763 | 100.1% | N/A | 0.5 | N/A |
| 764 | 100.0% | 87.0% | 0.5 | 0.4 |
| 765 | 99.9% | 32.0% | 0.5 | 0.2 |
| 766 | 99.7% | 11.7% | 0.5 | 0.1 |
| 767 | 99.6% | 4.3% | 0.5 | 0.0 |
| 768 | 99.5% | 1.6% | 0.5 | 0.0 |
| 769 | 99.3% | 0.6% | 0.5 | 0.0 |
| 770 | 99.2% | 0.2% | 0.5 | 0.0 |

Table 22: Expected Wait Times of Varying Number of Daughter Carts with Medium Process Variability

| Number i-kit carts in service | Utilization | P(no carts available)* | *given carts avail = 0* Wait time, 1st i-kit in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 765 | 100.0% | N/A | 0.5 | N/A |
| 766 | 99.9% | 38.2% | 0.5 | 0.2 |
| 767 | 99.7% | 14.0% | 0.5 | 0.1 |
| 768 | 99.6% | 5.1% | 0.5 | 0.0 |
| 769 | 99.5% | 1.9% | 0.5 | 0.0 |
| 770 | 99.4% | 0.7% | 0.5 | 0.0 |
| 771 | 99.2% | 0.3% | 0.5 | 0.0 |
| 772 | 99.1% | 0.1% | 0.5 | 0.0 |

Table 23: Expected Wait Times of Varying Number of Daughter Carts with High Process Variability

| Number i-kit carts in service | Utilization | P(no carts available)* | *given carts avail = 0* Wait time, 1st i-kit in queue (min) | E[wait time] (min) |
|---|---|---|---|---|
| 765 | 100.1% | N/A | 0.5 | N/A |
| 766 | 100.0% | 81.9% | 0.5 | 0.4 |
| 767 | 99.8% | 30.1% | 0.5 | 0.1 |
| 768 | 99.7% | 11.0% | 0.5 | 0.1 |
| 769 | 99.6% | 4.1% | 0.5 | 0.0 |
| 770 | 99.5% | 1.5% | 0.5 | 0.0 |
| 771 | 99.3% | 0.5% | 0.5 | 0.0 |
| 772 | 99.2% | 0.2% | 0.5 | 0.0 |

This analysis suggests that 767 carts will be required at low levels of variability and 769 carts will be required for medium and high levels of variability (the operations manager would most likely choose to buy 770, or even 800, to appease the cart supplier with a round number order size).

## 5.4 Fulfillment Delivery Capability

Fulfillment delivery capability refers to the expected time to process a kit request, stage the kit onto a tug, and deliver the kit from the warehouse to production. This time is especially relevant to the performance of the system in processing emergent kit requests. The expected fulfillment delivery capability was calculated for e-kit requests processed on a FIFO basis and a priority basis. This calculation was done for each scenario of expected underlying variability (low, medium, and high).

### 5.4.1 FIFO

Table 24 shows expected times from kit request to kit delivery for each level of process variability.

**Table 24: Expected Fulfillment Capabilities when Managing Emergent Requests by FIFO**

| | Low COVs | | Medium COVs | | High COVs | |
|---|---|---|---|---|---|---|
| **Time in Process (minutes)** | **Standard i-kits** | **e-kits** | **Standard i-kits** | **e-kits** | **Standard i-kits** | **e-kits** |
| Wait Time, 4.0 P, K, I | 1.07 | 1.07 | 2.92 | 2.92 | 3.74 | 3.74 |
| Cycle Time, 4.0 P, K, I | 15.00 | 15.00 | 15.00 | 15.00 | 15.00 | 15.00 |
| Wait Time, 5.0 Kit Staging | 0.56 | 0.56 | 0.40 | 0.40 | 1.11 | 1.11 |
| Cycle Time, 5.0 Kit Staging | 5.00 | 5.00 | 5.00 | 5.00 | 5.00 | 5.00 |
| Cycle Time, 6.0 Delivery | 7.78 | 3.11 | 7.78 | 3.11 | 7.78 | 3.11 |
| **E[time from "request" to receive]** | **29.42** | **24.75** | **31.10** | **26.44** | **32.63** | **27.97** |

Managing emergent requests according to FIFO means that e-kits are processed through pick, kit, and integrate and kit staging at the same rate as standard i-kits. The only difference in fulfillment time is due to the time to deliver a kit from the warehouse to production (e-kits will not be delivered in batches while standard i-kits will be delivered in batches of four). This means that the average emergent kit request can be fulfilled 4.7 minutes faster than the average standard i-kit, as shown in Figure 7.

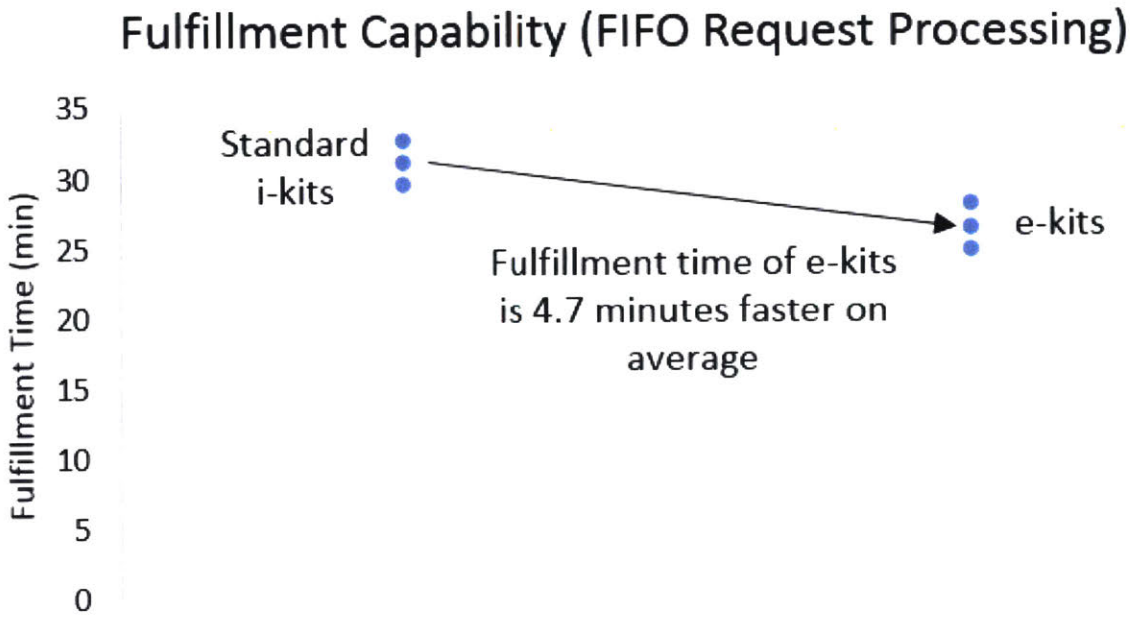


**Figure 7: Fulfillment Capabilities when Managing Emergent Requests by FIFO**

### 5.4.2 Emergent Request Prioritization

Table 25 shows expected times from kit request to kit delivery for each level of process variability when emergent requests are prioritized over standard i-kits.

**Table 25: Expected Fulfillment Capabilities when Prioritizing Emergent Requests**

| | Low COVs | | Medium COVs | | High COVs | |
|---|---|---|---|---|---|---|
| **Time in Process (minutes)** | **Standard i-kits** | **e-kits** | **Standard i-kits** | **e-kits** | **Standard i-kits** | **e-kits** |
| Wait Time, 4.0 P, K, I | 1.09 | 0.23 | 2.97 | 0.07 | 3.80 | 0.02 |
| Cycle Time, 4.0 P, K, I | 15.00 | 15.00 | 15.00 | 15.00 | 15.00 | 15.00 |
| Wait Time, 5.0 Kit Staging | 0.56 | 0.56 | 0.42 | 0.13 | 1.17 | 0.13 |
| Cycle Time, 5.0 Kit Staging | 5.00 | 5.00 | 5.00 | 5.00 | 5.00 | 5.00 |
| Cycle Time, 6.0 Delivery | 7.78 | 3.11 | 7.78 | 3.11 | 7.78 | 3.11 |
| **E[time from "request" to receive]** | **29.43** | **23.90** | **31.16** | **23.31** | **32.75** | **23.26** |

Prioritizing emergent requests eliminates a significant amount of the wait time experienced by e-kits during 4.0 Pick, Kit, and Integrate and 5.0 Kit Staging. This change in policy adds negligible additional fulfillment time to standard i-kit requests, as shown in Figure 8.

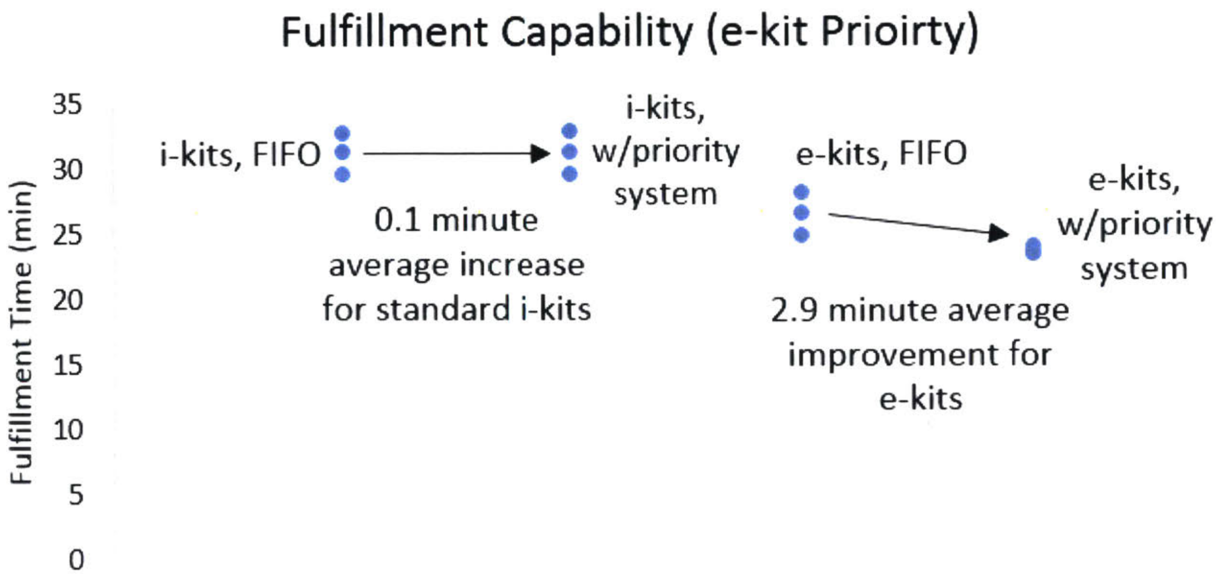


**Figure 8: Fulfillment Capabilities when Prioritizing Emergent Requests**

## 5.5 Assessing Impact of Poor Quality

Quality in this system is gauged by the rate of perfect deliveries (*OTIF%*) and production operations quality (*PQ%*). As stated in chapter four, the quality levels were assumed to be relatively good (*OTIF%* = 99.5%, *PQ%* = 99%). To assess the impact of poor quality on this system, a baseline performance measure is needed for comparison at varying levels of quality. One way to do this is to estimate the recurring cost as it relates to the number of servers required, *N*. Recurring cost factors should be unique to each process and exclusive of costs not associated with internal logistics operations (such as production operations or raw material purchasing costs). Nominal recurring cost factors are shown in Table 26.

**Table 26: Nominal Recurring Cost Factors per Number of Servers for Each Process**

| Process Name | Recurring Cost Factor (per N) |
|---|---|
| 1.0 Receiving | 2 |
| 2.0 Quality Check | 1 |
| 3.0 Put-away | 1 |
| 4.0 Pick, Kit, and Integrate | 1 |
| 5.0 Kit Staging | 3 |
| 6.0 Delivery[11] | 1 |
| 7.0 Tug Unloading | 1 |
| 8.0 Consumed Kit Processing | 1 |
| 9.0 Shipping | 2 |

This assumption allows the system designer to create a recurring cost index to compare the performance of the system across differing levels of variation. Table 26 shows the relative expected recurring costs of each process after applying nominal cost factors to required capacity levels.

**Table 27: Recurring Cost Index of Each Level of Process Variability**

| Process Name | Low_COVs | Med_COVs | High_COVs |
|---|---|---|---|
| 1.0 Receiving | 18 | 20 | 22 |
| 2.0 Quality Check | 2 | 3 | 3 |
| 3.0 Put-away | 6 | 7 | 8 |
| 4.0 Pick, Kit, and Integrate | 16 | 17 | 18 |
| 5.0 Kit Staging | 3 | 6 | 6 |
| 6.0 Delivery | 16 | 16 | 16 |
| 7.0 Tug Unloading | 3 | 4 | 5 |
| 8.0 Consumed Kit Processing | 11 | 12 | 13 |
| 9.0 Shipping | 10 | 12 | 14 |
| **Total Recurring Cost Index** | **85** | **97** | **105** |
| **Normalized** | **100%** | **114%** | **124%** |

[11] Cost factor for 6.0 Delivery is based on number of electric tugs.

The impact of poor quality was assessed according to this recurring cost index. The capacity required was recalculated for $OTIF\% = PQ\%$ at 95% and 90%. Then recurring cost factors were applied to the calculated capacities to produce Figure 9.

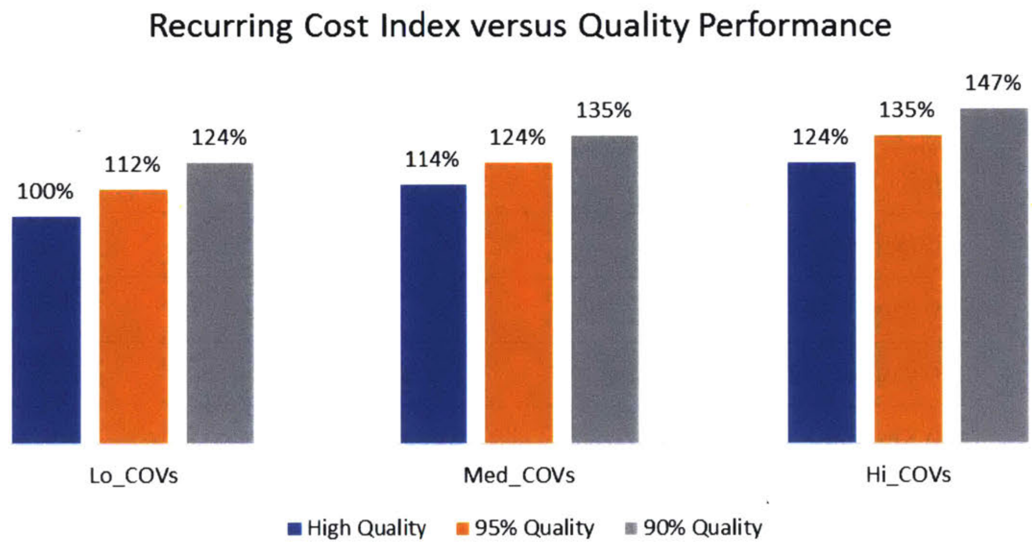


**Figure 9: Recurring Cost Index of System at Baseline, 95%, and 90% Quality Levels**

Using the assumed recurring cost factors, this analysis suggests that a ~4% decrease in quality corresponds to a 9-12% increase in recurring costs while a ~9% decrease in quality results in a 21-24% increase in recurring costs.

# 6 Discussion of Findings

This chapter will discuss the results of the data analysis to synthesize several key points of consideration. The sections of discussion in this chapter include comments on the impacts of process variability, the value of DES as a validation technique, the impact of design parameters ($k$ and $\rho^n\_max$), approaches for managing emergent requests, system quality, and the explanatory power of underlying assumptions.

## 6.1 Impact of Process Variation on Capacity Requirements

Consistent throughout this analysis was the use of three distinct levels of process variation: low, medium, and high. For each "level," this analysis made the simplifying assumption that the coefficient of variation of inter-arrival rates was equal to the coefficient of variation of service rates. Low, medium, and high levels of variation meant COV values equal to 25%, 75%, and 125%, respectively. For the internal logistics processes under consideration, average actual COV values are unknown and almost certainly different for each unique process.

The G/G/N queuing model that was used demonstrates a strong positive relationship between process COV values and the expected queue size. Figure 10 displays this relationship for varying levels of utilization of a hypothetical system with $N = 10$ servers:

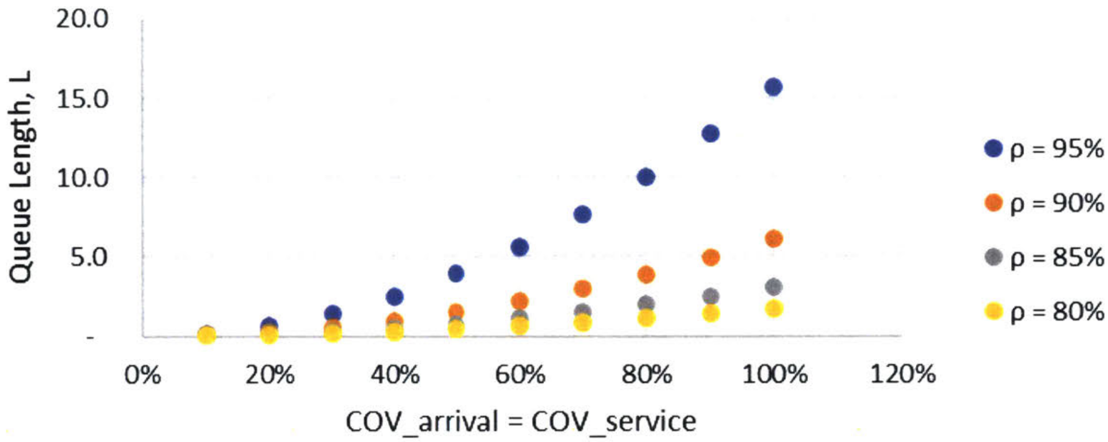


**Figure 10: Predicted Queue Lengths from G/G/N Model versus Process Coefficient of Variation**

The design rule used for selecting *N* in this analysis is centered around the tradeoff displayed by this graph: utilization should be maximized (in order to increase process efficiency) while avoiding unnecessarily long queues and wait times (in order to manage WIP inventory levels). As process variation increases, queues grow at a parabolic rate and, eventually, additional capacity is required.

While COV values of 25% were deemed as "low" for this analysis, COV values could be closer to zero in the presence of strict adherence to schedules, automated processes, and minimal variability. Conversely, the "high" COV values of 125% may have been *too* extreme for this analysis. In the absence of known average variances, it was reasonable to make a "conservative" assumption for these values. It is unlikely that processes in the internal logistics system, especially process service rates, would exhibit the level of distribution displayed by the histogram for COV of 125% shown in Figure 11 (where nearly 20% of values are less than a third of the mean and 30% of values are greater than double the mean).

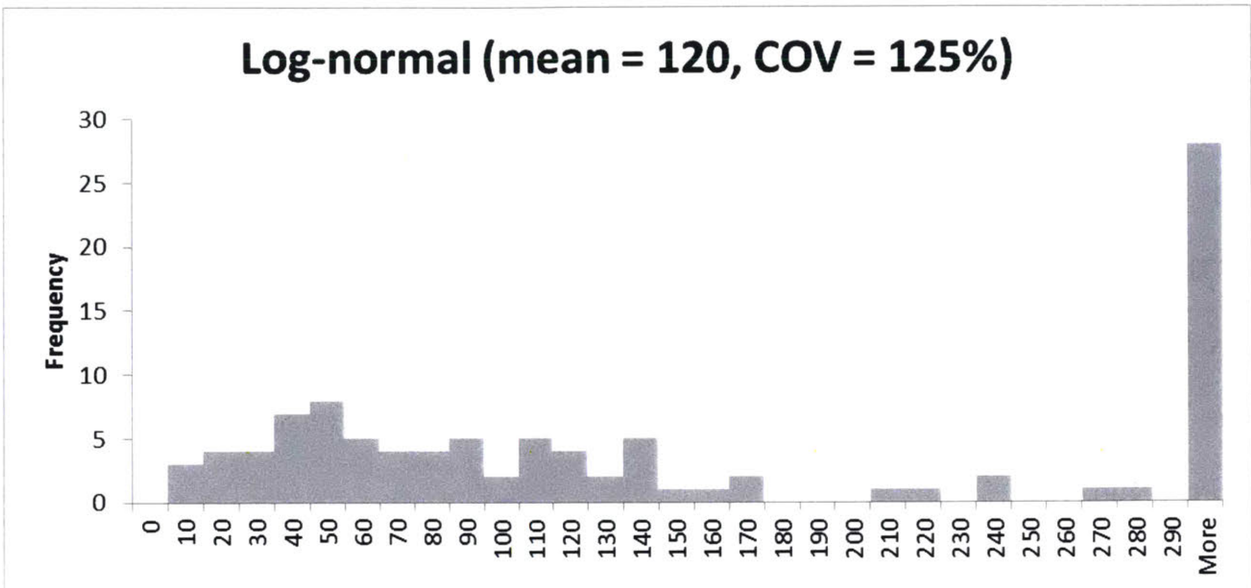

**Figure 11: Histogram of Log-normal Randomly Distributed Values of Mean = 120 and COV = 125%**

After re-evaluating the selections that were made for modeling system variability, it's reasonable to view the "high" COVs as the extreme worst case scenario.

What this analysis reinforces then, is that successful efforts to reduce process variability will result in reduced capacity requirements. While there are many different methods to reduce process variability, one particular method relevant to this analysis is scheduling. Adherence to a regular schedule for i-kit preparation, staging, and delivery (processes 4-6) will essentially eliminate the variability of kit requests for standard i-kits (~95% of all expected deliveries). Therefore the entirety of the variability of inter-arrival times would be explained by the frequency of emergent kit requests. This is just one example, but it helps to emphasize the value of properly understanding and limiting system variability.

## 6.2 DES Validation of Predictive Model

Validating the predictive model with DES trials provided an understanding of the usefulness and limitations of the methodology that was developed. DES trials provided a means for evaluating the predictive power of the analytical approach. It also helped our designer to understand the bounds and distributions of expected queue lengths and wait times, which will be useful for planning the layout of facilities supporting these processes.

### 6.2.1 Predictive Power of Analytical Model

The predicted wait time values are quite consistent with wait time values obtained from DES trials. Before removing particularly poor predictions from the data set, the MAPE of predicted values is 19.4%. Figure 12 shows the MAPE of each process (1, 2… 9) versus the process E[A]/c_t ratio.

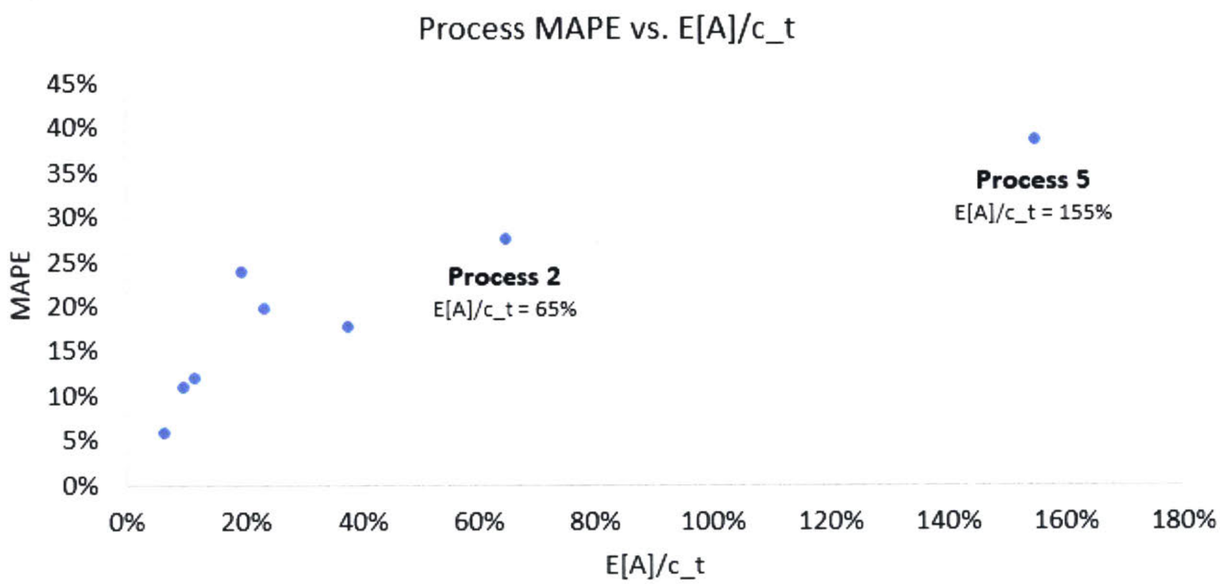


**Figure 12: MAPE of Predicted Wait Times versus E[A]/c_t Ratio of Each Process**

Figure 12 shows a strong relationship between the mean absolute value of percent errors and the E[A]/c_t ratio of the process under consideration. This suggests that the predictive model has stronger predictive power for processes of lower ratios of E[A]/c_t. Removing processes 2 and 5 from the data set improves overall MAPE from 19.4% to 14.9% (as shown in Figure 4).

This is a useful reminder that the underlying theory of the predictive model is based on the G/G/N queuing model. Figure 5, from the previous chapter, shows a demonstrable bias in the G/G/N model towards overestimating queue lengths (reflected by average predicted wait time values greater than values observed by simulation). Of the 24 DES trials that were run (for eight processes at three different levels of variation), only three trials observed a wait time greater than the value predicted by the G/G/N model. Including all 24 trials, predicted wait times were, on average, 16.3% greater than observed wait time values.

However, for the purposes of capacity planning, this level of conservative bias in the predictive model should still prove useful for understanding the expected wait times that will be experienced in the proposed system design.

### 6.2.2 Distribution of Queue Sizes

One underlying assumption supporting both the G/G/N model and the DES trials was the allowance of infinite queue lengths. Unbounded queues will not be feasible for Ashley, the process designer. The predictive model does not provide Ashley with any information about the maximum length of the queue she can expect or the distribution of the number of requests (or other units) in the queue.

This is another area where the DES trials provide value. For each process simulation that was executed, the mean and standard deviation of each run were captured. For example, for process 4.0 (Pick, Kit, and Integrate) and COV = 75%, the mean queue length was 2.7 requests (± 0.10 requests) across all 100 simulated trials while the average standard deviation of queue lengths was 3.7 requests (± 0.12 requests). For Ashley, she will have to determine what the maximum allowable queue length to be allowed for each process in her system. A good starting point may be the mean queue length plus one standard deviation, but this is certainly an area that merits further investigation.

## 6.3 Impact of Design Parameters (k and $\rho^n$_max)

An important component of the capacity planning analysis that has not been discussed in detail so far was the decision to select a capacity level, *N*, based on some design parameter threshold. For selecting the number of process servers, the minimum value of the ratio of *VA/NVA* was set to $k = 3$. For selecting the amount of equipment capacity needed, the maximum value of $\rho^n$ was set to $\rho^n\_max = 5\%$ (where $\rho^n$ is equal to the probability of no equipment available at any given time). Certainly, the selection of these values had a significant impact on the amount of capacity that was selected for each process.

Sensitivity analysis of these values was not included in the scope of this thesis, but there are some clear trends that can be understood in light of these parameters. Increasing the value of $k$ (or decreasing the value of $\rho^n\_max$) would have the following effects:

- <u>Increased capacity required, *N*.</u> If the minimum allowable value of *VA/NVA* ratio was increased, then additional capacity would be required to further reduce the expected wait times of requests arriving to the process area. This would lead to increased expected upfront and recurring costs of the system.
- <u>Decreased utilization, ρ.</u> If additional capacity is added, then the expected process utilization would decrease. Process utilization is a good measure of the efficiency of the system, so increasing the value of $k$ would lead to decreased process efficiency (and likely increased unit cost of production).
- <u>Decreased wait time, *W*.</u> Expected wait times would decrease due to the greater level of service capacity available. This would decrease the time-in-system of parts and inventory, leading to improved return on assets (another measurement of production efficiency).

Likewise, decreasing the value of $k$ (or increasing the value of $\rho''\_max$) would have the inverse effect of the results listed above. These system parameters could be more finely tuned by a number of methods. Observation of processes generally agreed to be "high performing" would yield clarity into the levels of $k$ or $\rho''\_max$ that are inherently accepted within current operations. Additionally, cost modeling could be applied to understand the expected impact, in terms of $\Delta\$/\Delta N$, $\Delta\$/\Delta\rho$, and $\Delta\$/\Delta W$, corresponding with changes in these design parameters. No matter the approach selected, significant further investigation is needed to produce a more robust understanding of the correct parameter values for this application.

## 6.4 Emergent Request Fulfillment Capability

The results of the fulfillment delivery capability analysis indicate that emergent kit requests should be prioritized over scheduled standard kit preparation. The analysis from chapter five indicated that prioritizing emergent requests represented an average of 2.9 minutes faster delivery time compared to managing requests according to FIFO (an 11% improvement). Because of the nature of emergent kit requests, this is a reasonable conclusion to draw. Emergent requests will only be made when a production operator is missing the parts or tools they need to complete their planned job. Missing parts and tools leads to downtime on the floor and waste in the production system. The faster that emergent requests can be processed, the greater degree to which this waste can be minimized in the production process.

During the ramp-up of production, processes will operate at less than 100% expected steady state rate of operation. Therefore, if the logistics system is operating according to the capacity levels recommended by this analysis (which assumed 100% of steady state production rate) then the system will have excess capacity during the early stages of production. However, early stages of production may also experience decreased levels of quality which would require additional capacity for processing emergent kit requests. Therefore, operations managers may consider dedicating certain servers in processes 4-6 (4.0 Pick, Kit, and Delivery, 5.0 Kit Staging, and 6.0 Delivery) to managing emergent requests during early stages of production.

## 6.5 System Quality

As previously discussed, poor quality, whether in production or in the internal logistics processes, increases the demand placed on the internal logistics system. A principle underlying truth of this analysis is that greater demand leads to greater capacity required. There are methods for increasing capacity after production start – through overtime, outsourcing, facility expansion, etc. – but these methods require additional costs that BCA would prefer to avoid. Data from the previous chapter indicates that the cost of capacity required can be reduced significantly by maximizing quality performance and minimizing process variability.

A culture committed to continuous improvement will be required to obtain these objectives. Emergent kit requests – which are naturally the result of quality defects – should trigger a root cause investigation that uncovers the source of each defect. Operations managers must facilitate a culture that will apply corrective actions to these root causes and measure the effect on the system. Unsuccessful corrective actions should be reevaluated while successful corrective actions should become standard operating procedures and communicated throughout the organization.

## 6.6 Reevaluating Process Assumptions

As shown by the capacity planning analysis for equipment requirements, process variability had fairly minimal impact on the final recommendation. Across the three levels of variation, 16 tugs and 767-769 kit carts were recommended. This was partly due to the fact that increased process variability was addressed by increased server capacity for each scenario, which controlled the wait times experienced by tugs and kit carts. However, this also suggests that other more powerful determining factors must have been held constant for this analysis. Indeed, the majority of process parameters, introduced in Table 1 in chapter four, were assumed as constant descriptors of the internal logistics system (with the notable exception of the quality parameters that were tested for sensitivity in chapter five).

Therefore, this thesis presented recommendations of capacity requirements that were based on underlying assumptions with significant explanatory power that was only partially tested for sensitivity. The benefit of this analysis, then, is not a strong recommendation for the number of truck bays that should be built or the number of electric tugs to purchase, but rather a consistent methodology to obtaining the answers to these questions along with an understanding of the impact that certain key variables may have on recommended values.

This gets to the purpose of the model that was developed alongside Ashley and her team of process designers. **Process designers responsible for capacity planning were in need of a relatively user-friendly method for understanding the relationship and the importance of assumed parameters.** The predictive model, built in Microsoft Excel, can be easily interpreted to understand the impact of these assumptions on capacity recommendations. Underlying assumptions may (and should) be refined over time to provide a more accurate final capacity recommendation. The *usefulness* to Ashely and her team was just as important as the *accuracy* of the model, which is why a MAPE of 14.9% is reasonable in terms of predicted wait times. This predictive model is significantly more sensitive to assumptions around production rates, inter-arrival times, and cycle times, then the predicted wait times determined by G/G/N and Little's Law.

# 7 Conclusions

This chapter will present a final summary of findings and recommendations of this thesis as well as a brief proposal of additional areas of research.

## 7.1 Summary and Recommendations

The predictive model proposed by this research combined the principles of G/G/N queuing theory and Little's Law in order to approximate expected wait times of various processes under consideration. Values of predicted wait times were validated by observed outputs of DES and Monte Carlo analysis. Predicted values demonstrated a reasonably acceptable level of accuracy compared to DES observations (MAPE = 14.9% for processes of $E[A]/c\_t < 50\%$).

Capacity requirements were determined by relating the utilization, expected wait times, and expected equipment availability to specified design parameters: $k$ and $\rho''\_max$. The sensitivity of capacity recommendations was not tested for these parameters, but their directional effect can be easily predicted. Various options are available to refine these parameters for the specific processes under consideration.

Additionally, the process model constructed relies on dozens of static parameters with significant explanatory power. The model delivered as a result of this research can be easily updated to assess the impact that these parameters have on capacity requirements. It can be reasonably concluded that parameters of significant impact are process cycle times (mean and COV), inter-arrival times (mean and COV), quality parameters, and production parameters (e.g. rate, shift structure, and number of POU locations). At this point, the most effective way to improve the predictive value of the model is to continue refining the certainty of parameter inputs.

During periods of increasing production (when production rate is less than 100% of steady state) the internal logistics system should operate with additional capacity. This additional capacity will help to mitigate the increased demand due to expected process variability and quality levels. An organizational commitment to continuous improvement during this phase will have a profound impact on the long-term capability of the system to operate to the high level of quality expected.

With these quality expectations in mind, special consideration should be given to the treatment of emergent requests. The fulfillment capability of the internal logistics system will be a critical determining measure of its success. Emergent requests should be prioritized over regularly scheduled kit preparation and deliveries, as verified by the data analysis of this research. Management can make several other decisions that will further improve the internal logistics fulfillment capability level. All emergent kit requests should undergo a consistent root cause analysis and corrective action process in order to decrease the demand on logistics processes and improve quality throughout the production system. Process designers may also pay special attention to reducing the cycle times of processes directly related to emergent request fulfillment (4.0 Pick, Kit, and Integrate, 5.0 Kit Staging, and 6.0 Delivery). Additionally, internal logistics managers may consider maintaining extra capacity (perhaps in the form of increased *k-values*) for these specific processes, especially during earlier stages of operation.

## 7.2 Opportunities for Further Study

Three principle research opportunities were identified: (1) further refinement of process inputs, especially cycle times; (2) further refinement of design parameters ($k$ and $\rho^{n}\_max$); and (3) investigation of process variability.

### 7.2.1 Refining Process Model Inputs

The mean and standard deviations of cycle times that were used as inputs for the predictive model were mostly based on estimates made by knowledgeable people familiar with these processes. That does not ensure accuracy, but rather, provides system designers with a reasonable starting point. The predictive model developed from this research requires accurate input parameters to produce accurate outputs. Estimated values of process cycle time means and standard deviations could be improved by thoroughly studying processes in operation similar to the processes under consideration. For processes different from current operations at Boeing, looking outside the organization may be a feasible option, as well.

### 7.2.2 Refining Design Parameters (k and $\rho^n$_max)

As discussed in chapter six, there is additional room for understanding the impact that these design parameters have on recommended capacity levels. For example, it is reasonable to suspect that the "best" value of $k$ (or $\rho^n\_max$) may not be the same for every process under consideration. There are a variety of methods that could be pursued to refine these design values. Process engineers could elect to observe well-performing processes already in operation to assess acceptable levels of *VA/NVA* (more precisely, cycle time/wait time) or $\rho^n$. Cost modeling of capacity ($N$), utilization ($\rho$), and wait time ($W$) would also prove useful for setting up an optimization problem for each design parameter. Additionally, simulation techniques, such as DES, could be used to further deepen this understanding.

### 7.2.3 Investigating Process Variability

The levels of variability considered by this thesis were generally limited to three different COV values (25%, 75%, and 125%). It is reasonable for process engineers and operations managers to pursue COVs for inter-arrival times and cycle times that are as small as possible.

While the sources of variability in these complex processes are seemingly endless, so too are the variety of options available to process managers. For example, the variability of inter-arrival times can be reduced significantly by adhering to strict schedules and delivery windows. Cycle time variability could be improved by any number of means including value steam mapping, movement studies, improvements to tooling and process equipment, automation, material presentation, "5S" and layout changes, and standardized work. All of the internal logistics processes within the scope of this thesis could stand to benefit from a careful analysis of the sources of variability and a study of corrective treatments.

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