University of Alberta

On the Performance of a Manufacturing Process with Employee Learning and Turnover

by

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Dedicated to

Sunday,

Abstract

In order for a manufacturing company to sustain profits and a competitive position it must achieve high utilization of its production resources. This is not trivial due to the stochastic nature of these systems. Discrete-event simulation (DES) is a method of mimicking the behavior of a real system and has the ability to model complex systems and phenomena. In this study a DES model of a real production system was developed. The model provides an accurate representation of the real system and insight into the underlying behavior of the system. The production line of interest assembles medical garments for the health care industry. Data from the real system was used to accurately characterize: random assembly cycle times, random times until machine failures, random times until machine repairs, improvements that result from worker experience (i.e. learning) and random durations of worker employment. Numerical experiments were conducted to examine the impact of important factors on the production line, and to suggest system design improvements. If the changes recommended in this study are implemented a 13.5% increase in throughput rate of the production line may be realized. The results of this study contribute to the understanding of production systems and guide production managers in the designs of these systems.

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CHAPTER 1

Introduction

Manufacturing is an important source of wealth, employment and innovation [104]. An important factor in the economic success of a country is the success of its manufacturing sector. One way a manufacturing company can achieve a competitive advantage is the efficient utilization of resources (e.g. humans, materials, machines, space). This can be achieved by optimizing production line design factors such as work assignment, material flow, temporary storage of work-in-process, etcetera. However, the optimal design of production systems is not an easy task to accomplish. One reason is the complex interactions that occur within a production system. Ignizio [62] defines a production system as “a nonlinear, dynamic, stochastic system with feedback.” This definition illustrates the complexity of production systems. As a result the analysis of production systems is not trivial. However, most production managers rely on basic methods, rules of thumb and intuition as decision tools. These methods almost always fail to provide a good understanding of the system in question and make the design of efficient production systems difficult. This work presents more advanced methods that can be used to design and predict the behavior of production systems and the results of a discrete event simulation to further the understanding of these systems.

1.1 Background

Although exact, analytical and approximate numerical methods have been developed to model some production systems (see chapter 2), these methods are currently limited to simple systems or depend on approximations and assumptions. For many real systems the only method of accurately modeling these complex systems is to use discrete-event simulation (DES). DES is a method of mimicking the dynamic, stochastic nature of a real system. A flow-chart illustrating this method is given in Figure 1.1 below.

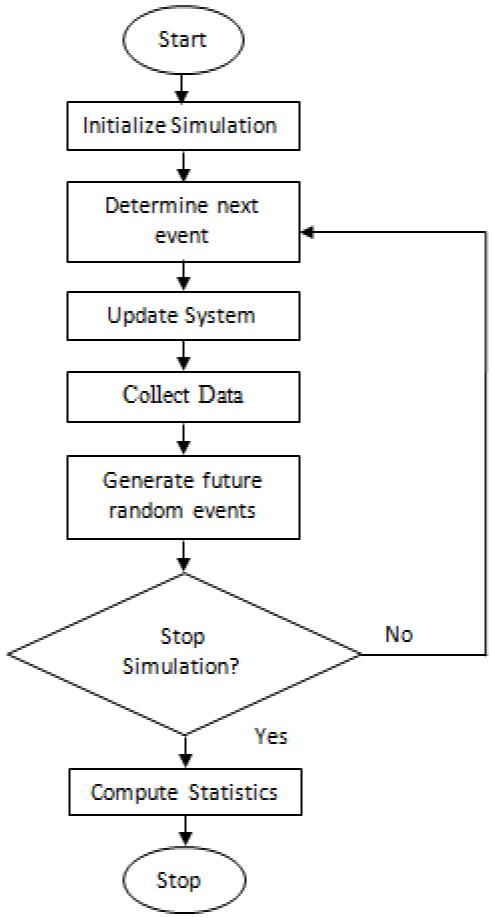

Figure 1.1*: Discrete-event simulation flow chart.*

Figure 1.1 illustrates how a discrete-event simulation executes. From an initial condition, the system is updated to the next discrete, random event derived from a set of input parameters and the pseudo-random number generator. As the system evolves important statistics are collected until a stopping criterion is met. DES has the advantage of condensing time and space so that the evolution of a system over a long period (several years in most cases) can be observed in a small amount of real time. Furthermore, information can be collected from the simulation that is difficult or impossible to obtain by observing the real system. DES has the advantage of accurately modeling systems and providing important performance data but does not provide explicit insight into the underlying behavior of the system. Thus conclusions must be inferred. Nevertheless, DES is a useful tool that helps drive efficiencies and reduce costs in a production environment.

1.2 Problem Setting and Definition

This study involves modeling a production line. The model is representative of a real production line that manufactures medical garments for the health care industry. A summary of the assembly operations and equipment involved in the production line of interest is given in Table 1.1 below.

Table 1.1*: Summary of production line of interest.*

Workstation	Operation	Equipment
1	Seaming Sleeves	Ultrasonic seaming machine
2	Sewing Cuffs	Industrial serging machine
3	Staking Belt	Ultrasonic staking machine
4	Sewing Neck Tie	Industrial sewing machine
5	Folding	None

A process flow diagram of one production line, in its current state, is given in Figure 1.2 below. In this production line workstations may consist of multiple servers in parallel as a result of differences in the cycle times of assembly operations. Multiple servers in parallel are used in efforts to achieve an overall balance of workstation cycle times (although overall balance of workstation cycle time is still difficult or impossible to achieve). Servers in workstations 1-4 involve the use of machines for which operators are 100% dedicated to each machine. Machines are relatively inexpensive and are not considered to be a constraint of the system. Garments are transferred in tote bins containing 100 garments (referred to as a batch). Between workstations space is provided to allow for work-in-process (also referred to as buffer or queue capacity). There is no enforced limit on the amount of work-in-process allowed to accumulate between workstations; however, there is a practical limit of approximately 45 batches between any pair of adjacent workstations due to limited available space. When work-in-process accumulates in front of a workstation (as a result of variability and line imbalance) the current practice is to increase the capacity of the downstream workstation by "borrowing" an operator from another production line assembling a similar product and having identical assembly operations. Due to current company practices it can be assumed that the first workstation always has raw material available and the last workstation always has room to deposit finished goods.

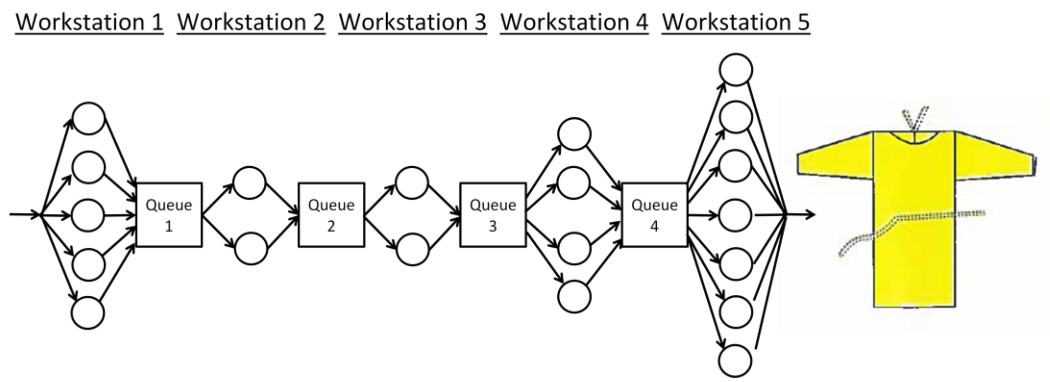

***Figure 1.2**: Production line of interest.*

The sponsoring company is facing increasing competition and customer pressure to reduce its selling price. As a result, the company is interested in exploring options to reduce its manufacturing costs and increase the efficiency of its production lines.

1.3 Objectives of the Present Work

The objective of this study is to develop a credible DES model of the sponsoring company's production line, implement changes that have the potential to improve the sponsoring company's competitive position and quantify the improvements that can be expected. DES was chosen over other methods for its ability to accurately model complex systems and phenomena. Changes to the production line that are examined in this study are:

1. **Increase or decrease in operator turnover**. The sponsoring companies manufacturing facility is located in a developing country and experiences a relatively high monthly turnover rate. However, the effect of employee turnovers at the production level is not well understood and difficult to quantify. A purpose of this study is to better understand the effect turnovers

have on a production line so manufacturing managers can make better decisions with regards to hiring, firing, training and retaining employees.

2. **Cross-training operators to perform multiple tasks**. The sponsoring company is interested in the effect of cross-training operators as a means of mitigating the effects of turnover and compensating for variable demand of products. A cross-training policy that is of interest is one where workers rotate through workstations daily and gradually gain experience at all operations. However, cross-training presents several challenges. First, workers are reluctant to participate in cross-training and prefer to remain at the workstation for which they have acquired a high skill level. This may be a result of the current method of compensation which is on a piece rate basis. If cross-training is to be implemented alternative methods of compensation may need to be investigated. The second problem emerges from the decrease in production capacity that has been observed from previous attempts at cross-training. This suggests that specialized workers obtain high proficiencies at their respective tasks and that cross-trained workers may have a negative effect on production. An objective of this study is to accurately model the relationship between experience and proficiency in order to improve the consistency between the model and the real system providing a realistic analysis of the effects of cross-training.
3. **Improvement in operational control**. As mentioned previously, the current practice is to borrow operators from another production line as needed. However, the effect of this policy on overall production rate is not well understood. It's possible that the overall system is out of balance and that the jockeying of workers merely hides losses in the system. One way to eliminate this problem is to design production lines that are balanced and isolated (i.e. do not interact with other production lines). If isolated production lines are balanced then the overall system will of course be balanced and the potential for inefficiencies (which exists in the current system) will be eliminated. An objective of this study is to investigate the following two alternative production line designs: 1) eliminate the practice of borrowing workers and permanently

assign workers to stations and 2) have a "floating worker" who is dedicated to a production line but willing to be assigned to any workstation as needed.

4. **Automating the folding operation**. The folding operation is currently manual. As a means of reducing labour requirements the sponsoring company is interested in developing equipment to assist in the folding operation. The folding operation is difficult to automate in its entirety and may require manual loading and unloading. However, even semi-automation of this operation will lead to a cycle time reduction and possibly improve worker satisfaction since the manual folding is a strenuous task. Furthermore, there may be additional benefits to automating the folding operation as a result of reduce skill requirements and rapid learning. This study seeks to quantify additional benefits that may result from automating the folding operation.
5. **Reducing work-in-process (WIP)**. A customer of the sponsoring organization is requesting a reduction in work-in-process. This is largely a result of the customer's interest in "lean manufacturing". Lean manufacturing was a term coined by James P. Womack in his book "The Machine That Changed the World" [67], which described findings of an MIT study regarding the automobile industry in the 1980's. During that time American automobile manufacturers were losing market share to Japanese manufactures. Japanese car makers had developed a novel method of production which became known as lean manufacturing (or the Toyota Production System). One of the practices of lean manufacturing is to have a very small amount of work-in-process (WIP). Reduced WIP is known to have some advantages (e.g. decreased total cycle time, reduced holding cost, and easier mitigation of quality problems). However, limited WIP is also known to negatively affect production rate – a relationship that has been overlooked by some lean manufacturing advocates [30]. As a result many companies who were eager to adopt lean manufacturing failed to realize the benefits promised by this method [57]. An objective of this study is to accurately model the system so that the effects of WIP capacity are well understood. This will allow production management to make an informed

decision regarding its WIP policy and whether it is in their best interest to reduce WIP in the system by implementing an enforced limit on WIP capacity.

1.4 Overview of the Thesis

This study can be divided into three phases: 1) data collection and analysis, 2) verification of the discrete event simulation model and 3) numerical experiments and sensitivity analysis. All three phases are important contributions in the area of manufacturing management. The next chapter supports this statement by introducing previous literature relevant to the study. It will be explained how this study examines neglected areas of modeling manufacturing systems. The third chapter presents the methods used in this study. This chapter: 1) explains how data for this study was obtained, 2) provides details of the statistical methods used in the analysis of data, 3) explains the methods used to determine whether or not the simulation model was constructed properly and 4) discusses, in more detail, the changes to the system and how the effects were quantified. The fourth chapter presents the results of applying the methods presented in chapter 3 and the fifth and final chapter summarizes the main findings of this study and presents opportunities for future research.

CHAPTER 2

Literature Review

Models of production lines are important for the efficient utilization of resources. The earliest attempts to formulate mathematical models of production systems were by Frederick W. Taylor (1856 – 1915). Although, none of Taylor's equations were adopted, his work introduced the idea of using scientific principles to solve management problems. This chapter presents a historical review of models of production systems and how they have influenced our understanding of the behavior of production systems. For the purpose of this study, only models of discrete parts, serial production lines are considered in the literature review since these models are relevant to the mass production system in this study. Models not considered in the literature review include job shops and merging lines. Readers interested in models concerned with these systems are referred to the following articles [81], [32], [117], [18], [83], [88], [41].

The remaining sections of this chapter begin with a discussion of analytical models that have been developed. The advantages, disadvantages and limitations of analytical models will be discussed. Then it will be shown how simulation studies have extended our understanding of production lines to more realistic cases than those that can be considered using analytical models. Following this discussion, an important phenomenon that has largely been ignored in the area of modeling production systems will be introduced (namely the learning curve). The few studies that do consider learning in models of production lines will be presented and the gaps in these studies will be identified.

2.0 Analytical Models

Determinist models were the first models of production systems to be developed and are still widely used today (see Groover [2007], Groover [2008] and Jacobs et al. [2008]). These models use an allowance factor to adjust for effects of variability and interactions between entities of a manufacturing system. An example, from Groover [2007], of a deterministic model that has been used to determine the time to perform an assembly operation is given below.

$$T_{std} = T_{nw}\left(1 + A_{pdf}\right) + \max\left\{T_{nwi}\left(1 + A_{pdf}\right), T_m(1 + A_m)\right\} \qquad \ldots (1)$$

where, T_{std} is the standard cycle time, T_{nw} is the normal time for activities that cannot be performed while the machine is in use, A_{pdf} is an allowance for manual activities, T_{nwi} is the normal time for activities that can be done while the machine is in use, T_m is the machine cycle time and A_m is an allowance factor for the machine.

The problem with the determinist approach is that allowance factors need to be estimated using judgment or historical data. Furthermore, the allowance factors include interaction effects that will vary for different production line designs. In attempts to improve the accuracy of production system models researchers developed stochastic models that include variability and interaction effects.

Stochastic models of production systems originated from queueing theory which is the study of systems involving a line (or queue) where customers may have to wait before receiving service. Comprehensive overviews of queueing theory can be found in the text by Gross and Harris [48] or the article by Disney and Konig [32]. Results relevant to discrete parts, serial production systems will be presented next beginning with an important result by Little [87].

Little provided a proof of the relationship between the average number of units (or customers) in a system and the average time a unit spends in the system. The relationship is given in equation 2 below and is commonly referred to as “Little’s Formula” or “Little’s Law.”

$$L = \lambda \cdot W \ . \qquad \ldots (2)$$

In equation 2, L is the average number of units in a system, λ is the average arrival rate of units to the system and W is the average time a unit spends in the system. Little's proof was obtained without specifying arrival or service time distributions and does not assume a particular queueing system. Thus Little's Law is quite general. Little's Law has proven to be very important in the analysis of manufacturing systems and can be applied to most problems without loss of generality. Lead-time (or flow time or system cycle time) and average work-in-process are important performance measures of a manufacturing system and impact economics and customer satisfaction. Given one of these performance measures and the arrival rate, the other performance measure can be determined. For example, if work-in-process is monitored over an extended period of time then it is possible to estimate the time goods spend in the system (lead time) using Little's Law. But Little's Law is of no help if work-in-process has not been recorded or cannot be predicted. Fortunately, the stochastic models presented next allow one to predict the average work-in-process in manufacturing systems and the relationship between this performance parameter and others.

The simplest problem that can be considered is shown in Figure 2.1 below. In this system customers arrive at random times to a system and await service from a single server (service time is also random).

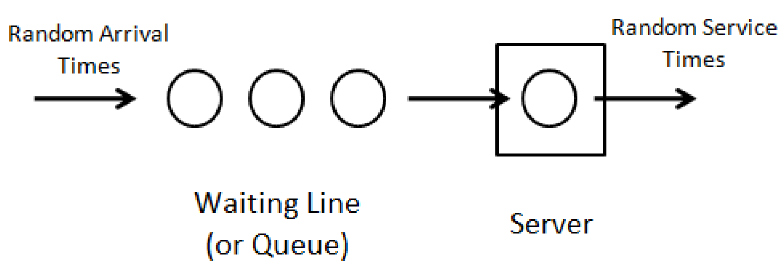

***Figure 2.1**: Single server queue.*

A. K. Erlang (responsible for much of the pioneering work in the field of queueing theory) was able to analyze the system shown in Figure 2.1 by introducing the notation of stationary equilibrium and the so-called balance-of-state equations [48]. If interarrival and service times are exponential random variables, then the probability of finding a given number of customers in the system can be found using the equations below where λ and μ are the long run arrival and service rates respectively.

$$P\{n\ customers\ in\ the\ system, t = \infty\} = p_n = p_0 \prod_{i=1}^{n} \frac{\lambda_{i-1}}{\mu_i} \qquad \ldots (3)$$

$$P\{zero\ customers\ in\ the\ system, t = \infty\} = p_0$$

$$= \left(1 + \sum_{n=1}^{\infty} \prod_{i=1}^{n} \frac{\lambda_{i-1}}{\mu_i}\right)^{-1}. \qquad \ldots (4)$$

These equations can be used to find important performance measures such as the average throughput rate of the system and the average number of customers in the system. Using Little's Law the average waiting time in the system can also be found.

In the case of a single server and no limit on the number of customers that can line up at one time (denoted as M/M/1 using Kendall notation) equations (3) and (4) reduce to

$$p_n = p_0 \left(\frac{\lambda}{\mu}\right)^n = p_0 \rho^n \qquad \ldots (5)$$

$$p_0 = (1 - \rho) \qquad \ldots (6)$$

where ρ is known as the "traffic intensity." For this case the expected number of customers in the system is determined as

$$L = E[n] = \sum_{n=0}^{\infty} n p_n = \frac{\lambda}{\mu - \lambda}. \qquad \ldots (7)$$

From equation (7) it can be seen that μ must be strictly less than λ. Otherwise, the size of the queue grows to infinity. Thus, in order for this system to have a steady-state solution ρ must be strictly less than one. This is the case for queueing systems that have no restrictions on queue capacity. This is an important result regarding the design of manufacturing systems since it dictates that work cannot be released into a production system at a rate greater than the maximum throughput rate. Otherwise, work-in-process will accumulate indefinitely. This conclusion can also be extended to workstations in series (explained in the following paragraphs).

Equations (3) and (4) can be directly applied to simple production systems where the work pieces (customers) wait to be processed by a human and/or machine. Furthermore, these equations also apply to systems where there are multiple servers and/or there is a limit to the number of customers that can line up at one time. However, this result only applies to a single workstation, and generally a production system involves multiple workstations. An important result by Burke [17] allows for the analysis of workstations in series as shown in Figure 2.2 below.

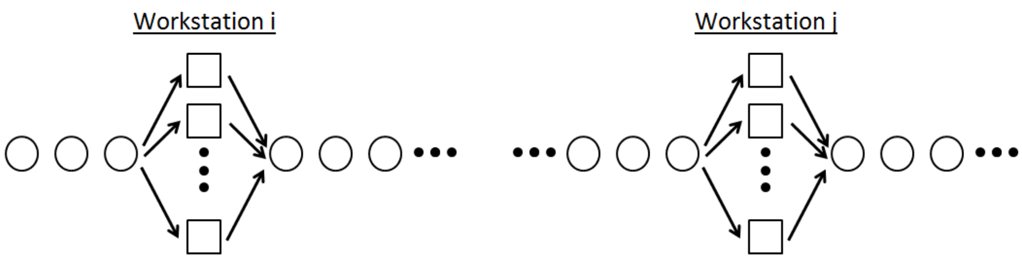

Figure 2.2*: Multiple workstations in series.*

Although others [93, 100] stated that the output of a Markovian queuing system with one line is also Markovian, it was Burke [17] who provided the mathematical proof. As a result series of Markovian queuing systems could be analyzed given that infinite capacity for work-in-process is allowed between queueing systems. In this case each queueing system (or workstation) can be analyzed independently and the performance measures of the system can be analyzed using the principle of superposition. However, in order for a steady-state solution to exist the arrival rate to any workstation must be less than its service rate. As a result a serial production line with no restriction on work-in-process capacity cannot be perfectly balanced (which is often the design objective). Instead the service rate from any workstation must be less than the service rate of all upstream workstations and greater than the service rate of all downstream workstations.

The solutions presented thus far allow for the analysis of serial production lines. However, the solutions assume exponential interarrival and service times and an infinite capacity for work-in-process. A production line often experiences less variable service times [33]. And a company cannot provide infinite capacity for work-in-process in its production process. This would require an infinite amount of space between workstations which is not economical. The models presented next address these issues.

In the case where arrival and service times are described by a general distribution, most solutions are approximate. Kingman [74, 73] was the first to study these types of systems. Kingman showed that in heavy traffic (i.e. when the arrival rate approaches the service rate) the waiting time distribution of the G/G/1 (general distributions of interarrival and service times and a single server) queueing system approaches a negative exponential distribution and the following approximation for mean waiting time, often referred to as the Kingman equation, can be used.

$$G/G/1: E[w] \approx \left(\frac{C_a^2 + C_s^2}{2}\right)\frac{\rho}{1-\rho}\frac{1}{\mu}\ . \qquad \ldots (8)$$

In equation 8 w is the time one unit (or customer) spends in the system, C_a^2 and C_s^2 are the coefficient of variations of the arrival and service processes respectively, ρ is the traffic intensity and μ is the service rate.

Others improved upon the Kingman equation and extended the solution to include G/G/m queueing systems. Sakasegawa [109] provided the following approximations for the mean waiting time of G/G/1 and G/G/m queueing systems.

$$G/G/1: E[w] \approx \left(\frac{C_a^2 + C_s^2}{2}\right)\left(\frac{\rho^2}{1-\rho}\right)\frac{1}{\mu} \qquad \ldots (9)$$

$$G/G/m: E[w] \approx \left(\frac{C_a^2 + C_s^2}{2}\right)\left(\frac{\rho^{\sqrt{2(m+1)}}}{m(1-\rho)}\right)\frac{1}{\mu} \qquad \ldots (10)$$

where C_a^2, C_s^2, ρ and μ are defined as previously and m is the number of servers in parallel. The approximations presented above are the most frequently used to analyze the G/G/1 and G/G/m queueing systems. However, they are all based on the assumption of heavy traffic. For an approximation that relaxes this conditions see Whitt [121].

In order to analyze series of G/G/1 or G/G/m queueing systems a linking equation [57] can be used to characterize the input process between workstations as shown below.

$$c_{input} = 1 + \left(1 - \rho_{upstream}^2\right)\left(C_{a_{upstream}}^2 - 1\right) + \frac{\rho_{upstream}^2}{\sqrt{m_{upstream}}}\left(C_{s_{upstream}}^2 - 1\right). \qquad \ldots (11)$$

Equations presented thus far allow one to evaluate workstations in series characterized by either Markovian or general service time distributions, provided an unlimited capacity for work-in-process is available. However, many manufacturing systems enforce a limit on the amount of work-in-process that can accumulate between workstations (also referred to as buffer capacity). The solution to a single workstation with limited buffer capacity has already been presented (see equations (3) and (4)). However, when workstations in series are separated by a buffer with limited capacity there are two important consequences: 1) if an upstream workstation completes a work piece and finds the immediate downstream buffer full, that workstation becomes “blocked” and must wait for material to be removed from the buffer. 2) If a downstream workstation completes a work piece and finds the immediate upstream buffer empty, that workstation becomes “starved” and must wait for material to arrive to the buffer. Because of blocking and starving, placing a limit on buffer capacity reduces workstation utilizations. Hunt [60] was the first to consider servers in series with limited buffer capacity. Hunt considered the two station system shown in Figure 2.3 below with exponential interarrival and service times.

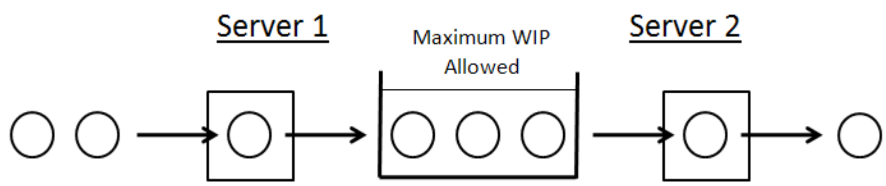

Figure 2.3*: System with two servers in series connected by an intermediate buffer with limited capacity.*

Using a Markov model Hunt found that the maximum system efficiency (or traffic intensity), defined as $\rho_{\max} = \lambda_{\max}/\mu_1$, could be expressed as

$$\rho_{max} = \mu_2\left(\mu_1^{q+1} - \mu_2^{q+1}\right)/\left(\mu_1^{q+2} - \mu_2^{q+2}\right) \qquad \ldots (12)$$

where, λ_{max} is the maximum possible arrival rate to achieve a steady state solution (which is equal to the maximum throughput rate of the system), μ_1 and μ_2 are the service rates of server 1 and server 2 respectively and q is one plus the intermediate buffer capacity (i.e. buffer capacity = q – 1). Hunt's historical paper illustrates the negative effect limiting work-in-process has on throughput rate. For example, for equal service rates and no buffer capacity the throughput rate is 66.7% of what it would be with no limit on buffer capacity (i.e. 33.3% loss in throughput rate as a result of variable cycle times and no buffer capacity). This is an important result with respect to manufacturing management since both work-in-process and throughput have an economic impact on an organization. Hunt also provides a method of determining maximum utilization when a series of more than two servers is involved. However, most of the work done in this area is credited to Hillier and Boling [53, 52, 51].

Hillier and Boling [52] presented a method of generating the state transition matrix for a series of servers with finite intermediate queues having exponential or Erlang service time distributions. Given the state transition matrix, all steady-state probabilities can be determined and thus all performance parameters can be evaluated. However, the state transition matrix grows very rapidly as the length of the line and size of queues increases making this method computationally intractable for large problems. Hillier and Boling also provided an approximate method for determining throughput when service time distributions are exponential. Using their exact analytical method Hillier and Boling [51] discovered the now famous “bowl phenomena” and “reversibility property.” Hillier and Boling examined 2, 3 and 4 station lines with exponential service times. Explicit solutions were obtained for a 2 station line and 3 station line with no capacity for work-in-process. For the 3 station line it was found that the throughput rate function was symmetric with respect to stations 1 and 3. Therefore, interchanging stations 1 and 3 would have no effect on throughput rate. This is known as the “reversibility property” and was later proven for lines of any length and arbitrary service time distributions [95]. Examining lines with 3 and 4 workstation lines revealed an unexpected result: unbalancing lines resulted in increased throughput! It was found that a symmetrical line where the interior stations are assigned a smaller portion of the work content will outperform a perfectly balanced line. Hillier and Boling [53] later extended their study to include longer lines and Erlang (or phase type) service time distributions and again concluded that workload assigned in a bowl arrangement increases throughput rate. There has been some debate (discussed later) but the existence of the bowl phenomenon has been largely accepted.

Hillier and Boling provided great contributions into the behavior of serial production lines. However, their exact solution method was limited to relatively short production lines with small buffer capacities. As a result Gershwin [42, 40] developed an approximate numerical method to simplify the analysis. Gershwin’s approach was to decompose a long serial line into a series of two station lines for which a tractable solution exits. Then an iterative method was used to adjust the parameters of each isolated two stations lines to what they might be if the two station lines were part of a long serial line. To determine the parameters of the decomposed line a set of conditions are imposed: 1) conservation of flow, 2) the flow-rate idle time relationship and 3) the resumption of flow condition. Gershwin’s method is much more computationally efficient than Hillier and Boling’s method and allows for the analysis of much longer lines and larger buffer capacities. However, Gershwin assumed deterministic cycle times and as a result his method is more applicable to automated rather than manual systems.

David, Dallery and Xie [126] later extended Gershwin's method to include random exponential cycle times making the method applicable to manual production systems. In addition, David, Dallery and Xie's solution explicitly considers machine failures/repairs making the method suitable for semi-automated production systems as well. These decomposition methods had the advantages of providing tractable numerical solutions to long production lines. However, the decomposition method occasionally suffers from convergence problems [84].

Lim, Meerkov and Top [86] developed an alternative method to analyze long serial lines. Instead of decomposing the line into multiple two-station lines Lim, Meerkov and Top aggregated a long line into a single server. The advantage of this method is that it is proven to converge [84]. The aggregation method has also been extended to include problems where random variables are continuous exponential [21] and even to cases where non-exponential machine failure and repair times are considered [82].

This section has presented exact analytical and approximate numerical methods that allow one to analyze production systems. Research in this area is still very active as researchers search for methods that describe more complex production systems. However, currently an accurate model of many real production systems can only been obtained using simulation.

2.2 Simulation of Production Systems

Historically, simulation has been an important tool in understanding production systems. Simulation is often used to extend analytical results, optimize production line design factors, verify analytical and numerical results and analyze complex systems. The next section presents some historical simulation studies that have contributed to these areas. Readers interested in the details of simulation modeling and analysis are referred to the following texts [8, 79 and 80]. However, a detailed overview of simulation modeling is beyond the scope of this work.

2.2.1 Simulations of Unbalanced Serial Production Lines

Davis [28] performed an early simulation study of a production line and stirred up a lot of controversy regarding unbalanced production lines. Davis studied a three station serial line. In one experiment all three workers had the same mean processing times and in a second experiment the line consisted of a slow, medium and fast worker. The cycle time distributions used by Davis were normal approximations to the Pearson's III distribution which are a better representation of manual cycle times than the exponential distribution used by Hillier and Boling [51]. Davis examined all arrangements of the heterogeneous workforce and found a fast, medium slow arrangement to be the best performing (even outperforming a perfectly balanced line). This result is contrary to the bowl arrangement suggested by Hillier and Boling. However, other simulation studies supported this finding. Payne, Slack and Wild [101] performed a simulation study of a 20 station line and found that stations with higher mean cycle times or higher coefficients of variability should be assigned at the end of the line. Kala and Hitchings [69] examined the effect of cycle time variability and also concluded that stations with higher variability should be placed at the end of the line. However, Kottas and Lau [77] provide an explanation for the contradiction between the results of these simulation studies and Hillier and Boling's results.

Kottas and Lau [77] pointed out that the simulations performed by Payne et al. [101] and Kala et al. [69] did not use simulation run lengths capable of reaching steady-state. As a result their studies examined the transient behavior of lines. It is easy to see that - when lines begin with no work-in-process - the transient period favors faster workstations at the beginning of the line; since during this period the end workstations are waiting for material to arrive. Hillier and Boling's results are for the long run behavior of lines and cannot be compared to the transient performance of a line. Kottas and Lau repeated the studies performed by Payne et al. and Kala et al. with longer simulation runs and state that they did observe the bowl phenomena once the steady-state was achieved. Support of the existence of the bowl phenomenon was provided by others [106, 20, 34] and [96]. However, some continued to debate the existence of the bowl phenomenon.

Smunt and Perkins [114] performed a series of simulations and concluded that the bowl phenomenon was entirely situation specific. Smunt and Perkins' simulations examined the 3 and 4 station lines studied by Hillier and Boling [51] and investigated the application of the bowl arrangement to: 1) an 8 station line, 2) normally distributed cycle times over a range of coefficient of variabilities and 3) a range of buffer capacities. Smunt and Perkins found that – for normally distributed cycle times with moderate to low variability – a small amount of buffer capacity eliminated the benefits of using the bowl arrangement and a perfectly balanced line outperformed the bowl arrangement used in their study. As a result Smunt and Perkins suggest that, in many cases, production managers should strive for a perfectly balanced line; since the bowl arrangement may only benefit the short lines, with high cycle time variability and low buffer capacity studied by Hillier and Boling. However, So [115] repeated the simulation study performed by Smunt and Perkins using a different workload imbalance based on the recommendations by Hillier and Boling [53]. So found that the bowl phenomenon did indeed exist using an optimal workload imbalance. On average the workload imbalance used by So resulted in a 0.3% improvement in line performance.

The main conclusions from the bowl phenomenon debate are: the bowl phenomenon does exist but is more pronounced in small lines, with high variability and low buffer capacity. Although, the improvements are small (typically less than 1% increase in throughput), in a mass production environment this may be a substantial improvement. However, care needs to be taken to find the appropriate workload imbalance since deviating from the optimal imbalance may be detrimental to line efficiency (as shown by Smunt and Perkins [114]). The optimal workload imbalance is usually flat in the middle and steep towards the end of the line (with faster workstations at the ends). Whether a production manager chooses to use a workload imbalance according to the bowl arrangement or a perfectly balanced production line will depend on the easy of achieving either of these arrangements.

2.2.2 Buffer Capacity in Production Lines

Hunt's work was presented earlier in this chapter and illustrated the importance of buffer capacity in a production line. However, Hunt's study was limited to a two station line with exponential service times. Barten [9] also performed one of the earliest simulation studies (in addition to Davis' work presented earlier) and examined the effects of buffer capacity on serial lines with two, four, six and ten workstations. Furthermore, Barten used normally distributed cycle times with a coefficient of variation of 0.3. He found that throughput rate increased with an increase in buffer capacity and decreased with an increase in line length. Barten provided negative exponential equations to describe the relationship between throughput rate and buffer capacity for each line length. He then used this relationship to formulate a cost model that could be used to determine the optimal buffer capacity for a line. Barten's work provided insight into the behavior of production lines far beyond the reach of any analytical solutions of the time.

Anderson and Moodie [2] continued work on buffer capacity with their factorial simulation experiment examining buffer capacities of 0, 4, 8, 12, 16, 20 and line lengths of 2, 3, 4 and 5 in perfectly balanced lines. Anderson and Moodie used normally distributed cycle times with a mean of one and standard deviation of 0.55. Using regression analysis they developed equations to find the average delay and average in-process inventory as a function of line length and buffer capacity (other authors that used simulation to develop empirical equations describing production lines are Freemen [38], Knott [76] Muth [96], Hira and Pandey[56] and Blumenfeld [14]). Similar to Barten, they used these relationships to develop a cost model to find the optimal buffer capacity of a line. Anderson and Moodie also attempted to characterize performance parameters during the transient period. Their formula is only useful when the length of the transient period is known.

Slack & Wild [113] developed a set of expressions to determine the duration of the transient period for the manual assembly lines in their simulation study.

Other authors used simulation to examine the effect of buffer capacity on production line performance [49], [11], [123]. However, one of the most comprehensive studies was performed by Conway et al. [24] using simulation. Conway et al. examined the effect of increasing buffer capacity for a variety of line lengths and degrees of cycle time variability. He found a relationship between efficiency and the ratio of buffer capacity to cycle time coefficient of variability that was independent of line length. This is a useful result since it suggests that the performance of lines of any length, buffer capacity, and cycle time variability can be easily estimated. Conway et al. also examined the optimal allocation of buffer capacity in a perfectly balanced line (whereas much of the previous work considered lines with an equal allocation of buffer capacity). He found that the buffer allocation should be symmetrical and centralized and there should not be a difference of more than one buffer slot between any of the buffers. Other studies also agreed with this conclusion [54], [105]. In addition to perfectly balanced lines Conway et al. also examined the more realistic case of an arbitrarily imbalanced line (not an optimal imbalance which was the topic of earlier discussion). Conway et al. studied a three station line with one station having a higher cycle time than the other two (i.e. a bottleneck). Conway found that buffer capacities on either side of the bottleneck are equally important. However, as the severity of the bottleneck increased, less buffer capacity is required since upstream workstations readily fill buffers upstream of the bottleneck, and downstream workstations readily empty buffers downstream of the bottleneck resulting in high utilization of the bottleneck.

Powell and Pyke [105] extended the study of optimal buffer allocation to lines with 4, 6, 8 and station lines and one station being the bottleneck. They used cycle times with a lognormal distribution and in the base case a mean of 1 and standard deviation of 0.5. They found that the optimal buffer allocation has larger buffers upstream and downstream of the bottleneck as suggested by Conway [24].

However, they provided further insight, suggesting that the bottleneck tends to draw buffer capacity from the farthest buffer towards itself (but not necessarily to the bottleneck). Pyke and Powell's results suggest that a large difference in cycle time is required for the optimal buffer allocation to be positioned immediately upstream and downstream of the bottleneck. And in some cases, even with a large difference in cycle time, the optimal buffer allocation still does not have all of the buffer slots surrounding the bottleneck. The reason is that other stations in the line still have random cycle times and removing all of the buffer capacity between those stations results in additional losses in throughput. As a result an equal buffer allocation is optimal in many production lines with a single bottleneck unless the bottleneck is severe. And in cases of a moderate bottleneck, buffer capacity should be allocated towards the bottleneck but not necessarily immediately upstream or downstream of the bottleneck.

This section has illustrated the importance of simulation in understanding buffer capacity as a design factor in production lines. It has been found that increasing buffer capacity in a production line has a positive effect on throughput but with diminishing returns. The optimal buffer allocation in a perfectly balanced line is symmetrical and centralized and there should not be a difference of more than one buffer slot between any of the buffers. When a bottleneck exists in a production line slightly larger buffer capacities should be provided to buffers upstream and downstream of the bottleneck. However, buffer capacity is still very important elsewhere in the line.

2.2.3 Simulation in Industry

The ability of simulation to model complex systems has been presented in the previous section. Simulation is able to model large systems and general probability distributions. For this reason simulation has been widely accepted in many industries. Evidence of this can be seen by the numerous case studies that appear annually in the winter simulation conference (www.wintersim.org). An interesting case in point is the LEAPFROG project [119] that resulted in the automated garment assembly line shown in Figure 2.4 below. The LEAPFROG project was concerned with transforming apparel manufacturing into a highly automated process in order to support manufacturing in high labor wage countries.

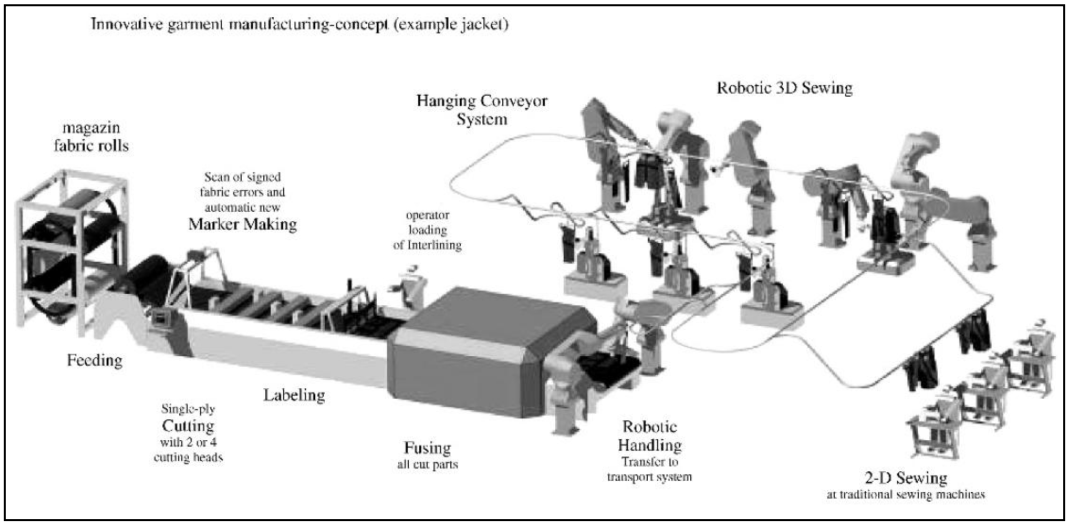

Figure 2.4*: Automated garment assembly line. Permission to reproduce image obtained from Phillip Moll GmBH & co kg, Aachen, Germany (see Appendix A-6).*

The LEAPFROG project chose simulation as a tool to determine the performance of the automated assembly line, evaluate different line configurations and optimize the production schedule. The result of the simulation was a configuration that allowed for high flexibility and short lead times.

Other researchers also used simulation to evaluate the performance of garment assembly lines in the apparel industry [13], [70], [36, 37], [120]. This section refers to cases where simulation was used to model garment assembly lines in the apparel industry because the process is very similar to garment assembly in the medical device industry. However, none of the references in this section address an important issue when modeling production systems: the fact that new workers perform worse than experienced workers. And turnover on a production line introduces new workers into a production line, which negatively affects performance. This is surprising since - apart from the LEAPFROG project - most of the studies consider highly manual processes for which a great deal of learning occurs. The few studies that have considered the effect of new workers on the performance of production systems will be presented later. However, first a review of learning curve models is presented.

2.3 Learning Curve Models

This section presents mathematical models that have been developed to describe the relationship between experience and performance, known as the learning curve. Most of the information has been collected from the papers by Yelle [125], Bandiru [5] and the book by Dar-El [27].

The first mathematical description of the learning curve is credited to Wright [122]. Wright observed a reduction in direct labor hours in the manufacture of airplanes as a result of experience. In particular, Wright found a 20% reduction in direct labor hours required to manufacture an airplane as the number of airplanes manufactured doubled. Wright's model is commonly referred to as the "power model" and is given as

$$t_n = t_1 \cdot n^{-b} \qquad \dots (13)$$

where t_n is the cycle time of the nth cycle, t_1 is the cycle time of the first cycle, n is the number of cycles completed and b is the learning factor. The learning factor is related to the learning percentage, p, by

$$b = -\log_{10}(p) \,/\, \log_{10}(2)\ . \qquad \dots (14)$$

The learning percentage, p, is one minus the amount of reduction in cycle time that can be expected every time the number of cycles doubles.

The power model remains the most popular learning curve model (according to Yelle [125]). However, a disadvantage of this model is that cycle time tends to zero as experience tends to infinity. When a large number of cycles is involved (such as in a mass production environment), the power model may tend to overestimate productivity gains as a result of experience. DeJong [29] proposed a modification to the power model which rectified the problem of limitless cycle time reduction. DeJong's model is given by

$$t_n = t_1[M + (1 - M)n^{-b}] \quad \ldots (15)$$

where M is an incompressibility factor ($0 \leq M \leq 1$) that determines the limit upon which no further improvement is possible.

The Sanford-B model was also an early equation the emerged to describe US shipbuilding activities during World War II [125]. This model accounts for prior learning and is given as

$$t_n = t_1(n + B)^{-b} \quad \ldots (16)$$

where t_n, t_1, n and b are defined as in equation (13) and B is the number of previously completed units.

Bevis, Finnear and Towell [12] assumed that the inverse of cycle time (i.e. throughput) obeyed the same relationship as many physical systems. Their equation is given as

$$TP(t) = TP_0 + TP_\infty\left[1 - e^{-(t/\tau)}\right] \quad \ldots (17)$$

where $TP(t)$ is the throughput rate at time t, TP_0 is the initial throughput rate, TP_∞ is the steady-state throughput rate and τ is the time constant which determines the rate at which throughput increases. The model proposed by Bevis et al. also has the advantage of imposing a limit on productivity gains that result from experience.

Pegel [102] also suggested an exponential relationship of the form

$$t_n = \alpha(a)^{n-1} + \beta \quad \ldots (18)$$

where α, a and β are parameters determined from empirical data.

More recently, Dar-El and Altman [25] proposed introducing a variable learning constant into the power model. They suggest that the learning constant should vary with the number of cycles completed according to the following relationship

$$b_n = \alpha - \beta \ln(n) \, . \quad \ldots (19)$$

Varying the learning constant as proposed in equation (19) has the advantage of limiting productivity gains. However, if the parameters α and β are not universal the model may be difficult to apply since parameter estimation becomes difficult. According to Dar-El [27] this model is in the development stages and no papers have emerged addressing the parameters of the model. Other models that suffer from the same problem are: the S-curve proposed by Cochran [22], the polynomial proposed by Carlson and Rowe [19], Knecht's [75] upturn model and multivariate models.

Multivariate models attempt to account for multiple factors that can influence learning. An example of a multivariate model is the bivariate model given below.

$$t_n = \beta_0 n_1^{\beta_1} n_2^{\beta_2} \; . \qquad \ldots (20)$$

Equation (20) has two independent variables. An example where this model may apply is in a manufacturing environment where the two independent variables are the number of cycles during training and number of regular production cycles which can both affect employee performance. As mentioned previously, the difficulty with this model is in determining appropriate parameters. Furthermore, according to Badiru [5] the fit of the power model is nearly as good as the bivariate model. Thus, although multivariate models provide a slightly better fit and more information about the process, the costs associated with applying these models (e.g. extensive data collection and analysis) may hinder their use in industry. This is also the case with learning curve models that include forgetting and relearning.

Modeling forgetting and relearning is a relatively new area of learning curve research. Forgetting and relearning is difficult to characterize since it depends on many factors (such as the nature of the task, previous experience, break length and others). However, several promising models have emerged by Jaber and Bonny [64], Nembhard and Uzumeri [97] and Sikstrom and Jaber [112]. In spite of this, incorporating forgetting and relearning into the learning curve model may not always be necessary. Studies by Bailey [6] and Hewitt et al. [50] suggest that the effect of forgetting and relearning is insignificant for the case of simple tasks and short breaks since the relearning curve rapidly merges with the original learning curve. Therefore, in many production environments the additional cost and complexity associated with incorporating forgetting and relearning into a learning curve model may not provide any significant benefits when compared to traditional learning curve models.

This section has provided an overview of learning curve models. Of the models described in this section Wright's power model and DeJong's modification to the power model remain the most popular. The reason these models have been so successful is because they have few parameters that need to be estimated and the fit to empirical data is generally good [125, 85]. Furthermore, there is an abundance of case studies providing benchmark parameters. In fact, a list of learning percentages for various industries/tasks can be found in most texts discussing the learning curve [27, 47, 66].

The most widely used application of the learning curve has been as an aid in setting labor standards [125]. When a new worker performs a task additional time is provided since he/she cannot be expected to perform at the same level as an experienced worker. This has a negative impact on the performance of production lines. In spite of this many models of production lines continue to ignore the impact of learning. The next section presents the few studies that have considered learning when modeling production systems.

2.4 Human Learning and Production Line Design

Boucher [16], Dar-El and Rubinovitz [26], Goralnick (see the reference in Dar-El [27]) and Cohen and Dar-El [23] performed deterministic analysis of new assembly lines and include the learning curve in their analysis. These methods are appropriate for new products and short product runs. However, they do not provide information concerning the long run performance of a production line (which is the focus of the current study). It is hypothesized that losses in throughput rate occur largely due to turnover and the introduction of new workers into a production line. Pettman [103], Price [107] and Mobley [90] published books addressing the issue of turnover. However, most of the work in this area is concerned with the causes of turnover and not the impact of turnover on production line performance. Globerson [46] may be the first to include learning and turnover in his deterministic analysis of a single server. Globerson suggests that there is a relationship between turnover and job enlargement and provides a formula for determining the optimal cycle time when training and turnover costs are considered. Hutchinson [61], on the other hand was the first to develop a stochastic model of a production system which included learning and random turnovers in the model.

Hutchinson [61] collected data from a manufacturing facility in the maquila-dora industry in Mexico to support his simulation model of a five station serial production line. The maquila-dora industry experiences a relatively high turnover rate. In attempts to mitigate the effects of turnover Hutchinson considered three replacement policies and three work imbalance arrangements. His work is consistent with earlier studies of production lines that did not include learning and turnover. In particular, Hutchinson applied results obtained by Hillier and Boling [51] and Davis [28]. Hutchinson found an improvement in production line performance when attempts were made to achieve a balanced line by assigning new workers a smaller portion of the total workload. The fast to slow arrangement (suggested by Davis) with less workload given to slow workers obtained the largest increase in throughput rate over a passive policy which makes no effort to modify worker arrangement or workload. The fast to slow arrangement resulted in 1% - 4% gain in throughput rate (depending employee turnover rate). A disadvantage of the methods proposed by Hutchinson is that when a turnover occurs all operators move to a different workstation and must learn a new task. Hutchinson assumes that operators acquire a great deal of transferrable experience and does not provide any supporting evidence for this claim. Therefore, it’s possible that the benefits reported by Hutchinson may not be realized when implemented in a real production system.

Perhaps the most important result reported by Hutchinson is the large reduction in throughput rate as a result of turnover. A 12.6% and 16.3% reduction in throughput rate was associated with 6% and 12% monthly turnover respectively (compared to production lines with no turnover). This result suggests that turnover may be a major source of losses in a production system and should be included in models of production systems. Furthermore, the behavior of production systems may be significantly altered when learning and turnover is considered affecting design factors such as work-in-process (which received little attention from Hutchinson).

Munoz [94] extended the work of Hutchinson. Munzo performed two simulation experiments: 1) that examined a three station line and compared traditional, high-med-low (suggested by Hutchinson, [61]) and bucket brigade (see Bartholdi and Eisenstein [10] for details regarding bucket brigade systems) arrangements and 2) an experiment that examined a six station line and compared the traditional and bucked brigade production lines. In the first experiment Munzo found that a bucket brigade line outperformed traditional and high-med-low production lines by 4.9% and 3.6% respectively. However, Munzo neglected the time to transfer and reposition work pieces in the first experiment. In the second experiment Munzo assumed 3 seconds to transfer and reposition a work piece and reported a 7.4% increase in throughput when using the bucket brigades system instead of the traditional balanced production line.

Although Munzo did not explicitly report the losses associated with turnover, reductions in throughput rate of 20% and 21.8% due to 6% and 12% monthly turnover can be calculated from the results of his first experiment. A 22.6% and 25.3% reduction in throughput due to 6% and 12% monthly turnover can be calculated from the results of his second experiment. These losses are even higher than those reported by Hutchinson, again supporting the notion that learning and turnovers should be included in models of production systems.

Other simulation studies have recently emerged that consider learning but are not specifically relevant to this study. For example Shafer et al. [111] and Montano et al. [91] consider learning but do not consider turnover. And studies of job shop environments have recently considered learning (but not turnover) [71], [35], [124], [98], [72], [15]. However, the job shop is a low volume production system where this study is concerned with high volume production systems.

There are currently a limited number of studies examining the effect of learning and turnover on a high volume production system. However, research in this area is expected to continue due to the past interest in serial assembly lines and recent evidence suggesting substantial losses as a result of learning and turnover.

2.5 Chapter Summary

This chapter presented a review of literature related to modeling discrete parts, serial production lines. Methods of modeling these systems can be categorized as: exact analytical, approximate numerical or simulation based. Early analytical studies illustrated the importance of queue (or buffer) capacity in serial assembly lines due to variability in the system. The now famous “bowl phenomenon” was also a discovery that appeared in an early analytical study. The bowl phenomenon suggests that a properly imbalanced line, with a larger share of the workload given to exterior stations, will outperform a balanced line. Simulation has been used to extend early analytical studies to longer lines and more realistic cycle time distributions. The conclusion that has emerged is that the bowl phenomenon exists but is less pronounced as line length increase, cycle time variability decrease and/or buffer capacity increases. Furthermore, care needs to be taken when using an imbalanced line since the same workload imbalance does not apply to all lines or lines that have not reached a steady-state.

Simulation has also been used to examine the effect of buffer capacity on the performance of serial production lines. Studies in this area suggest that in most cases buffer capacity should be allocated equally throughout the line. If a severe bottleneck exists then a portion of the buffer capacity from the farthest buffer should be moved towards the bottleneck.

Simulation has been widely accepted for its ability to model complex systems. However, few studies have included learning and turnovers when modeling production systems. The few studies that have included learning and turnover in models of productions systems suggest that it significantly affects system performance.

The work presented in the remainder of the thesis attempts to improve the understanding of production systems by including learning and turnover in a simulation model of a real production system and investigates methods of improving system performance

CHAPTER 3

Method

This study involved using model-based simulation to investigate the behavior of a real production line and quantify the effect of design changes. This approach has the advantage of providing accurate, quantitative information regarding system design changes without the risk and cost that can result from experimenting with the real system.

The study consisted of three phases. The first phase consisted of a data collection and analysis effort with the purpose of determining input parameters to be used in the simulation model. Figure 3.1 below shows the phenomena considered in the simulation model and the required parameters and Figure 3.2 gives a screenshot of the simulation user interface. Matlab's SimEvents [89] was the DES software used in this study.

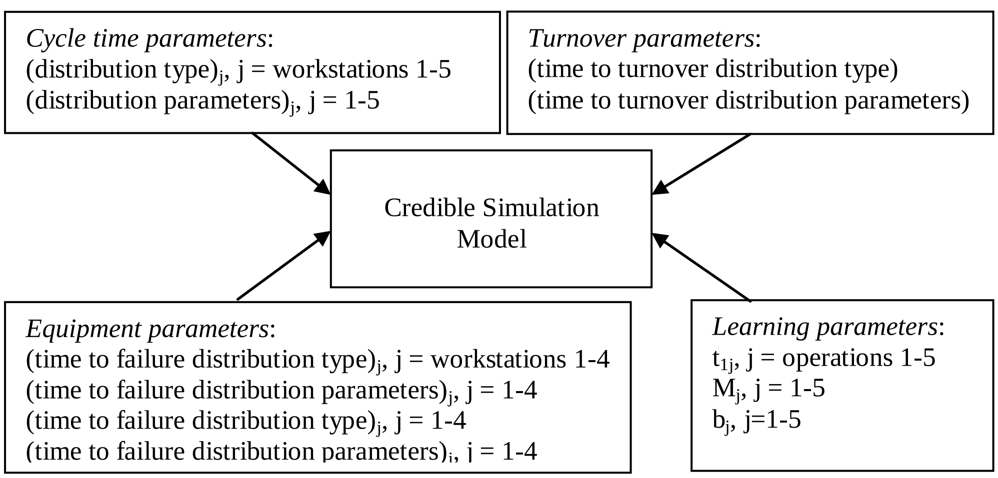

***Figure 3.1**: Simulation input parameters.*

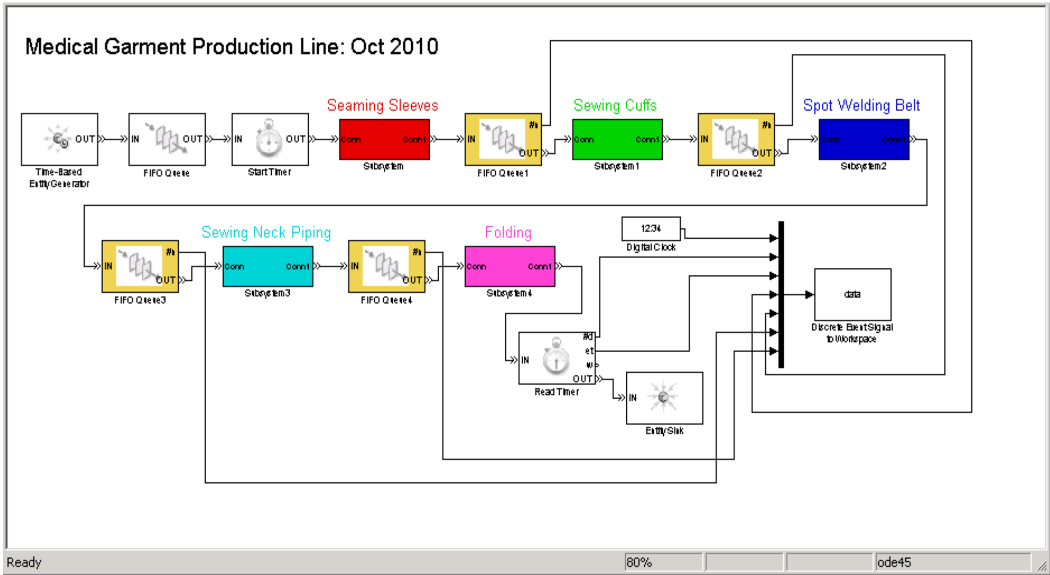

***Figure 3.2**: Simulation software.*

The second phase of this study consisted of verifying the simulation model. Verification is performed to ensure that the model has been assembled correctly (where a special purpose program has been used). And the third phase of this study consists of numerical experiments and sensitivity analysis to examine the effects of major changes to the system. The three phases of this study are described in more detail in the following sections.

3.1 Phase 1 - Data Collection and Analysis

3.1.1 Cycle Time Distributions and Parameters

Data was collected via a time study. A video camera was used to collect observations of each assembly operation. 10 observations, for each operation, were recorded – on the hour – throughout the course of the day. Each day one individual for each operation was selected for observation so that the effects of fatigue could be observed. The time study was performed over the course of four days, thus 4 individuals for each operation (a total of 20 individuals) were observed in the study. An example of the form that was used to record one data sample is given in Appendix A-1. This method of collecting cycle time data involves the following assumptions and sources of error:

- Observing the operators may introduce a bias into the data. This bias is assumed to be minimal since an operator's compensation is based on his/her performance.
- Cycle times were recorded to the nearest second as that is the smallest resolution of the video player used.
- Individual cycle times were recorded from the time an operator begins to load a garment to the time an operator is finished unloading. However, there is some ambiguity in determining the exact time when one cycle ends and a new one begins.
- An operator is responsible for monitoring the quality of the products they produce. If there is a quality issue the operator will either rework or scrap the piece. The cycle time for one garment is assumed to be the total time to complete a good quality gown. Thus, if a garment is scrapped then the cycle time does not end until the next good piece is finished.
- Seeking and moving a batch to the operator's workstation was recorded as a separate time (referred to as transportation time). The time needed for the operator to position him/herself comfortably and adjust the position of garments to be processed was included in the transportation time.
- The transportation time may be overestimated. If a workstation is "starved" for garments then the observed transportation time includes the time associated with being "starved." It is not the objective to observe this phenomenon; instead the simulation model is intended to provide information regarding workstation blocking and starving.
- The number of observations of batch transportation is limited. Therefore, the population distribution is assumed to be normal.
- Analysis of variance tests are performed using the assumption that samples are from a population with a normal probability distribution.
- Some data was discarded to avoid a bimodal cycle time distribution for the assembly of individual garments.

The data that was collected was used to: 1) determine if fatigue is a factor that needs to be accounted for in these operations, 2) characterize the stochastic nature of cycle times and 3) determine the characteristics of batch cycle times (which refers to processing one batch and seeking out a new batch for processing and is explained in more detail later).

Determining if Fatigue is a Factor

Several recent studies ([7], [31], and [65]) have been concerned with the effect of physiological factors on production line performance. This study identified whether or not fatigue is a significant factor affecting the performance of human workers in order to determine whether or not fatigue needed to be included in the simulation model. The method used to determine if fatigue was a factor was the analysis of variance (ANOVA). ANOVA was used to determine whether a group of samples that have undergone different treatments have statistically similar means (in this study the different treatments are the different times of the day when observations were made). This method assumes the model

$$y_{ij} = \mu + \tau_i + \epsilon_{ij} \qquad \text{... (21)}$$

where,

y_{ij} – is the jth observation of the ith treatment (i = 1, 2,.., a; j = 1, 2, …, n)

τ_i –is a parameter associated with the ith treatment

ϵ_{ij} – is a random error component.

The hypotheses to be tested are

H_0: $\tau_1 = \tau_2 = \cdots = \tau_a = 0$, and

H_1: $\tau_i \neq 0$ for at least one i.

In order to determine whether or not the null hypothesis is rejected the variability in the data needs to be evaluated. Using a sum of squares approach it can be shown that the variability in the data can be partitioned into two components: the variability between treatments and the variability within treatments as shown below.

$$SS_{total} = SS_{between} + SS_{within} \; . \qquad \ldots (22)$$

Where SS stands for sum of squares and SS_{total}, $SS_{between}$ and $SS_{withing}$ are evaluated as

$$SS_{total} = \sum_{i=1}^{a} \sum_{j=1}^{n} y_{ij}^{2} - \frac{1}{N} \left(\sum_{i=1}^{a} \sum_{j=1}^{n} y_{ij} \right)^{2} \qquad \ldots (23)$$

$$SS_{between} = \frac{1}{n} \sum_{i=1}^{a} \left(\sum_{j=1}^{n} y_{ij} \right)^{2} - \frac{1}{N} \left(\sum_{i=1}^{a} \sum_{j=1}^{n} y_{ij} \right)^{2} \qquad \ldots (24)$$

$$SS_{within} = SS_{total} - SS_{treatments} = \sum_{i=1}^{a} \sum_{j=1}^{n} y_{ij}^{2} - \frac{1}{n} \sum_{i=1}^{a} \left(\sum_{j=1}^{n} y_{ij} \right)^{2} \qquad \ldots (25)$$

and N (= a·n) is the total number of observations. The test statistic is evaluated as

$$F_0 = \frac{SS_{between}/(a-1)}{SS_{within}/(N-a)} \; . \qquad \ldots (26)$$

If the test statistic is less than the critical statistic ($F_{a-1,N-a}$ from the F-distribution) then the null hypothesis should not be rejected.

If the null hypothesis is accepted then it can be concluded that fatigue is NOT a factor. If the null hypothesis is rejected then further investigation is required. Additional assessment work is required in that case because this result only indicates that there is a difference between treatments; but it does not necessarily suggest that fatigue is the cause.

Characterizing Cycle Times

Here, cycle time refers to the time to process a single work piece. These times were recorded in the time study. Analysis of batch cycle times is described later. The method used to characterize cycle times from the time study data involves: 1) identifying possible distributions that may fit the data, 2) determining the parameters of the distributions and 3) determining the goodness of fit of the distributions to the data.

1) Identifying Possible Distribution Types

An analysis of histograms was used to identify possible distribution types. The Matlab m-file 'customhist.m' (see appendix A-2) was created in order to allow easy replication of histograms using various numbers of bins and bin widths. This file allows the user to select an appropriate number of bins and bin widths in attempts to satisfy the following conditions:

1. A smooth histogram is observed.
2. Each bin contains at least five observations.

The following seven distribution types were tested for goodness of fit against the data which are all of the continuous distributions available in MatLab's "Statistics" toolbox.

- Exponential (Exp)
- Gamma (Gam)
- Generalized Extreme Value (GEV)
- Lognormal (Logn)
- Normal (Norm)
- Rayleigh (Rayl)
- Weibul (Wbl)

2) The Chi-Square Goodness of Fit Test

Once possible distribution types were identified, and the number of bins and bin widths selected, a chi-square goodness of fit test was performed in order to quantify the appropriateness of the hypothesized distribution. The reason the chi-square test was used as opposed to other available test (the Kolmogorov-Smirnov or Anderson-Darling tests for example) is because the distribution parameters were estimated from the data rendering other methods invalid [79]. The goodness of fit is determined by evaluating the chi statistic according to the following equation.

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \qquad \dots (27)$$

where,

χ – is the chi statistic

O_i – is the observed number of events in bin 'i', i = 1, 2, …, k

E_i – is the expected number of events in bin 'i' calculated as the probability of the event occurring in the bin interval multiplied by the total number of observations.

The chi statistic is compared to the critical statistic $\chi^2_{k-p-1,1-\alpha}$ found from the chi distribution for a confidence level of 100-α and *k-p-1* degrees of freedom, where

α – is the probability of committing a type I error

k – is the number of bins

p – is the number of parameters estimated from the data.

The acceptance rule is

If $\chi^2 < \chi^2_{k-p-1,1-\alpha}$: accept the hypothesis that the data is from the hypothesized distribution

If $\chi^2 > \chi^2_{k-p-1,1-\alpha}$: reject the hypothesis that the data is from the hypothesized distribution

3) Estimating Distribution Parameters

The maximum likelihood method was used to estimate parameters from the data. Maximum likelihood estimates of parameters are found by maximizing the likelihood function. The likelihood function can be written as

$$L(\theta_1, \dots, \theta_m) = f_{\theta_1,\dots,\theta_m}(X_1) \cdot f_{\theta_1,\dots,\theta_m}(X_2) \cdots f_{\theta_1,\dots,\theta_m}(X_n) \qquad \dots (28)$$

where,

$f_{\theta_1,\dots,\theta_m}(X_i)$ – is the probability density function of the hypothesized distribution with parameters $\theta_1,\dots, \theta_m$ evaluated at X_i where $X_1,\dots,X_n$ is the set of observed data.

The likelihood function is the probability of obtaining the set of data X_1, ..., X_n given the parameters θ_1, ..., θ_2 and can be maximized by taking the first derivative with respect to each parameter and setting the resulting set of equations equal to zero. These equations are then solved for the parameters, denoted $\hat{\theta}_1, \dots, \hat{\theta}_m$, that make the equality true and these parameters become the maximum likelihood estimates (often abbreviated MLE) for the hypothesized distribution. In this study MATLAB's '*mle*' function is used to find the MLE's given a set of data and specified distribution type.

MATLAB's '*mle*' function will also return a confidence interval with specified confidence level 100-α if desired. This function uses the Cramér-Rao lower bound to approximate the variance of parameters estimated from the data. The Cramér-Rao lower bound is evaluated as

$$V\left[\sqrt{n}\left(\hat{\theta} - \theta\right)\right] = V\left(\sqrt{n}\hat{\theta}\right) = \frac{1}{E\left[\frac{d}{d\theta}\ln f(X,\theta)\right]^2}\,. \qquad \dots (29)$$

MLE's have the property that for large n the variance of estimated parameters approaches the Cramér-Rao lower bound [55]. For small n the Cramér-Rao lower bound is only an approximation. However, for this study the number of observations is large and therefore the error is assumed to be negligible.

Characterizing Batch Cycle Times

In this system, garments are produced and moved in batches of 100. When an operator completes one batch he/she is responsible for seeking out an available batch and moving it to his/her workstation. It is desirable to represent the activities of seeking out and processing one batch as a single event. This allows for greater computational efficiency which improves the ability to observe the long run behavior of the simulation model and optimize the system. However, characterizing the stochastic nature of the combined activities as a single event (referred hereto as "batch cycle times") is significantly more difficult than characterizing the cycle times of individual garments. Explained below are three options for characterizing the batch cycle times.

1) Derive an Equation to Describe the Batch Cycle Time Distribution

The distribution of batch cycle times can be determined analytically. If the cycle times of individual garments as well as the time it takes to seek out and move a batch are independent random variables with known probability distributions then the sum of these random variables can be determined analytically as shown below.

Define the cycle times of individual garments as random variables, $X_{1,single}, X_{2,single}, \dots, X_{100,single}$ and define the time it takes to seek out and acquire a new batch of garments as $X_{transportation}$. Then the sum of these random variables, $X_{batch} = X_{1,single} + X_{2,single} + \cdots + X_{100,single} + X_{transportation}$ can be evaluated using characteristic functions as follows.

If for $X_{1,single}$, $X_{2,single}$, …, $X_{100,single}$ the respective probability density functions are $f_{1,single}(x) = f_{2,single}(x) = \cdots = f_{100,single}(x) = f_{single}(x)$ and the transportation probability density function is $f_{transportation}(x)$, then the characteristic functions are

$$\phi_{X_{single}} = \int_{-\infty}^{\infty} e^{i\omega x} f_{single}(x)dx \qquad \dots (30)$$

$$\phi_{X_{transportation}} = \int_{-\infty}^{\infty} e^{i\omega x} f_{transportation}(x)dx\ . \qquad \dots (31)$$

And using the assumption of independence

$$\phi_{X_{batch}} = \phi_{X_{single}+X_{single}+\cdots+X_{single}+X_{transportation}} =$$
$$\phi_{X_{single}} \cdot \phi_{X_{single}} \cdots \phi_{X_{single}} \cdot \phi_{X_{transportation}} . \qquad \ldots (32)$$

Then, the distribution of batch cycle times is evaluated as

$$f_{X_{batch}}(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} e^{-i\omega x}\phi_{X_{batch}} d\omega . \qquad \ldots (33)$$

The problem with this approach is that the above equations may not be easy to evaluate and the resulting expressing is difficult to implement into the simulation model. The next two methods are more suited for use with the simulation model.

2) Apply the central limit theorem

The central limit theorem states that, under some general conditions, the sum of a set of independent random variables tends to a normal distribution. The central limit is assumed to be valid if no one random variable contributes significantly to the mean or variance and if there is a large number of independent random variables in the summation.

If the central limit theorem is applied then the batch cycle times are assumed to have a normal probability distribution,

$$X_{batch} = \frac{1}{\sigma_{batch}\sqrt{2\pi}} e^{-(x-\mu_{batch})^2/4\sigma_{batch}^2} \qquad \ldots (34)$$

with mean and variance

$$\mu_{batch} = 100 \cdot \mu_{single} + \mu_{transportation} \qquad \ldots (35)$$

$$\sigma_{batch}^2 = 100 \cdot \sigma_{single}^2 + \sigma_{transportation}^2 . \qquad \ldots (36)$$

This method is significantly easier to evaluate than the first method presented; and the results are easily implemented in the simulation model. However, this method should only be used if the assumptions supporting the central limit theorem hold, which can only be judged qualitatively.

3) Use Monte Carlo Simulation

Monte Carlo simulation is a method of analyzing a static, stochastic system (one that does not evolve over time). This method is not limited by the same assumptions as the central limit theorem. Monte Carlo simulation can also be used to determine whether the assumptions supporting the central limit theorem hold.

To apply this method to the batch cycle time problem, pseudo random numbers are selected from the specified probability distributions of individual cycle times and transportation times. Then the sum is evaluated. This process is repeated, using a new random number seed for each replication. The results do not provide a specific distribution and parameters as the previous two methods did. However, further analysis can yield distribution types and parameters. For example, the maximum likelihood method can be used to estimate parameters of a hypothesized distribution. The chi-square test can be used to verify the goodness of fit.

The combination of this method and the previous method presents a unique opportunity. Since the previous method provides a distribution type and parameter, Monte Carlo simulation can be used to verify whether or not the assumptions of the central limit hold. In this study, the central limit theorem method will be used to determine batch cycle time distribution types and parameters and Monte Carlo simulations will be used to verify or dismiss the results of this method. If the central limit theorem method does not provide acceptable results then a new distribution will be hypothesized and the maximum likelihood method used to determine the parameters of the new distribution.

3.1.2 Characterizing Equipment Failure and Repairs

As presented in chapter 1, the production line of interest utilizes several pieces of equipment in the manufacturing process. The use of equipment complicates the analysis of this production line because they contribute to variability in the system. This variability is a result of random failures and random times to repair machines. In order to model equipment in the production line random times to failure and times to repair machines need to be defined. The same method that was used to characterize cycle times from time study data was used to determine the equipment failure and repair time distribution types and parameters. Data was obtained from company records which provide time stamps of when the equipment required maintenance and when the repair was completed.

The data and method used to determine the equipment failure and repair distributions and parameters involve the following assumptions and sources of error.

- Failures and repairs are analyzed in the aggregate and thus machines and maintenance personnel are assumed to be homogeneous.
- Machines are assumed to be in one of two possible states: 1) the operating state and 2) the failure state. In reality, there may be more than two states and the machine may experience varying levels of performance degradation.
- It is assumed that the transition from a state occurs at the recorded time of failure and time of repair. However, the time of failure and time of repair are recorded by the mechanic and may include errors. These errors may be a result of: the lead time associated with the occurrence of a failure and the arrival of a mechanic; lead time associated with the time the machine was operational and the time the mechanic completed the maintenance (possibly including clean-up) and entered the data into the record; and potentially even falsification of data due to alternative motives. Furthermore, it was stated earlier that there may be varying levels of performance degradation. If this is true, then the decision of when the machine has entered the failure state and is in need of repair is a decision made by an operator which involves the use of judgment and can be a source of error and heterogeneity.
- The data available in the company records provide times <u>of</u> failure and the times <u>of</u> repair. However, the required data are the times <u>to</u> failure and times <u>to</u> repair. In order to convert the times <u>of</u> failure/repair into the times <u>to</u> failure/repair the difference between each time of failure/repair and the time of the previous failure/repair were taken. However, often times to failure/repair

are greater than one workday. Therefore, the actual operating time of machines must be assumed: the company operates on two ten hour shifts where one half hour is allotted for each shifts lunch break. Therefore, it was assumed that the machines were operating nineteen hours per day. Weekends were not considered and it is impossible to determine times when the machine may have actually been idle.

- It is possible that some minor problems with short times to repair may have not been recorded (e.g. simple mechanical adjustments).

3.1.3 Learning Curve Parameters

DeJong's formula was used to model operator learning. DeJong's formula has the advantage of including a limit upon which no further reduction in cycle time is possible. The power model has no such limit so theoretically a cycle time of zero is possible. The power model is a very popular model and still widely used. However, DeJong's model is more suited to modeling learning in a mass production environment where operators may perform many cycles.

DeJong's formula involves three independent parameters. Company data was available to estimate these parameters. However, the data may contribute to errors in the study as a result of the following.

- Operator cycle times were not available. The company records only provide the total daily production of new operators. Knowledge of daily production (instead of cycle times) has two disadvantages: 1) DeJong's formula is not directly applicable but instead requires manipulation (described later) to evaluate daily production instead of cycle time. In order to simplify the mathematics an assumption is made in the manipulation of DeJong's formula which may contribute to error in the study. And 2) since daily production is to be used the time spent producing garments needs to be determined. Operators work a 10 hour shift and are given a 0.5 hour break for lunch. Thus, it is assumed that each operator performs a 9.5 hour workday. However, there may be instances where the operator is not working. For example, if a trainer is demonstrating how the operation should be performed, if the operator has taken breaks besides the scheduled lunch break or left work early.

- Only the production of good quality pieces is available from the data. Therefore, it is possible that the performance data of new operators is deflated.
- The data was recorded in a foreign language. Mistranslation of operation descriptions was possible. However, in the cases where translations were unclear the data was omitted.
- Performance of new operators was only available for a relatively short period of learning (typically several days or less). As a result the learning model may not be as accurate for an experienced worker as for a new worker. Furthermore, the data is not suited for estimating the limit of improvement and thus one of the parameters in the learning curve model has to be estimated.

The next sections explain: 1) how DeJong's formula was manipulated so that it could be used with the data available 2) how the parameters of the formula were determined from the data 3) how one of the parameters of the formula was estimated to provide a more accurate limit of improvement and 4) how the standard deviation of cycle times were determined.

Manipulating the Learning Curve Models

In order to use DeJong's formula with the daily production data of new operators a new variable, T_{ij}, was defined. T_{ij} is defined is the time to complete i to j cycles where i and j are values of cumulative cycles completed and $i < j$. Then using DeJong's formula T_{ij} can be evaluated as

$$T_{i,j} = \sum_{n=i}^{j} t_n = \sum_{n=i}^{j} t_1[M + (1-M)n^{-b}] \approx \int_i^j t_1[M + (1-M)n^{-b}]dn$$

$$= t_1\left[M(j-i) + \frac{1-M}{1-b}(j^{1-b} - i^{1-b})\right] = f(t_1, M, b, i, j) \qquad \ldots (37)$$

where the summation has been approximated by an integral in order to simplify the mathematics (which is a common simplification [46, 27]). In this form the equation can be used with the available data since now T_{ij} corresponds to one workday (assumed to be 9.5hrs) and *j* minus *i* is the daily production for the corresponding workday.

Determining Parameters

The method of non-linear, least squares regression was used to fit the industrial data to the manipulated DeJong model. This method assumes that each observation contains a random source of error as shown below.

$$T_{i,j} = f(t_1, M, b, i, j) + \epsilon = t_1 \left[M(j-i) + \frac{1-M}{1-b}\left(j^{1-b} - i^{1-b}\right) \right] + \epsilon \qquad \ldots (38)$$

where, ϵ is a random error with zero mean and standard deviation σ_{ϵ}^2.

In order to estimate the parameters t_1, M and b the method of least squares is applied. Thus, a solution to the following nonlinear optimization problem is required

$$\min_{t_1,b} \left[\left(T_{i,j\,(observed)} - T_{i,j\,(predicted)} \right)^2 \right] \qquad \ldots (39)$$

Solving this problem using calculus proves to be very difficult. Therefore, a numerical method was employed. MATLAB's *nlinfit* function is designed to solve for the parameters that solve the above problem. This function uses the Gauss-Newton algorithm with Levenberg-Marquardt modifications for global convergence. The application of this function to solve the above problem can be found in Appendix A-2.

Estimating the Limit of Improvement

As mentioned earlier the available data could not provide a reliable estimate of the limit of improvement. As a result the coefficient of incompressibility in DeJong's formula was estimated using other means. In particular, the limit of improvement was assumed to be slightly less than the average cycle times that were observed in the time study. The operators observed in the time study were (by chance) quite experienced and thus it's possible that they will experience some further improvement but are likely approaching the limit of improvement. Thus the coefficient of incompressibility can be defined using its definition as the ratio of cycle time as experience tends to infinity to the cycle time of the first cycle, and represented algebraically as

$$M = \xi CT/t_1 \qquad \ldots (40)$$

where,

ξ – is an adjustment factor between 0 and 1,

CT – is the observed cycle time,

t_1 – is the time to produce the first piece.

Then the manipulated DeJong model becomes

$$T_{i,j} = t_1 \left[\xi S/t_1 (j - i) + \frac{1 - \frac{\xi S}{t_1}}{1 - b} (j^{1-b} - i^{1-b}) \right]$$

$$= \xi S(j - i) + \frac{t_1 - \xi S}{1-b} (j^{1-b} - i^{1-b}) \ . \qquad \ldots (41)$$

Setting the value of ξ equal to 0.85 sets the limit of improvement to slightly less than the observed cycle times. The equation can be solved for the other two parameters (t_1 and b) using the regression method presented earlier.

Standard Deviation of Cycle Times

DeJong's model is deterministic. However, in this study cycle time variability is considered. In order to transform DeJong's model into a stochastic model it was assumed that the distribution type and the coefficient of variation are constant over the entire learning curve. Thus, the following equation holds.

$$CV = \sigma_n/\mu_n = Const. \qquad \ldots (42)$$

This result was obtained by Globerson [44] for the power model and, by the same approach, can be shown to hold for DeJong's model. Using equation (15) and the information obtained from the time study the distribution and parameters over the entire (stochastic) learning curve can be determined.

3.1.4 Operator Turnover Characteristics

This study models random operator turnovers. As a result an appropriate probability distribution and distribution parameters describing durations of employment should be determined. However, limited company data regarding factory worker turnover was available. Therefore, industry reports and previous studies were used in conjunction with company data to select an appropriate distribution and parameters for operator durations of employment. It was assumed that operator turnover characteristics are homogenous (although future research may be necessary to test this assumption).

3.2 Phase 2 – Model Verification

This study models several phenomena observed in a manufacturing environment. Traditional sources of variability such as natural cycle time variability, random equipment failures and repairs have been modeled as well as relatively unexplored sources of variability associated with worker learning and random turnover. To ensure that submodels, responsible for mimicking the above mentioned phenomena and other system design changes, were functioning properly the following tests were performed.

3.2.1 Machine Failure/Repair Test

In order to test that the machine failure/repair model was functioning properly a two machine line with limited intermediate work-in-process was modeled using the software (see Appendix A-3). In the case of exponential service times, failure times and repair times an analytical solution for throughput rate can be obtained [43]. The simulation model was tested against the analytical solution. If the results agree, within error, then the machine failure/repair model is assumed to be functioning properly.

3.2.2 Learning Curve and Operator Turnover Test

DeJong's model is used to model the reduction in cycle time as a result of gained experience. When a turnover occurs the operators experience is reset to zero in order to represent a new operator replacing the one who has left. In order to verify that cycle times are reduced according to DeJong's model and experience is reset to zero when a turnover occurs a deterministic simulation model was examined (details of the model can be found in Appendix A-3). In this case the cycle times should relate to DeJong's model exactly and experience should be reset to zero at a known time. If this is true the learning and turnover models will be assumed to be functioning properly. The addition of a random component to cycle times and turnover times is not expected to affect the function of these models.

3.2.3 Floating Worker Test

Two of the system design changes require extensive modeling efforts. Implementing a floating worker in the simulation model is difficult since a control mechanism needs to be constructed to ensure that the floating worker is only assigned to a single workstation and that the proper rules are applied in assigning the floating worker. A small simulation model was constructed in order to verify that the floating worker behaves properly in simulations.

3.2.4 Cross-training Test

Cross-trained workers need to rotate through workstations. In doing this each worker gains experience at all assembly tasks. However, the experience of each worker needs to be recorded during simulations and workers should only gain experience at a task when he/she is at the respective workstation. The cross-training test was used to ensure that the methods used to model cross-training in simulations satisfy the above criteria.

3.3 Phase 3 – Numerical Experiments and Sensitivity Analysis

The numerical experiments and sensitivity analysis phase consisted of: 1) a turnover sensitivity analysis, 2) examining the effect of cancelling the practice of "borrowing workers" and 3) examining major changes to the system via an efficient design of experiments.

3.3.1 Sensitivity to Turnover Rate

Company records provided daily production capacities of five production lines (all producing the same product but differing in the number of workers assigned to workstations). A simulation model of each was developed using SimEvents (details of the simulation models can be found in Appendix A-3). Then the daily production capacity of the five lines was observed when monthly turnover rate was 0%, 2.5% and 5% and compared to the company records. This sensitivity analysis was performed for two reasons: 1) to examine the effect of monthly turnover rate on the throughput rate of the current system and 2) to obtain an indication of the accuracy of the estimated turnover rate.

3.3.2 The Effect of Cancelling the Practice of Borrowing Workers

The second experiment examined cancelling the practice of borrowing workers in the five production lines presented in the previous section. Current company practice is to dynamically balance production lines by borrowing workers from other production lines making similar products. However, cancelling this practice is of interest for two reasons: 1) it simplifies the simulation model and 2) the effect on the factory as a whole, as a result of borrowing workers, is not known. It's possible that the current policy results in greater efficiencies of one production line at the expense of others. Examining the effect of cancelling the current practice of borrowing workers from other lines will quantify the benefit of the current practice and will simplify the simulation model. If the benefit is small then it may not be worth the risk involved in disrupting the efficiency of the factory as a whole. Once cancelling the practice of borrowing workers has been examined, other changes to the system will be implemented that are known not to have a negative impact on other production lines.

3.3.3 Examining Major Design Changes

Five major changes to a production line were examined using a fractional factorial design of experiments. However, due to the time required to model and simulate experiment runs, the changes were only implemented in one of the five production lines presented previously. The five experiment factors were:

- The effect of monthly turnover rate.
- The effect of cross-training workers.
- The effect of having a floating worker that can be dynamically allocated as needed.
- The effect of automating the folding operation.
- The effect of limiting capacity for work-in-process.

The sections below explain the reason the above factors were chosen, followed by a description of the method used to examine the effect of each factor, and the performance measures used to quantify effects. Details of how each change was implemented in SimEvents can be found in Appendix A-3.

Turnover Rate

Since there was limited data available to determine and characterize monthly turnover the confidence in the values that were found from empirical data is not high. Furthermore, the effect of turnover rate is of interest to companies since it has economic impacts on the organization. In addition to the HR costs associated with turnover there is a cost of lost production presented by Globerson [46] and referenced authors. However, these early studies used a deterministic approximation and did not consider the interaction between entities of a manufacturing system. Furthermore, there has been a dearth of empirical data supporting models that have been developed. Including turnover as a factor in these experiments contributes to knowledge of the effect of turnover within a practical range of monthly turnover rates.

Cross-Training Workers

Cross-training of workers to perform multiple tasks is appealing since human resources become flexible. This can be helpful if a manufacturing company suffers from disturbances such as demand variability and employee turnover. Furthermore, previous studies have reported improvements as a result of cross training [118], [58], [70], [71], [63], [39], [15]. However, these studies assume homogeneous workers and 100% competence across all tasks. In reality, there is a trade-off between cross-training and reduced competence. A worker that is cross-trained to perform many tasks gains less experience performing each particular task than a worker specializing in only one task. This study will examine a production line where workers rotate daily to gain experience in all tasks. The hypothesis is that rotating heterogeneous workers will improve throughput if appropriate work-in-process is provided and may offset the reduction in competence that results from cross-training. To understand why rotating heterogeneous workers might improve system performance, consider the two machine line with an intermediate buffer shown in Figure 3.3 below.

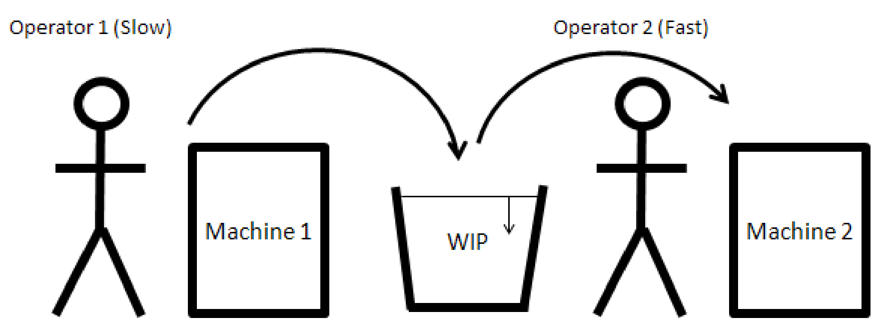

Figure 3.3*: Two machine line with a slow and fast worker.*

If there is work-in-process between the stations operator 2 will work at a faster pace than operator 1 and deplete the work-in-process. If operator 2 remains at machine 2 then after some period of time he/she will cause the buffer to empty and his/her production rate will become dependent on operator 1 (i.e. throughput is defined by the slowest station or “bottleneck”).

Now let’s assume heterogeneous workers and both operators can work at either machine. Also, each operators production rate is the same for either machine, but operator 2 is more experienced than operator 1 and thus has a higher production rate on both machines. To improve the average throughput of the line, when operator 2 empties the intermediate buffer the operators switch positions (see Figure 3.4 below).

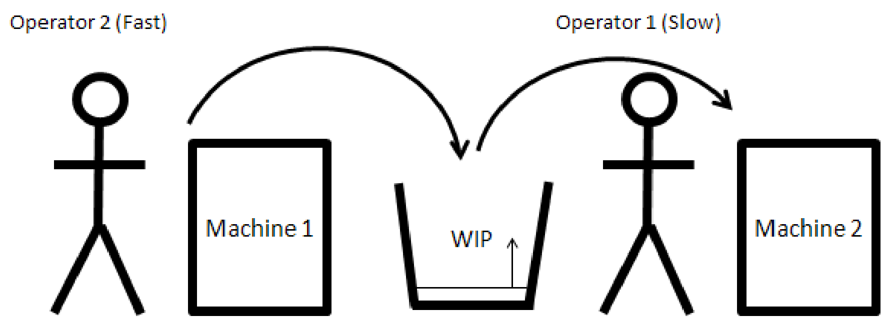

Figure 3.4*: Two machine line with fast worker upstream and slow worker downstream.*

In Figure 3.4 operator 2 (the faster of the two) is at machine 1 and the buffer fills with time. When the buffer reaches its maximum occupancy the production rate of operator 2 is again dependent on the throughput of operator 1 (the bottleneck). However, if the operators continue to rotate, and there is sufficient allowance for work-in-process, operator 2 continues to empty and fill the buffer and his/her production rate is no longer dependent on the production rate of operator 1 (see Figure 3.5). In this situation the average production rate of the line is greater than the slowest workstation!

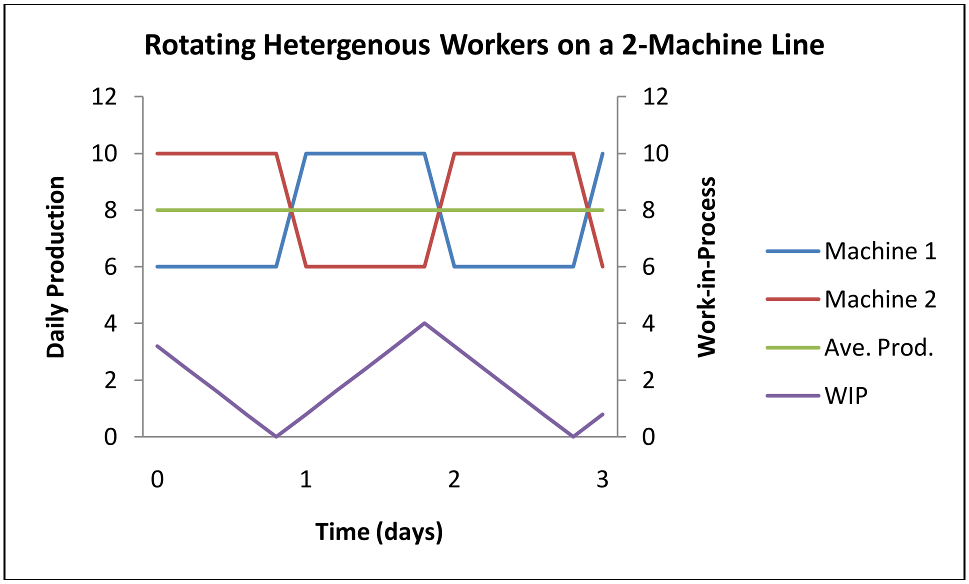

Figure 3.5*: Daily production of rotating heterogeneous workers.*

In this study cross-training of workers is examined as a method of mitigating the effects of introducing inexperienced operators into a production line as a result of random turnovers. This study differs from previous works by including the learning phenomena. As a result there is a trade-off for cross-training workers: cross-trained workers are less competent at a particular task than a worker who is specialized. Other benefits of cross-training such as increased flexibility and the potential correlation between cross-training and improved worker satisfaction and reduced turnover are not explicitly examined in this study and my warrant further investigation.

Utilizing a Floating Worker

“Floating worker” refers to an employee that is dedicated to a production line but willing to work on any task as directed. A floating worker has several potential benefits such as helping to balance the line and mitigating the effects of introducing a new worker to the production line as a result of random turnovers. Production lines in the company are difficult to balance since only an integer number of workers can be assigned to any given workstation. A floating worker can help to balance the line by spending a portion of his/her time at various workstations. Furthermore, when one workstation is performing poorly as a result of a turnover the floating worker can provide support to the workstation until the new worker gains experience.

Similar to the two machine line with cross-trained workers presented previously, it is beneficial to have an allowance for work-in-process between stations when utilizing a floating worker. The reasoning is as follows: A floating worker should increase the production rate of the slowest station to a rate greater than the second slowest station (if this is not the case the floating worker should be permanently deployed to the slowest station). Since the floating worker contributes more production capacity to the bottleneck station than needed, work-in-process should be allowed to accumulate in order to prevent blocking at the station assigned the floating worker. The floating worker will not always be needed at the bottleneck and the work-in-process that has accumulated will deplete when the floating worker is re-assigned.

Utilizing a floating worker in a production line requires some form of operational control in order to deploy the floating worker where he/she is needed most. In this study work-in-process will be used as the operational control signal. There are several reasons for choosing work-in-process as the operational control signal:

1. The accumulation of work-in-process is a known form of bottleneck identification [110].
2. Work-in-process is an observable feature. This means that supervisors can easily make decisions regarding the assignment of the floating worker. Other bottleneck identification methods (e.g. [110] and [108]) require extensive data collection and analysis that may not be practical or possible in the real system.
3. High utilization of the floating worker is desired. Placing the floating worker in a position where there is ample material upstream and available buffer capacity downstream of the floating worker will ensure that utilization of the floating worker is high.

The operational control executed in the “floating worker” simulation cases is such that the floating worker is assigned to the most upstream station with near maximum buffer occupancy upstream and less than near maximum buffer occupancy downstream of the workstation. The pseudo-code for the assignment of the floating worker to one of five workstations is shown in Figure 3.6 below.

```
if (buffer downstream of workstation 1 ≥ maximum buffer occupancy – 1)
        Floating worker assignment ← workstation 2
end

if (buffer downstream of workstation 2 ≥ maximum buffer occupancy – 1)
        Floating worker assignment ← workstation 3
end

if (buffer downstream of workstation 3 ≥ maximum buffer occupancy – 1)
        Floating worker assignment ← workstation 4
end

if (buffer downstream of workstation 4 ≥ maximum buffer occupancy – 1)
        Floating worker assignment ← workstation 5
end

if (all buffers have occupancy < maximum buffer occupancy -1)
        Floating worker assignment ← workstation 1
end
```

Figure 3.6. *Pseudo-code for assignment of worker to one of five workstations.*

The pseudo-code in Figure 3.6 illustrates how the buffer occupancies are evaluated. Buffers are evaluated in the order the most upstream buffer to the most downstream buffer – to ensure that the floating worker is assigned to the most downstream workstation with near maximum buffer occupancy upstream and less than near maximum buffer occupancy downstream of the workstation. This approach ensures that high utilization of the floating worker is achieved. A workstation is only selected if the additional capacity that the floating worker contributes will not result in an increase in blocking or starving of the workstation.

Automated Folding

The sponsoring company has expressed interest in automating the folding operation as a means of reducing human resource requirements. However, it is hypothesized that there are additional benefits to automated assembly, in addition to the reduction of human resource requirements, when learning and turnovers are considered. An automated assembly workstation will not be affected by random turnovers as much as a manual assembly workstation since the majority of the task is performed by a machine which does not have to relearn the task when a turnover occurs. In order to test this hypothesis the manual folding workstation in the simulation model was replaced with an automated workstation of equal capacity. The machine function and work design (and the resulting simulation parameters) were postulated by consulting the sponsoring company and an expert in the field of assembly automation.

Work-in-Process (WIP)

In a previous simulation study including learning and turnover Hutchison [61] claims that work-in-process has little effect on throughput and should not be examined further. However, a hypothesis of this study is that when practicing cross-training or utilizing a floating-worker, WIP is important and may have a significant effect on throughput and utilization of the production line. This study includes WIP as an experimental factor as a means of verifying or dismissing this hypothesis.

Experiment Design

A one-half fractional factorial design was chosen for the execution of experiments. The experiment factors and levels are summarized in Table 3.1 and the experiment design matrix with randomized runs is given in Table 3.2 below.

Table 3.1*: Experiment factors and levels.*

Factor		Level 1	Level 2
1	Turnover	2.5%	7.5%
2	CT	none	CT1
3	FW	none	F1
4	Auto	none	Auto
5	WIP	15	45

Table 3.2: *Experiment design matrix.*

Run	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
4	-1	-1	-1	-1	1
15	-1	-1	-1	1	-1
16	-1	-1	1	-1	-1
13	-1	-1	1	1	1
9	-1	1	-1	-1	-1
7	-1	1	-1	1	1
5	-1	1	1	-1	1
2	-1	1	1	1	-1
11	1	-1	-1	-1	-1
3	1	-1	-1	1	1
6	1	-1	1	-1	1
14	1	-1	1	1	-1
8	1	1	-1	-1	1
12	1	1	-1	1	-1
1	1	1	1	-1	-1
10	1	1	1	1	1

The one-half fractional factorial design was chosen to reduce the number of experiment runs and reduce the computation time (which was 1 hour for some experiment runs). Using this method, not all combinations of experiment factor levels are examined. It can be seen from Table 3.2 that WIP is not examined for all combinations of experiment factors. The advantage of the fractional factorial design over the full factorial design is that fewer runs are required. However, the disadvantage is some effects become confounded or aliased. This means that some effects cannot be isolated. In the 2^{5-1} experiment used in this study main effects are not aliased. However, two factor interactions are aliased with three factor interactions: if a two or three factor interaction is found to have a significant effect on the system it is not possible to tell which (the two or three factor interaction) is the true cause of the effect. Typically higher order interactions are negligible [92]. If higher order interactions are suspected to be significant a second fractional factorial experiment can be performed to eliminate confounding.

Performance Measures

The following performance measures were used to quantify factor effects: throughput rate, worker utilization, WIP and employee turnovers. A replication/deletion method was used to obtain performance measures that can be described statistically. Time plots were used to determine an appropriate warm-up period. All performance measures were evaluated using 2 years of data collected after simulations have run for a warm-up period of 2 years. A 2 year warm up period was required since simulations started with all workers having no experience. Throughout the warm-up period workers gain experience and random turnovers occur providing a distribution of workers with respect to their level of experience.

3.3.4 Economic Implications

Alluded to in the previous section, performance can be measured using a number of different metrics. However, each performance measure has different economic implications. Therefore, a profit equation was derived to examine the combined effects of performance measures on operating income. The equation is given below.

$$\text{Operating Income} = Net\ revenue - Costs\ of\ goods\ sold$$
$$-Sales\ General\ \&\ Administration \quad \ldots (43)$$

$$= Net\ revenue - (material\ costs + labor\ costs + holding\ costs$$
$$+ WIP\ allocation\ costs) - (turnover\ costs + other\ overhead\ costs) \ldots (44)$$

or,

$$I_{Op} = r_{sale} \cdot n_{sales} - c_{mat} \cdot n_{prod} - w_{worker} \cdot N_{worker} \cdot n_{hrs} - c_{hold} \cdot n_{hold} -$$
$$- c_{WIP} \cdot n_{WIP} - N_{turns}\left(c_{sep} + c_{sel} + c_{train}\right)$$
$$-c_{overhead}(w_{worker} \cdot N_{worker} \cdot n_{hrs}) \quad \ldots (45)$$

where,

I_{Op} ≡ operating income,

r_{sales} ≡ revenue per sold item,

n_{sales} ≡ number of items sold,

c_{mat} ≡ material cost per item,

n_{prod} ≡number of items produced,

w_{worker} ≡ hourly wage paid to workers,

N_{worker} ≡ number of workers employed on the production,

n_{hrs} ≡ number of hours worked per year by a single employee,

c_{hold} ≡ annual holding cost per item,

n_{hold} ≡ average number of items in the system per year,

c_{WIP} ≡ the cost of allocating space for one item of WIP,

n_{WIP} ≡ amount of space allocated for WIP (measured in units of items),

N_{turns} ≡ the number of annual turnovers,

c_{sep} ≡ separation costs of a turnover (e.g. severance, clerical work),

c_{sel} ≡ selection cost of a turnover (e.g. advertising, hiring),

c_{train} ≡ training cost per turnover (e.g. supervisors wage, scrap),

$c_{overhead}$ ≡ the allocated overhead cost per labor dollar.

If the number of items produced equals the number of items sold then,

$$\begin{aligned} I_{Op} = {} & r_{sale} \cdot TP \cdot n_{hrs} - c_{mat} \cdot TP \cdot n_{hrs} - w_{worker} \cdot N_{worker} \cdot n_{hrs} \cdot \\ & - c_{hold} \cdot n_{hold} - c_{WIP} \cdot n_{WIP} - N_{turns}\left(c_{sep} + c_{sel} + c_{train}\right) \\ & - c_{overhead}\left(w_{worker} \cdot N_{worker} \cdot n_{hrs}\right) \qquad \dots (46) \end{aligned}$$

Inaccuracies (and/or limitations) of the equation are:

- Additional turnover costs presented by Globerson [45] have not been included in the equation (namely, the cost of lost output and output recovery).These costs have not been considered because experiment simulations have modeled the learning phenomena and thus account for lost output and output recovery. However, there are situations where additional costs are incurred that simulations will not account for (e.g. if additional labour needs to be hired to increase output when a turnover occurs or if production needs to be outsourced as a result of lost production due to turnovers).

- There is an opportunity cost which has not been considered in the equation. An opportunity cost is defined as "the benefit that is forgone by engaging in a business resource in a chosen activity instead of engaging that same resource in a forgone activity" [99]. For example, money saved can be used to invest in assets (e.g. production machinery), research and development, marketing, etcetera. Similarly, space that is not allocated for WIP can be used by another resource and potentially generate additional revenue (allocation of human resources is analogous). An important opportunity is the reduction of the selling price of items providing a competitive advantage over other companies selling similar products. An opportunity cost has not been considered in the equation because, without knowledge of how money or resources will be allocated, it is difficult to formulate this term. Furthermore, opportunity costs are not reported on the income statement. However, opportunity costs are an important consideration in an economic analysis and may need to be included in a justification or business case supporting changes to a manufacturing system.

3.4 Chapter Summary

This chapter presented the methods used in the three phases of this study (i.e. data collection and analysis, model verification and numerical experiments and sensitivity analysis). Data was collected from the real system via time study and company records. The resulting data was analyzed in order to obtain input parameters to the simulation model. The simulation model was verified by testing individual components of the model to ensure that they function properly. Simulation experiments began with a sensitivity analysis examining the effect of monthly turnover rate on the daily production of five production lines. Then the effect of cancelling the practice of borrowing workers on the five production lines was examined. One of the five production lines was chosen to examine the effect of implementing five major changes to the system, namely: 1) an increase in employee turnovers, 2) implementing a cross-training policy, 3) utilizing a floating worker, 4) automating the folding operation and 5) increasing the system capacity for WIP. Performance was measured via throughput rate, system utilization, average WIP and the combined effect of performance measures were examined using an equation for operating income. The next chapter presents the results of applying these methods.

CHAPTER 4

Results and Conclusions

This chapter presents the results from the three phases of this study: 1) data collection and analysis, 2) model validation and 3) numerical experiments and sensitivity analysis. The main findings and an interpretation of results are presented. A summary of results is given in the next and final chapter.

4.1 Phase 1 Results – Data Collection and Analysis

This section presents the results of the data collection and analysis efforts which were used to determine the input parameters of the simulation model.

4.1.1 Cycle Time Distribution and Parameters

The time study data was analyzed to determine: 1) if fatigue was a factor that affects operator performance, 2) the distribution type and parameters of processing a single work piece and 3) the distribution type and parameters of batch cycle times (which includes processing one hundred work pieces and seeking out a new batch for processing).

Determining if Fatigue is a Factor

The results of this study (given below) suggest that fatigue is not a factor in any of the operations. 20 ANOVA tests were performed. The times when samples were observed were the "treatments" in the ANOVA tests. Of the 20 ANOVA tests performed only 4 tests failed to accept the null hypothesis at a 95% confidence level as shown in Table 4.1 below.

Table 4.1: *Results of ANOVA tests.*

Operation\Operator	1	2	3	4
Seaming sleeves	Accept H0	Reject H0	Reject H0	Accept H0
Sewing cuffs	Accept H0	Accept H0	Accept H0	Accept H0
Staking belt	Accept H0	Accept H0	Accept H0	Accept H0
Sewing neck tie	Accept H0	Reject H0	Accept H0	Accept H0
Folding	Accept H0	Accept H0	Reject H0	Accept H0

Since the majority of the ANOVA tests accepted the null hypothesis, the evidence suggests that the cycle time means are stationary throughout the day and fatigue is not a factor. However, to further examine the data that rejected the null hypothesis (see seaming sleeves operator 2, seaming sleeves operator 3, sewing neck tie operator 2 and folding operator 2 in table 4.1 above) a series of comparative t-tests were performed. The results are given in Tables 4.2, 4.3, 4.4 and 4.5 below.

Table 4.2: *Seaming sleeves, operator 2 comparative t-tests.*

Samples		Lower	Difference	Upper	Significant?
10:00	11:00	3.3	9.0	14.7	yes
10:00	13:00	-0.3	5.4	11.1	no
10:00	14:00	4.5	10.2	15.9	yes
10:00	15:00	4.0	9.7	15.4	yes
10:00	16:00	1.3	7.0	12.7	yes
11:00	13:00	-9.3	-3.6	2.1	no
11:00	14:00	-4.5	1.2	6.9	no
11:00	15:00	-5.0	0.7	6.4	no
11:00	16:00	-7.7	-2.0	3.7	no
13:00	14:00	-0.9	4.8	10.5	no
13:00	15:00	-1.4	4.3	10.0	no
13:00	16:00	-4.1	1.6	7.3	no
14:00	15:00	-6.2	-0.5	5.2	no
14:00	16:00	-8.9	-3.2	2.5	no
15:00	16:00	-8.4	-2.7	3.0	no

***Table 4.3**: Seaming sleeves, operator 3 comparative t-tests.*

Samples		Lower	Difference	Upper	Significant?
9:00	10:00	-1.6	0.3	2.1	no
9:00	11:00	-1.6	0.4	2.3	no
9:00	12:00	-3.7	-1.8	0.2	no
9:00	13:00	-1.8	0.1	2.1	no
9:00	14:00	-2.1	-0.3	1.5	no
9:00	15:00	-2.8	-0.9	1.1	no
9:00	16:00	-3.1	-1.2	0.7	no
10:00	11:00	-1.8	0.1	2.0	no
10:00	12:00	-3.9	-2.0	-0.1	yes
10:00	13:00	-2.0	-0.1	1.8	no
10:00	14:00	-2.3	-0.5	1.2	no
10:00	15:00	-3.0	-1.1	0.8	no
10:00	16:00	-3.3	-1.5	0.4	no
11:00	12:00	-4.1	-2.1	-0.1	yes
11:00	13:00	-2.2	-0.2	1.8	no
11:00	14:00	-2.5	-0.6	1.2	no
11:00	15:00	-3.2	-1.2	0.8	no
11:00	16:00	-3.5	-1.6	0.4	no
12:00	13:00	-0.1	1.9	3.9	no
12:00	14:00	-0.4	1.5	3.3	no
12:00	15:00	-1.1	0.9	2.9	no
12:00	16:00	-1.4	0.6	2.5	no
13:00	14:00	-2.3	-0.4	1.5	no
13:00	15:00	-3.0	-1.0	1.0	no
13:00	16:00	-3.3	-1.3	0.6	no
14:00	15:00	-2.5	-0.6	1.3	no
14:00	16:00	-2.8	-0.9	1.0	no
15:00	16:00	-2.3	-0.3	1.6	no

***Table 4.4**: Sewing neck tie, operator 2 comparative t-tests.*

Samples		Lower	Difference	Upper	Significant?
10:00	11:00	-3.3	4.1	11.6	no
10:00	12:00	6.3	14.3	22.4	yes
11:00	12:00	2.3	10.2	18.1	yes

***Table 4.5**: Folding, operator 3 comparative t-tests.*

Samples		Lower	Difference	Upper	Significant?
9:00	10:00	-9.4	-1.7	5.9	no
9:00	12:00	-11.2	-3.3	4.5	no
9:00	13:00	-6.4	1.4	9.3	no
9:00	14:00	-4.0	3.9	11.8	no
9:00	15:00	-3.2	4.7	12.5	no
9:00	16:00	-4.7	3.4	11.5	no
10:00	12:00	-9.3	-1.6	6.1	no
10:00	13:00	-4.5	3.2	10.9	no
10:00	14:00	-2.1	5.6	13.3	no
10:00	15:00	-1.3	6.4	14.1	no
10:00	16:00	-2.8	5.2	13.1	no
12:00	13:00	-3.1	4.8	12.7	no
12:00	14:00	-0.7	7.2	15.1	no
12:00	15:00	0.1	8.0	15.9	yes
12:00	16:00	-1.4	6.8	14.9	no
13:00	14:00	-5.4	2.4	10.3	no
13:00	15:00	-4.7	3.2	11.1	no
13:00	16:00	-6.1	2.0	10.1	no
14:00	15:00	-7.1	0.8	8.7	no
14:00	16:00	-8.6	-0.5	7.6	no
15:00	16:00	-9.4	-1.3	6.9	no

The difference in Tables 4.2, 4.3, 4.4 and 4.5 are calculated as column 1's mean minus column 2's mean and given in column 4. A negative difference supports the hypothesis that fatigue is a factor (since we expect fatigue to increase mean cycle times as the day progresses). In order to obtain statistical evidence of the hypothesis a 95% confidence interval was used to determine if the observed differences were statistically significant.

The cases that support the hypothesis that fatigue is a factor have been printed in red in Tables 4.2, 4.3, 4.4 and 4.5. It can be seen that only two instances support the fatigue hypothesis (both appear in table 4.3). Therefore, there is little evidence to support this hypothesis, and so results of this study indicate that fatigue is not a significant factor affecting the behavior and performance of the production line of interest. Thus, a fatigue model was not included in simulations.

Characterizing Cycle Time Distributions

The time study data collected was used to characterize cycle time distributions. A box plot of cycle time data obtained from the time study is shown in Figure 4.1 below. The boxes in Figure 4.1 display the median (red line). The lower and upper ends of boxes are the 25th and 75th percentiles. The operators observed in the time study were selected randomly. By chance, the operators were relatively experienced having, on average, 20 months of experience and no operator observed having less than 8 months of experience. This data was used to characterize cycle time distributions by identifying a distribution type and its parameters that closely approximate the observed cycle time distribution. Figure 4.2 below illustrates how histograms of the data were used to identify potential distribution types using the seaming sleeves operation as an example. The figure also has the three best fitting distributions superimposed on the data set.

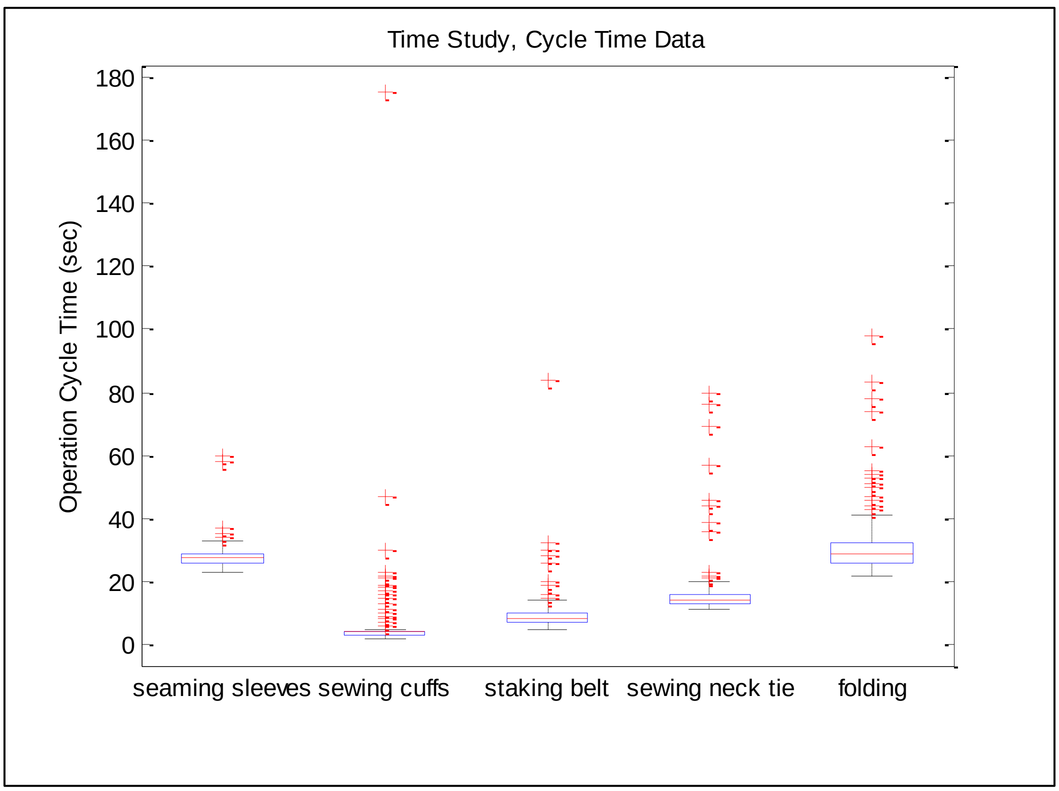

Figure 4.1*: Box plot of times study data.*

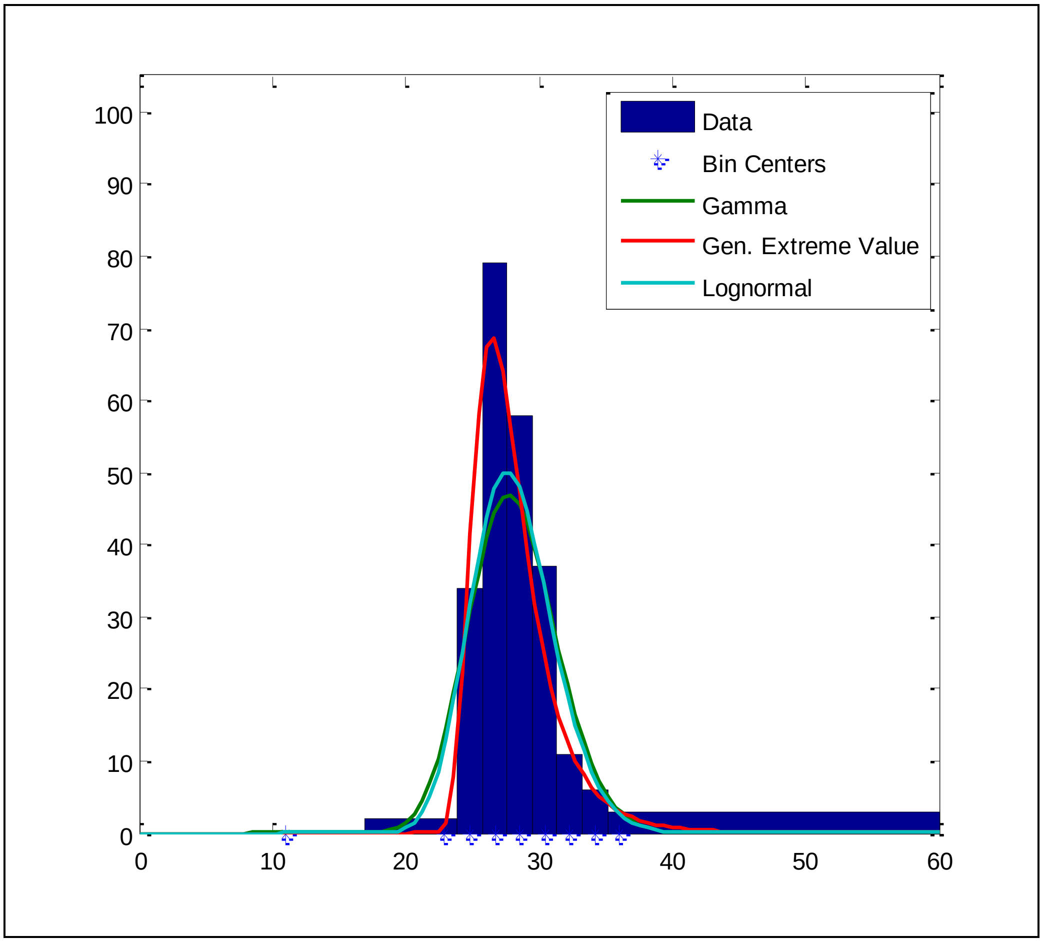

Figure 4.2*: Histogram and distribution of time study data for the seaming sleeves operation.*

The results of distribution fitting are summarized in Table 4.6 below and the resulting probability density functions shown in Figure 4.3. Cycle times were positively skewed for all operations as a result of minor delays and mechanical issues. Of the distributions tested the generalized extreme value (GEV) distribution was found to best fit the data for all distributions. The lognormal and gamma distributions were in the top three best fitting distributions (for all operations); but the fit of the lognormal and gamma distributions was poorer than the fit of the generalized extreme value.

Table 4.6*: Results of fitting cycle time data to probability distributions.*

Operation	MLEs for the GEV Distribution k	σ	μ	Mean (sec)	Variance (sec^2)	Sample Mean (sec)	Sample Variance (sec^2)
Seaming sleeves	0.11	2.06	26.66	28.10	9.79	28.11	14.29
Sewing cuffs	0.28	1.06	3.35	4.36	5.83	4.78	71.18
Staking belt	0.25	1.67	7.32	8.83	12.08	8.98	30.20
Sewing neck tie	0.38	2.14	13.54	16.05	53.83	16.51	85.45
Folding	0.28	3.87	27.35	31.05	77.69	31.23	93.90

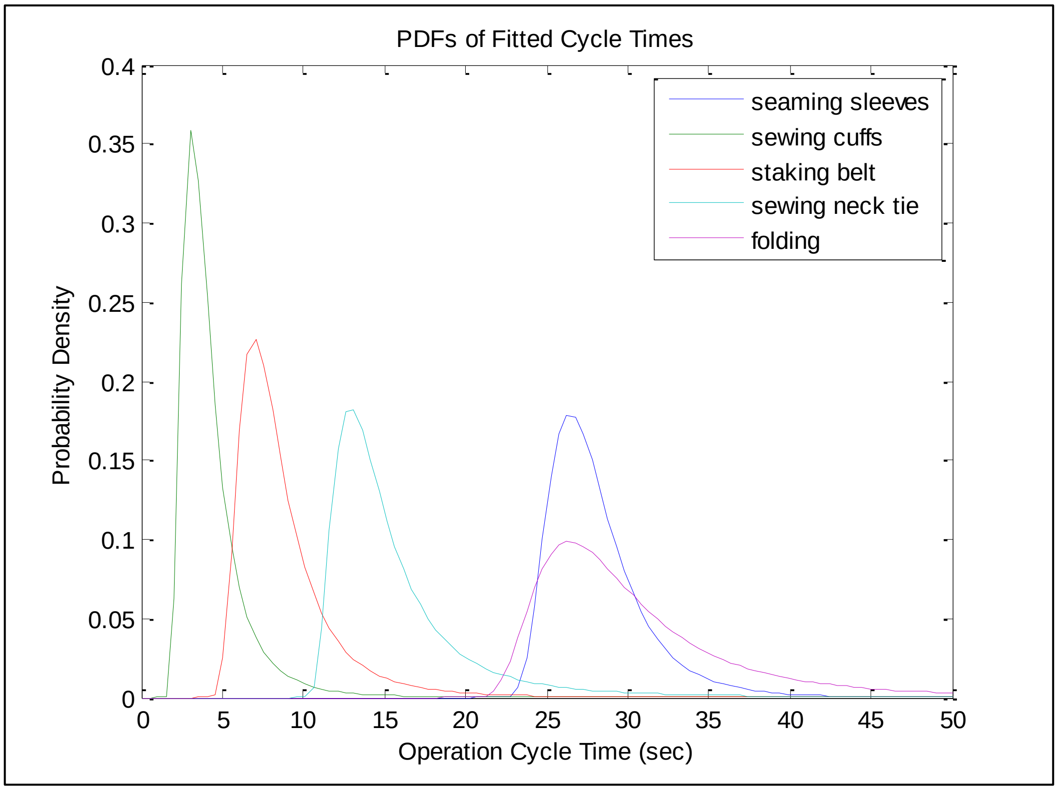

Figure 4.3*: Cycle time distributions for processing a single work piece.*

In Table 4.6 above it can be seen that the GEV distribution approximates the mean and variance of the data well. Chi-square tests failed to reject the hypothesized distributions at a 95% confidence level for all operations except the "sewing cuffs" operation for which no distribution was accepted at this confidence level. The reason it was difficult to fit a distribution to the sewing cuffs operation is due to the large positive skewness of cycle times. Usually the cycle time of the sewing cuffs operation is relatively short. However, at times the operator would experience long delays relative to most frequently observed cycle time. The cause was usually a broken thread that the operator was responsible for fixing which could take up to 175 seconds to repair. As a result it was very difficult to achieve an exact fit to the data. However, even thought the sewing cuffs distribution was not accepted at a 95% confidence level this is not expected to introduce significant errors in the experiments since the distribution approximately captures the behavior of the true operation (as shown in Figure 4.4 below).

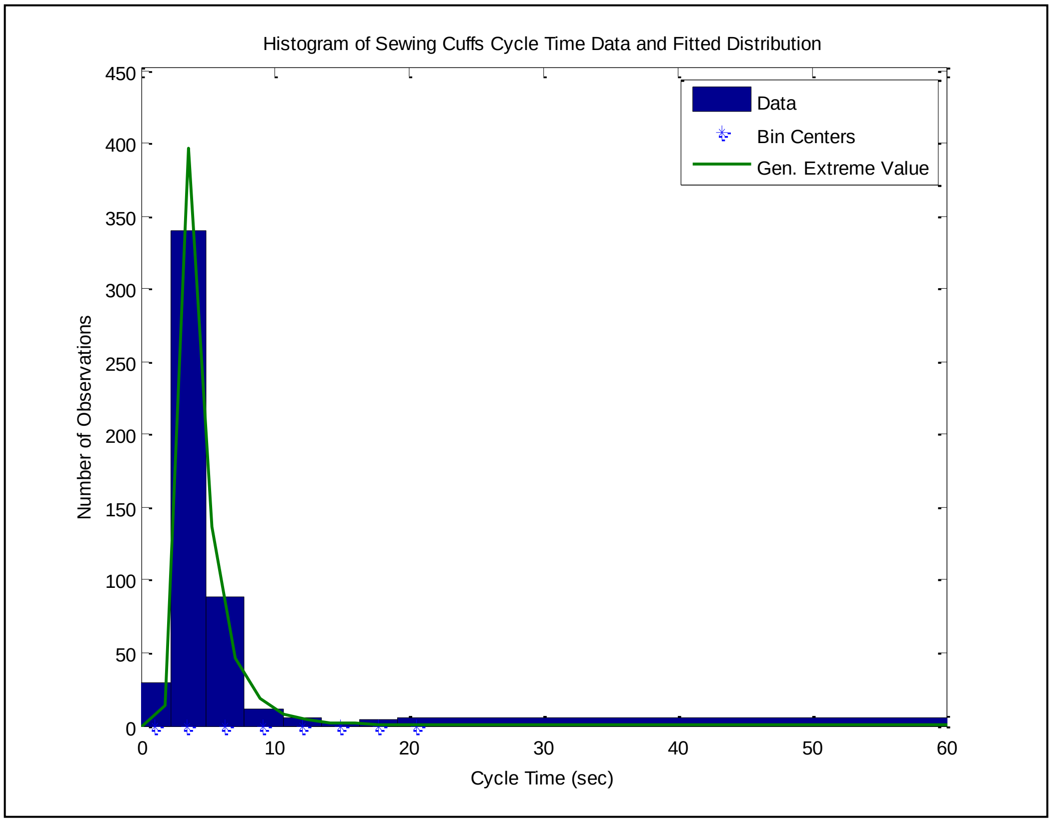

Figure 4.4: *Histogram of sewing cuffs cycle time data and fitted distribution.*

As mentioned previously, the results obtained characterize the cycle time for processing a single work piece. The next step is to characterize the activities of processing 100 pieces and seeking out a new batch for processing in a single event that will serve as an input into the simulation model.

Characterizing Batch Cycle Times

Batch cycle times consist of the time to process 100 work pieces and to seek a new batch for processing (referred hereto as transportation time). Limited data was available to estimate the transportation time distribution type and parameters.

Therefore, transportation times were assumed to be normally distributed. The eleven observations of transportation time yielded an average and standard deviation of 74.2 and 42.5 seconds respectively. The transportation time and the cycle time results were used to determine batch cycle times. The method presented in chapter 3 (utilizing the central limit theorem) was used to determine parameters of the batch cycle times. And although it is suspected that batch cycle times are normally distributed, Monte Carlo simulations were used to verify or dismiss this assumption. One thousand batch cycle times were generated using Monte Carlo simulation and the histograms of the results were created. Chi-square tests, using 95% confidence level, were used to accept or reject the hypothesis that the data was from a normally distributed population with parameters calculated using the equations 26 and 27 presented in the central limit theorem section in chapter 3. The distribution parameters and results of the chi-square tests are given in Table 4.7 below.

Table 4.7*: Normal distribution parameters of batch cycle times and chi-square tests results.*

Operation	Batch Cycle Time			Reject H_0?
	Mean (hrs)	St. Dev. (hrs)	Variance (hrs^2)	
Seaming sleeves	0.803	0.017	2.98E-04	No
Sewing elastic cuffs	0.143	0.009	8.48E-05	No
Staking belt	0.267	0.013	1.68E-04	No
Sewing neck tie	0.468	0.023	5.45E-04	Yes
Folding	0.884	0.029	8.45E-04	Yes

From Table 4.7 above it can be seen that the chi-square test did not accept the hypothesis that batch cycle times are normally distributed for the for the sewing neck tie and folding operations. Therefore, it’s possible that the sewing neck tie and folding batch cycle times are not normally distributed. This may be due to the large positive skewness of times to process individual work pieces or the large contribution to the batch cycle time mean and variance from the transportation time.

Since the assumption of normally distributed batch cycle times for the sewing neck tie and folding operations may contribute to errors in the study, data from the

Monte Carlo simulations was used to test whether or not another distribution would better fit the data. Several distributions were tested and the lognormal distribution resulted in the best fit for both the sewing neck tie and folding batch cycle times (neither of which were rejected at a 95% confidence level). The distribution types and parameters used in the simulation model are given in Table 4.8 below. These distributions are plotted in Figure 4.5.

***Table 4.8**: Batch cycle time distributions and parameters.*

Operation	Distribution	Parameters		Mean (hrs)	Variance (hrs2)
		μ	σ		
Seaming sleeves	Normal	0.803	0.017	0.803	2.98E-04
Sewing elastic cuffs	Normal	0.143	0.009	0.143	8.47E-05
Staking belt	Normal	0.267	0.013	0.267	1.67E-04
Sewing neck tie	Lognormal	-0.764	0.052	0.467	5.84E-04
Folding	Lognormal	-0.122	0.032	0.886	8.03E-04

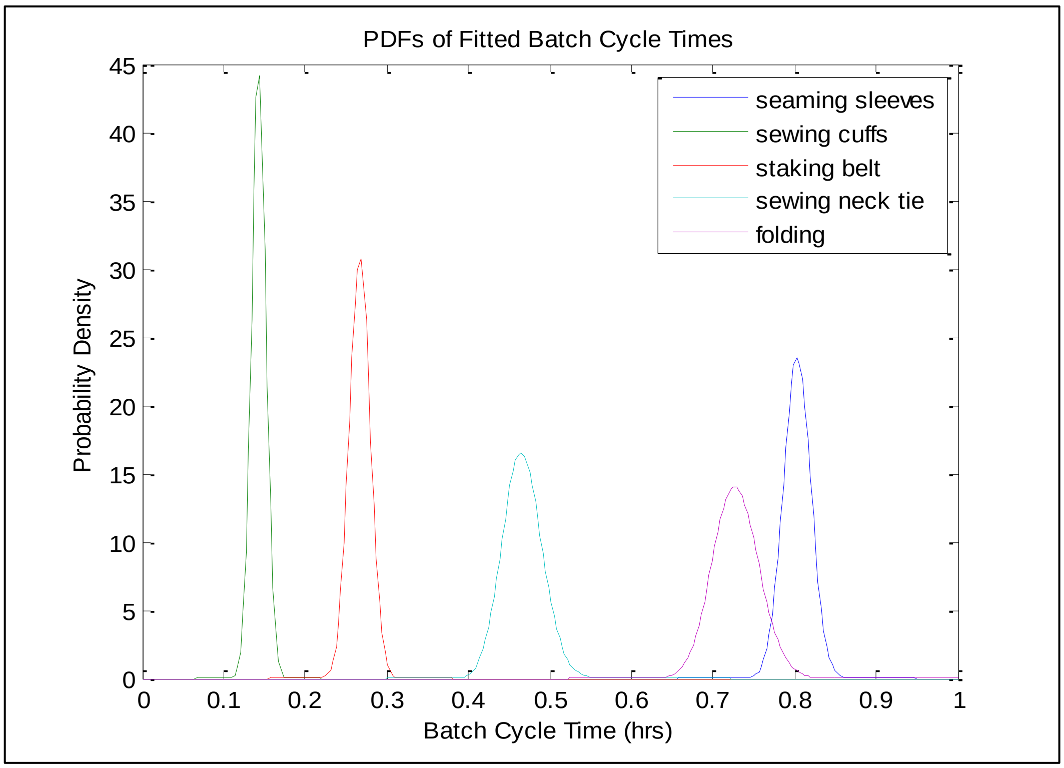

***Figure 4.5**: Batch cycle time probability distributions.*

The results of this section are quite significant. In this study times to process individual work pieces included minor mechanical and quality issues that are the responsibility of the operator. As a result cycle time distributions are positively skewed and have a relatively high variance. The average coefficient of variability of 0.36 is certainly higher than that suggested by Muth (1973). However, this value is still much less than unity. This result suggests that methods of analyzing production lines that assume exponential service time distributions are not applicable. Batch cycle times on the other hand, were all approximately normally distributed with an average coefficient of variance of 0.04. Even though the lognormal distribution provided a better fit to the batch cycle times for the sewing neck tie and folding operations – from Figure 4.5 it can be seen that there is very little skewness to the distributions. Therefore the assumption a normally distributed batch cycle times is appropriate. Using batch cycle times simplifies the simulation model and provides a familiar distribution as an input to the model. Furthermore, these results suggest that batch cycle time variability may not contribute significantly to the variability of the production line. Future research is warranted to examine ignoring this source of variability all together.

4.1.2 Equipment Failure and Repair Times

Company data was used to characterize equipment times to failure (TTF) and times to repair (TTR). Although, company records only provided times of failure and times of repair, under the assumption that machines are operational 19 hours per day, it was possible to transform the data into times to failure and times to repair. The number of observations available to characterize TTFs and TTRs are given in Table 4.9 below. From Table 4.9 it can be seen that there was a large number of observations available to characterize TTFs and TTRs.

Table 4.9*: Number of observations available to characterized equipment times to failure and times to repair.*

Machine	No. of TTF observations	No. of TTR observations
Ultrasonic seaming machine	339	429
Overlocking sewing machine	473	520
Ultrasonic staking machine	65	121
Sewing machine	326	372

The distributions that best fit the maintenance data are shown in Tables 4.10 and 4.11 respectively. The probability density functions of times to repair and times to failure are plotted in Figure 4.6 and 4.7.

Table 4.10*: Equipment time to failure distributions.*

Machine Type	Best Fitting Distribution	Distribution mean (hrs)	Distribution variance (hrs2)	Sample mean (hrs)	Sample variance (hrs2)
Ultrasonic seaming machine	Weibull	360	260,443	362	242,948
Overlocking sewing machine	Weibull	216	106,842	220	110,437
Ultrasonic staking machine	Exponential	256	65,782	256	115,556
Sewing machine	Weibull	291	241,697	293	216,742

Table 4.11*: Equipment time to repair distributions.*

Machine Type	Best Fitting Distribution	Distribution mean (hrs)	Distribution variance (hrs2)	Sample mean (hrs)	Sample variance (hrs2)
Ultrasonic seaming machine	Logn	0.604	0.267	0.622	0.439
Overlocking sewing machine	Logn	0.525	0.151	0.542	0.288
Ultrasonic staking machine	Rayl	0.307	0.026	0.304	0.028
Sewing machine	GEV	0.450	0.095	0.458	0.217

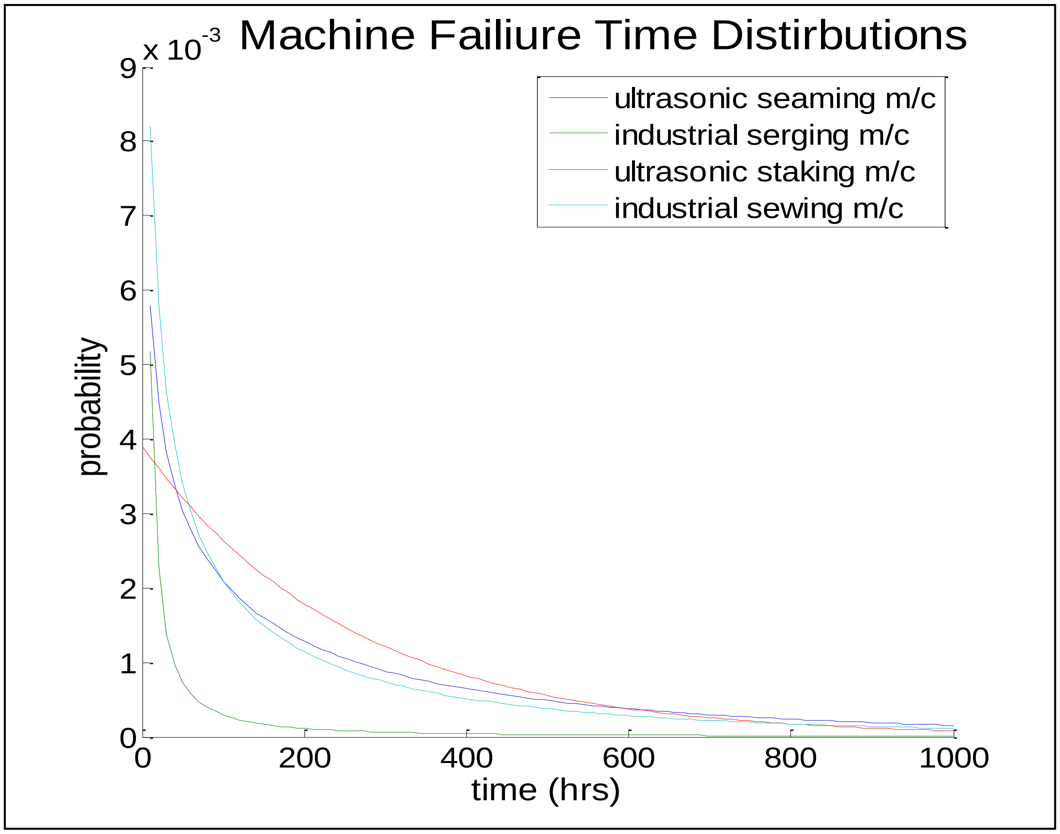

Figure 4.6*: Probability density functions for equipment times to failure.*

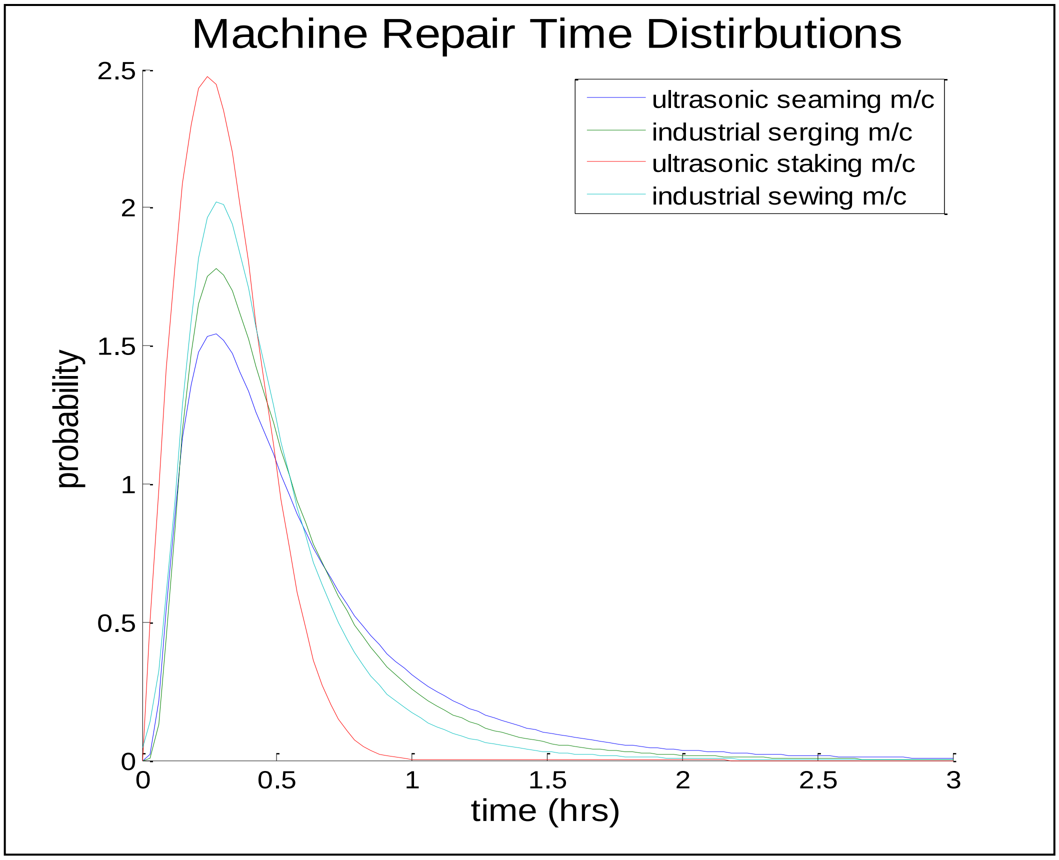

***Figure 4.7**: Probability density functions of equipment times to repair.*

Of the times to repair and times to failure, and of all machines, only the time to repair the overlocking (or serging) sewing machine could not be fit at a 95% confidence level to any of the distributions tested. This is not expected to introduce significant errors into the model since: 1) the distribution approximately captures the behavior of the machine and 2) machine availability is high (see Table 4.11 below). In fact, it is suspected that due to the high availability of equipment the exponential distribution may even be suitable to represent times to failure and times to repair for all machines. The exponential distribution is convenient since it is a single parameter distribution and allows for the application many analytical methods. However, this study will use the best fitting distributions since they are available and will minimize the error of this study.

Table 4.12*: Equipment availabilities.*

Machine Type	Availability (%)
Ultrasonic seaming machine	99.83%
Overlocking sewing machine	99.75%
Ultrasonic staking machine	99.88%
Sewing machine	99.84%

The results in Table 4.12 above seem to suggest that ignoring equipment failures may not introduce significant errors in the model. In fact, several simulation studies of apparel production systems do just this [120, 13, 36] and [37] (although no justification is provided). This study did not examine whether or not equipment failures could be ignored. However, there are certain cases where, even if machine availability is high, equipment failures/repairs can have a significant effect on throughput rate. One case is in a long serial line with limited or no capacity for WIP between workstations. In this case production is easily disrupted by a machine failure and the effects are cumulative as the length of the line increases. Another case is known as the repair crew interference problem (see [116] and [78]) and occurs when there are limited maintenance resources resulting in queuing of downed machines. This is not expected to be a problem in this study since: 1) The production line in this study is not long and 2) in the case of 16 machines having exponential times to failure with an average of 99.5hrs and exponential times to repair with an average of 0.5hrs and only a single mechanic on duty there is only a 0.6% chance of queueing (solution method available in Appendix A-4). Thus, there is a very small probability that downed machines will have to wait for service.

Machine failures/repairs are included in the model since the data was available and it improves the accuracy of the model. It is left for future work to determine whether or not this source of variability can be ignored or included in the cycle time variability.

4.1.3 Learning Curve Parameters

Company training records were used to determine the learning curve parameters. The training records contained the daily output of new operators. The number of operators for which there was training data is show in Table 4.13 below. Also shown in Table 4.13 is the average number of days that the daily output of new operators was recorded.

Table 4.13*: Number of new operators and average number of days output was recorded in the company's training records.*

Operation	Number of operators in the training record	Average No. of days output was recorded
Seaming Sleeves	41	8
Sewing Cuffs	3	8
Spot Welding Belt	3	5
Sewing Neck Tie	4	11
Folding	10	9

As mentioned previously, one of the limitations of the data was that the daily output was not recorded long enough to determine the incompressibility factor in DeJong's equation. Thus, the incompressibility factor was estimated using time study data and nonlinear regression was used to determine the other learning curve parameters. The incompressibility factor was selected in such a way that the limit of improvement was slightly less than the observed cycle times (since the operators observed in the time study were relatively experienced). It was assumed that the limit of improvement was 85% of the observed average batch cycle times. With the limit of improvement known the other two learning parameters in equation 29 (namely the time to complete the first piece, t_1, and the learning factor, b) could be determined. The effect of increasing or decreasing the limit of incompressibility was also examined and the results are given in Table 4.14 below.

__Table 4.14__: Learning curve parameters t_1 and b when the limit of improvement is varied.

Operation	$\xi = 1$		$\xi = 0.85$		$\xi = 0.7$	
	t1	b	t1	b	t1	b
Seaming Sleeves	4.58	0.37	4.60	0.35	4.62	0.34
Sewing Cuffs	2.42	0.42	2.40	0.41	2.37	0.39
Spot Welding Belt	2.19	0.32	2.19	0.31	2.20	0.30
Sewing Neck Tie	3.19	0.43	3.19	0.41	3.19	0.39
Folding	4.27	0.37	4.28	0.34	4.29	0.32

From Table 4.14 above it can be seen that the learning curve parameters t_1 and b are relatively insensitive to a change in the limit of incompressibility. A 30% change in the limit of incompressibility only resulted in a 2.1% and 12.5% change in the learning curve parameters t_1 and b respectively. As a result, if the true limit of incompressibility is not equal to the assumed value, it will not contribute significantly to errors in the model. Further evidence that the limit of incompressibility is in the vicinity of the true value is provided by Dar-El [27]. Dar-El suggests that there is relationship between the time to produce the first piece divided by the standard and the learning rate. Using his relationship the limit of incompressibility can be found using the observed learning rates. The results are shown in Table 4.15 below and are comparable to the limits of compressibility found assuming a limit of improvement slightly less than the observed cycle times.

__Table 4.15__: Limits of incompressibility found using the method in this study and Dar-El's method.

	M assuming $\xi = 0.85$	M found using Dar-El's method
Seaming Sleeves	0.15	0.11
Sewing Cuffs	0.05	0.09
Spot Welding Belt	0.10	0.13
Sewing Neck Tie	0.12	0.09
Folding	0.18	0.12

The learning curve parameters used in this study are given in Table 4.16 below where the standard deviation of the first cycle, σ_{t1}, was determined using batch cycle time means and standard deviations in equation (42).

***Table 4.16**: learning curve parameters.*

Operation	t1	σ_{t1}	M	b
Seaming sleeves	4.60	0.10	0.15	0.35
Sewing elastic cuffs	2.40	0.15	0.05	0.41
Staking belt	2.19	0.11	0.10	0.31
Sewing neck tie	3.19	0.17	0.12	0.41
Folding	4.28	0.17	0.18	0.34

The relatively low values of M (the incompressibility factor) suggest that workers on the production line experience a great deal of learning. However, the relatively high values of b (the learning factor) suggest that learning is rapid. This result has three implications: 1) the learning process is more cognitive than motor [27]. Thus training effort may benefit from emphasizing technique rather than speed. 2) Equipment used in the assembly operations do not appear to be a significant limiting factor with regards to cycle time. This may be due to the fact that machines used have an adjustable speed (sewing, seaming and serging machines) or a short cycle time (staking machine). Consequently, replacing or upgrading equipment may not yield improvements in cycle time unless the work design is improved (although replacing equipment may affect product quality, which is not examined in this study). 3) New operators are expected to perform poorly when they are first introduced into the production line but quickly become proficient at an assembly task. This suggests that efforts need to focus on assisting new operators but durations of assistance need not be long. A plot of the new employee cycle times for 1000 cycles is given in Figure 4.8 below.

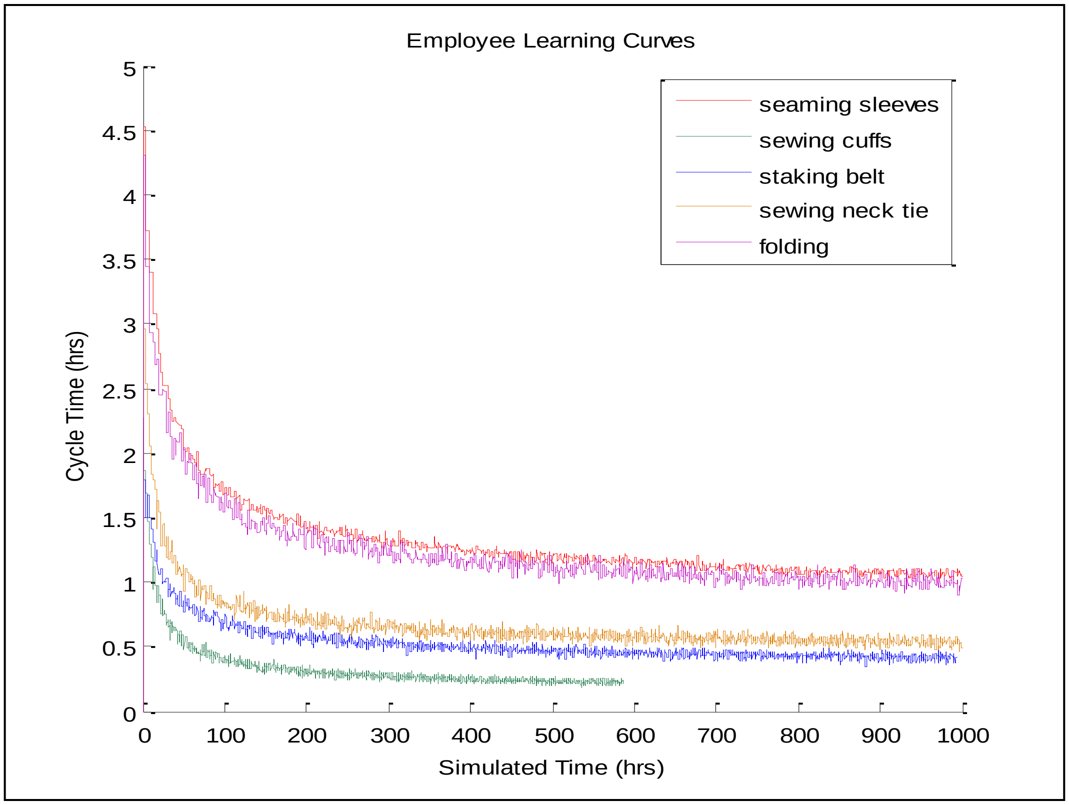

***Figure 4.8**: Employee Learning Curves.*

Figure 4.8 illustrates the decrease in cycle time that results from experience and the natural variability of cycle times (i.e. random fluctuations about the expected value). It can be seen that the learning phenomenon has a much greater influence on cycle time than natural cycle time variability.

4.1.4 Operator Turnovers

The behavior of operator turnovers was defined using a combination of company data, industry reports and scholarly articles. One month of company data suggested that the monthly turnover rate of factory workers is 5%. The data also, provided some information regarding the distribution of times until turnover. Fitting several distributions to the data gave the results shown in Table 4.17 below which have been plotted in Figure 4.9.

Table 4.17: Potential distributions of operator monthly turnovers.

	Parameter 1	Parameter 2	Mean	Standard Deviation	Monthly Turnover Rate
Exp ($\mu = 1/\lambda$)	354	—	354	354	7%
Lognormal (μ, σ)	5.79	0.772	439	396	6%
Weibull (β, α)	386	1.24	360	292	9%

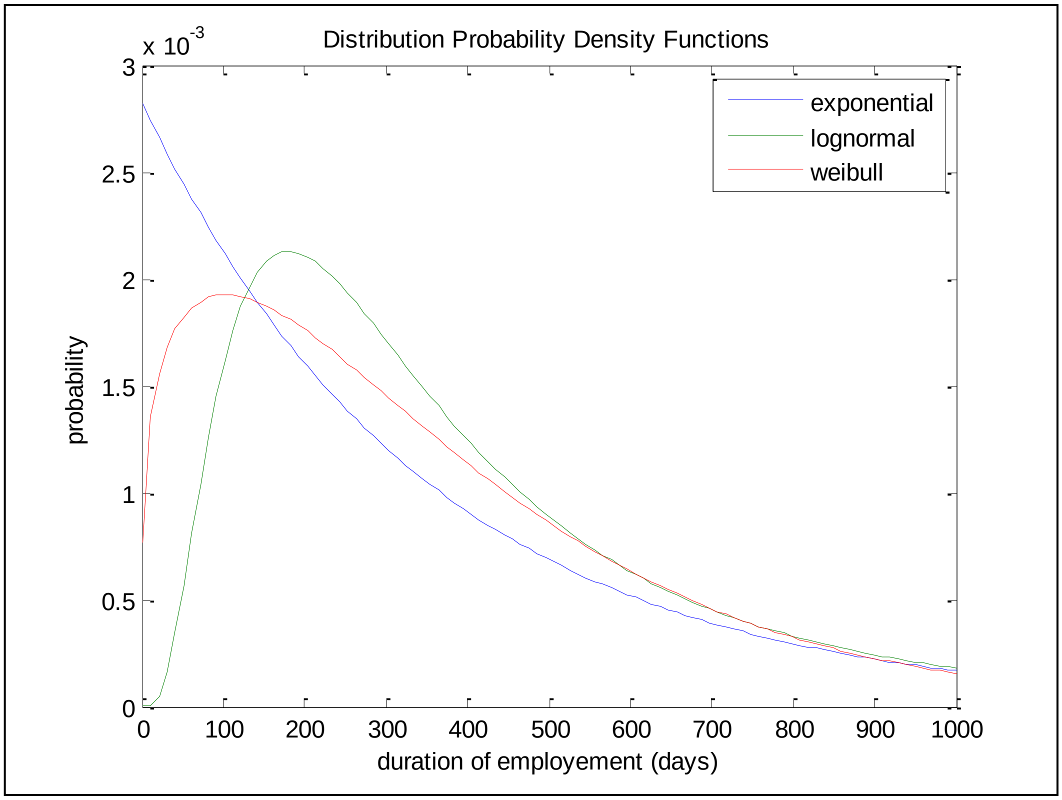

***Figure 4.9**: Distribution probability density functions.*

From Figure 4.9 it can be seen that all of the resulting probability distributions are positively skewed, which has been reported in other literature involving random turnovers [61]. Since the exponential distribution approximately represents the distribution of turnovers and is a single parameter distribution it will be used in the simulation study. However, the value of monthly turnover rate is still not known with confidence. Unfortunately, there was not enough company data to provide high confidence. Therefore, other sources were used to examine what values of turnover rate can be expected. The Hudson Report (China) [4], for example, suggests that the majority of companies in the manufacturing sector experience a monthly turnover rate of less than 5%, some experience a turnover rate of 6-10% and few experience a turnover rate >10%. The 2010 American Business in China White Paper [3] suggests that American firms in China have consistently experienced a monthly turnover rate of > 10% since 2001 (which is the earliest year the paper reports turnover rates). By comparison, the average monthly turnover rate in the US has been approximately 3% since 2001 [1]. In this study it will be assumed that monthly turnover rate at the factory is in the range of 2.5% to 7.5%. Sensitivity analysis will be used to support this hypothesis.

It is possible that the assumed monthly turnover rate is a source of error in the study. Future work should include a more accurate estimate of monthly turnover rate at the company. Furthermore, this study assumes that operators are homogeneous with respect to their turnover behavior (i.e. turnover distribution type and parameters are the same for all operators). It is possible that different product lines and workstations within production lines experience a variety of turnover rates and distributions. It is also possible that this behavior is not constant throughout the year. Future studies may want to formulate a dynamic, heterogeneous turnover model. However, in this study there was not enough empirical data to support a model development effort of this nature.

4.2 Phase 2 Results – Model Verification

Presented in chapter 3 were the methods used to verify that the components of the model behave properly. Results of the verification tests are given below.

4.2.1 Machine Failure/Repair Test

Many of the servers in the production line of interest involve the use of equipment. The equipment has been modeled in SimEvents as shown in Figure 4.10 below (details of the model can be found in Appendix A-3). The objective of this model is to identify the possible states of equipment (in this case up and operational or down and not available for use as shown in the Stateflow chart) and the random transition between states that can occur as a result of reliability issues inherent in all mechanical (or electro-mechanical) systems. In the model below machines can transition between states by either the occurrence of a failure or the subsequent completion of repair work. The times until failures are random variables. When a failure has occurred the generation of a new time until failure is deferred until the completion of the repair work. Similarly, the repair times are random variables. This model assumes an infinite repair crew and ignores repair crew interference. However, as mentioned earlier, this is not expected to be a significant source of error since there is only a 0.6% chance of queueing of downed machines.

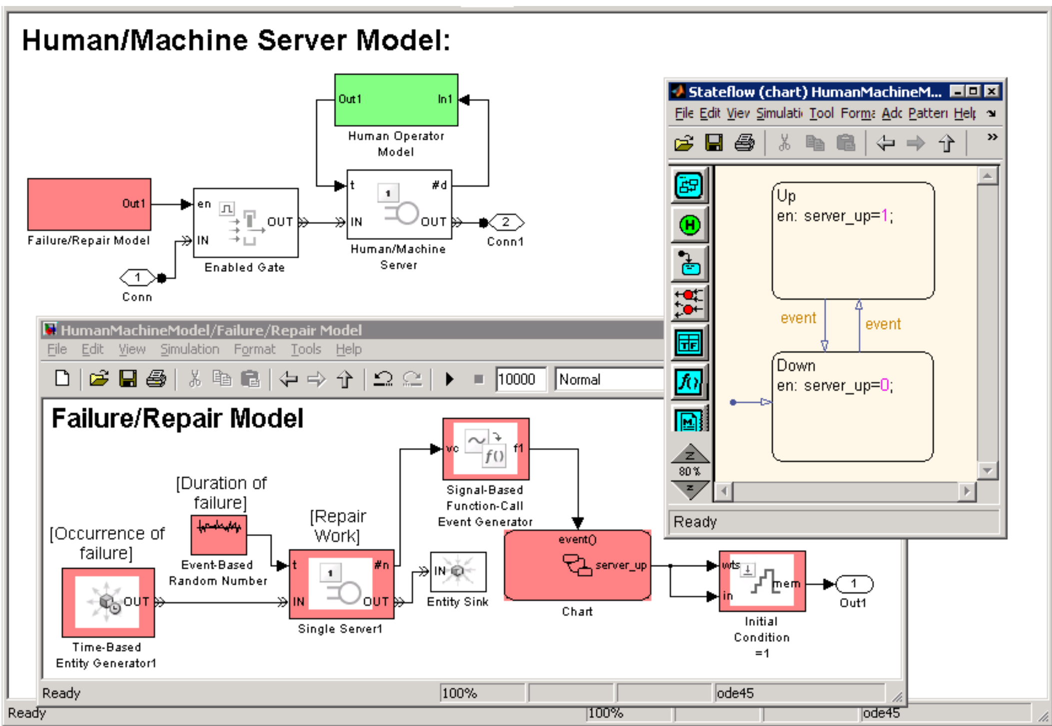

Figure 4.10: Machine failure/repair model in SimEvents.

The machine failure/repair model was verified by developing a production line with two stations in series with finite buffer capacity between workstations. The first workstation is never starved for raw material and the second workstation is never blocked. Service times are random exponential. Machines are subject to failure. Sufficient resources are available to repair both machines simultaneously. Times to failure and times to repair are random exponential. The parameters of this model are given in Table 4.18 below.

__Table 4.18__: Parameters of the serial, two-station production line with machine failures.

Parameter	Description	Value
μ1	Long run service rate of workstation 1	1
μ2	Long run service rate of workstation 2	1
MTTF	Mean time to failure for both machines	10
MTTR	Mean time to repair for both machines	1
N	Buffer capacity between workstation 1 and 2	Varies (0-10)

An analytical solution exists for the above model. Gershwin [43] derived an analytical solution to this problem. However, a solution can also be derived by generating the Chapman-Kolmogorov equations to this problem. A Matlab function 'TwoMs.m' given in Appendix A-2 was created to solve this problem by generating the Chapman-Kolmogorov equations and solving the resulting set of equations. For those interested in the derivation of these equations the state-flow transition diagram for this problem is given in Appendix A-5, and was not found in any previous literature. The analytical results versus the simulation results are given in Table 4.19 below when the simulation was run for 5000 units of time, discarding data for the first 2500 units of time and calculating throughput rate using the remaining data. Throughput rate versus buffer capacity for the analytical and simulations results are shown graphically in Figure 4.11.

Table 4.19: *Verification of the machine failure/repair simulation sub model.*

Buffer Capacity	System Throughput (Analytical Results)	System Throughput (Simulation Results) Mean	95% CI	Statistically Different?	Relative Error
0	0.5974	0.6329	0.0067	yes	5.9%
1	0.6699	0.6992	0.007	yes	4.4%
2	0.7144	0.7486	0.0077	yes	4.8%
3	0.7448	0.7855	0.0113	yes	5.5%
4	0.7669	0.8054	0.0158	yes	5.0%
5	0.7837	0.8301	0.0066	yes	5.9%
6	0.797	0.8354	0.0138	yes	4.8%
7	0.8077	0.8484	0.007	yes	5.0%
8	0.8166	0.86	0.0071	yes	5.3%
9	0.824	0.8535	0.0183	yes	3.6%
10	0.8303	0.8714	0.0073	yes	5.0%

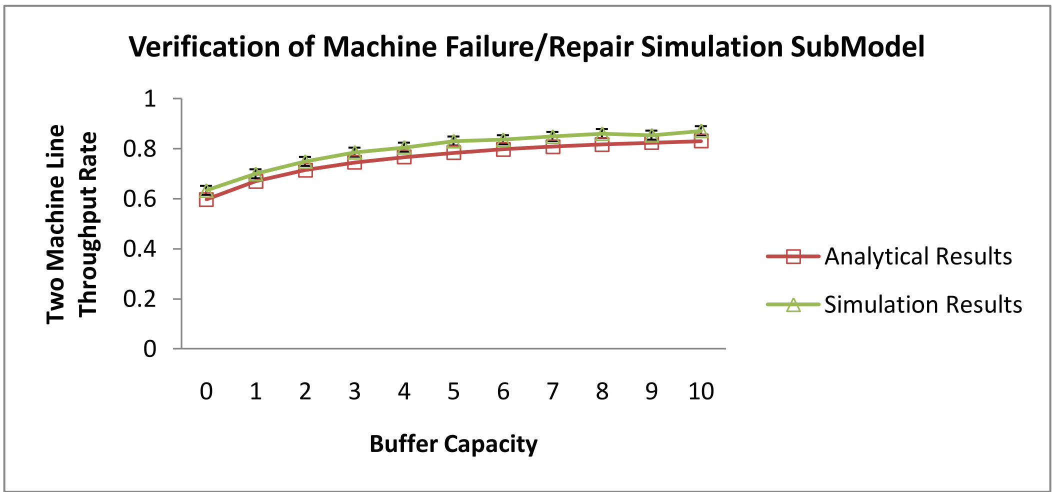

Figure 4.11: *Verification of machine/failure simulation submodel.*

From Figure 4.11 it can be seen that the relationship between throughput and buffer capacity is consistent between the analytical and simulation results. However, the simulation predicts slightly higher throughput than the analytical results. A relative error of approximately 5% is consistently observed for systems with buffer capacity between 0 and 10. There are several explanations for this error: 1) the simulation results are statistical and thus the error may simply be by chance. However, this explanation is unlikely since the error was repeatedly observed. 2) The difference results from the analytical model providing the steady-state throughput rate whereas it is practically impossible to observe the true stead-state throughput rate via simulation since this is only achieved in the limit as time $\rightarrow \infty$. This explanation is also unlikely since simulations were run for a long simulated time. Thus, although the observed simulation throughput rate may not be the true steady-state throughput rate it should be close. 3) The last and most likely explanation is a result of slight model differences. In the analytical model when a failure occurs the work piece that is currently being processed is not completed. For the analytical model, once the repair is complete the processing of the work piece is started over. In the simulation model, when a failure occurs the work piece that is currently being processed is finished and continues down the line. Therefore, the simulation model predicts a higher throughput than the analytical model since work pieces are not held when a failure occurs. A limitation of SimEvents is that it is very difficult to define the model exactly as the analytical model has been defined. Nevertheless, this is not expected to cause errors in the study since machine availabilities are quite high. To test this hypothesis the machine/failure test was repeated. However, the parameters in Table 4.20 were used and are such that machine availabilities are comparable to those observed in the real system. The results are shown in Table 4.21 and Figure 4.12 below.

Table 4.20*: Two station serial line with high machine availabilities.*

Parameter	Description	Value
$\mu 1$	Long run service rate of workstation 1	1
$\mu 2$	Long run service rate of workstation 2	1
MTTF	Mean time to failure for both machines	200
MTTR	Mean time to repair for both machines	1
N	Buffer capacity between workstation 1 and 2	Varies (0-10)

Table 4.21: *Throughput rate results of two station serial line with high machine availabilities.*

Buffer Capacity	System Throughput (Analytical Results)	System Throughput (Simulation Results) Mean	95% CI	Statistically Different?	Relative Error
0	0.6628	0.6579	0.0077	no	0.7%
1	0.7455	0.745	0.0075	no	0.1%
2	0.7952	0.7983	0.0097	no	0.4%
3	0.8283	0.8336	0.0064	no	0.6%
4	0.8521	0.8525	0.0117	no	0.0%
5	0.8699	0.8705	0.0092	no	0.1%
6	0.8837	0.8869	0.0135	no	0.4%
7	0.8948	0.8918	0.0147	no	0.3%
8	0.9039	0.8992	0.0109	no	0.5%
9	0.9115	0.906	0.0126	no	0.6%
10	0.9179	0.921	0.0165	no	0.3%

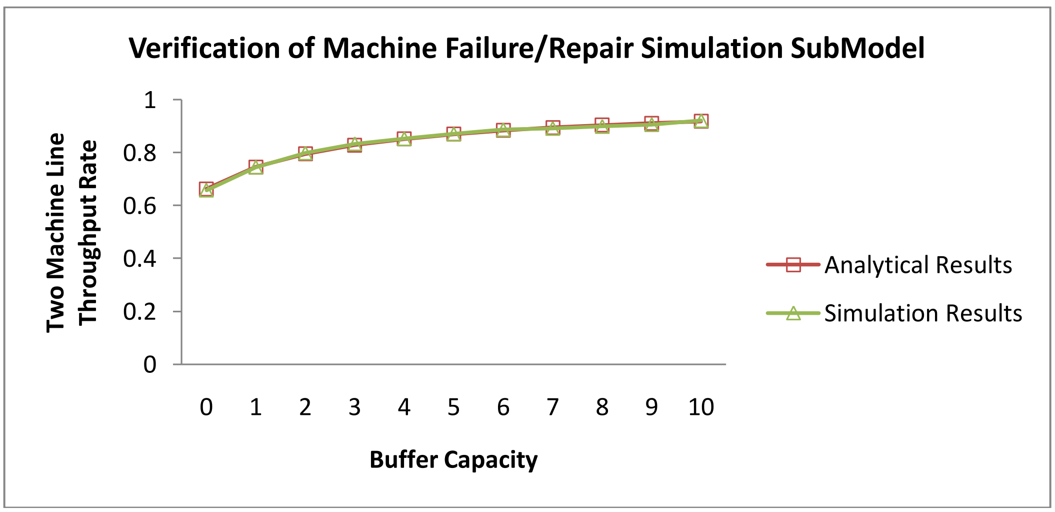

Figure 4.12: *Throughput rate results of two station serial line with high machine availabilities.*

From Table 4.21 and Figure 4.12 above it can be seen that when machine availabilities are high the slight difference between the analytical and simulation models does not result in significant differences in throughput rates. As a result the following conclusions can be made: 1) the machine/failure model has been properly constructed and 2) slight differences in the model formulation will not affect throughput rate results in this case.

Future work would be required to consider this aspect of model formulation since it was shown that when machine availabilities are low throughput rate results can be significantly affected.

4.2.2 Learning Curve and Operator Turnover Test

A novel aspect of this research is the human operator model that has been developed. The human operator model mimics random cycle times, a decrease in the expected cycle time as a result of learning and random operator turnovers. The SimEvents model that has been developed is shown in Figure 4.13 below (details of the model can be found in Appendix A-3).

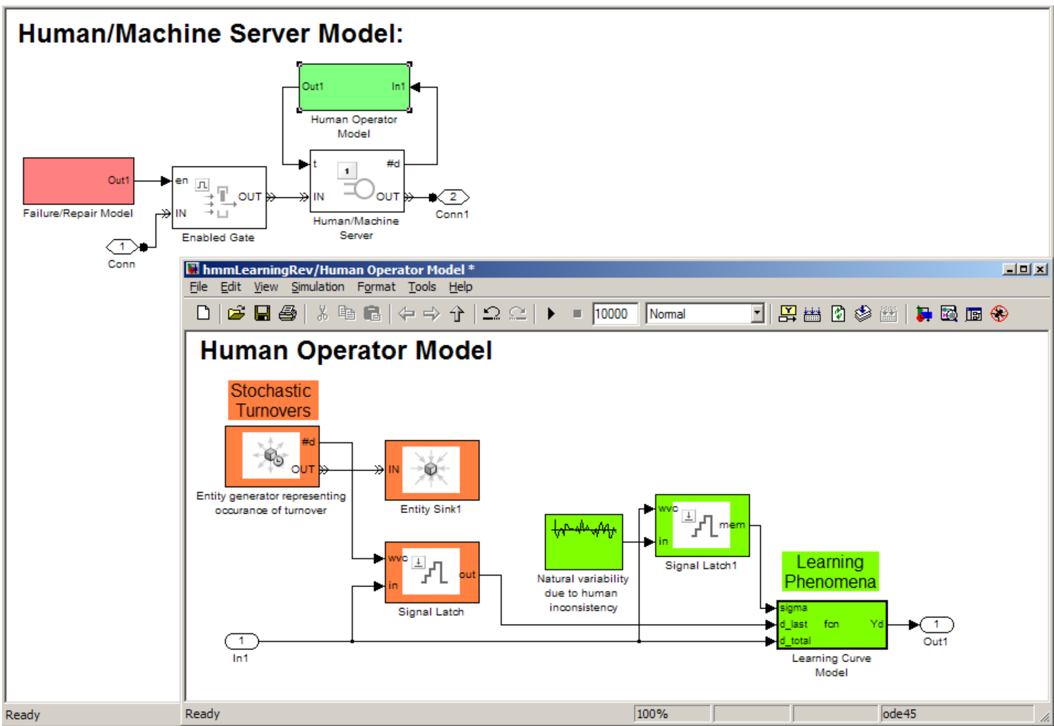

***Figure 4.13**: SimEvents human operator model.*

Construction of the model shown in Figure 4.13 was verified by setting the random elements to known constants and observing the output. The parameters of the now deterministic model are given in Table 4.22 below and a plot of the simulation cycle times versus time are shown in Figure 4.14 below.

Table 4.22: Human operator model parameters for the learning and turnover test.

Parameter	Description	Value
t_1	Cycle time for the 1^{st} cycle	10
M	Incompressibility factor	0.1
b	Learning factor	0.32
$t_{turnover}$	Time until turnover	1000

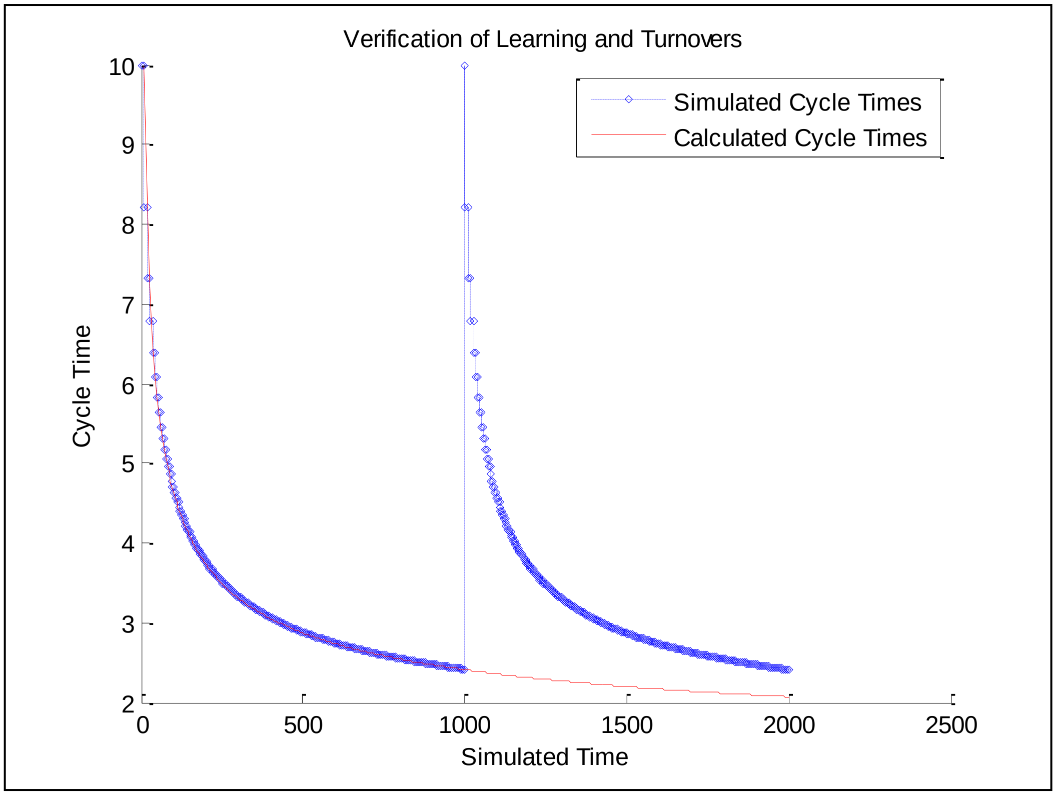

***Figure 4.14**: Learning curve and turnover tests results.*

From Figure 4.14 it can be seen that the simulated cycle times exactly coincide with cycle times calculated using DeJong's formula up until the known turnover time of 1000. At time equals 1000 the experience level is reset to zero and the cycle time returns to that of the first cycle – which is the desired effect. This effect represents an experienced worker leaving and being replaced by a new worker with no experience. The results of this test indicate that the human operator model responsible for learning and turnovers in the system has been constructed correctly. The addition of a random component to cycle times and random turnover times is not expected to alter the function of this model.

4.2.3 Floating Worker Test

In order to test methods used to model the floating worker a two station line was constructed in SimEvents (see Appendix A-3). One worker was assigned to each workstation. Cycle times were deterministic. However, the time to process a work piece at workstation 1 was 1 unit of time, whereas the time to process a work piece at workstation 2 was 0.8 units of time. A floating worker was added to the line and is assigned to either workstation 1 or 2 at the beginning of each day based on the amount of WIP in the intermediate buffer. Figure 4.16 shows the results of the floating worker test.

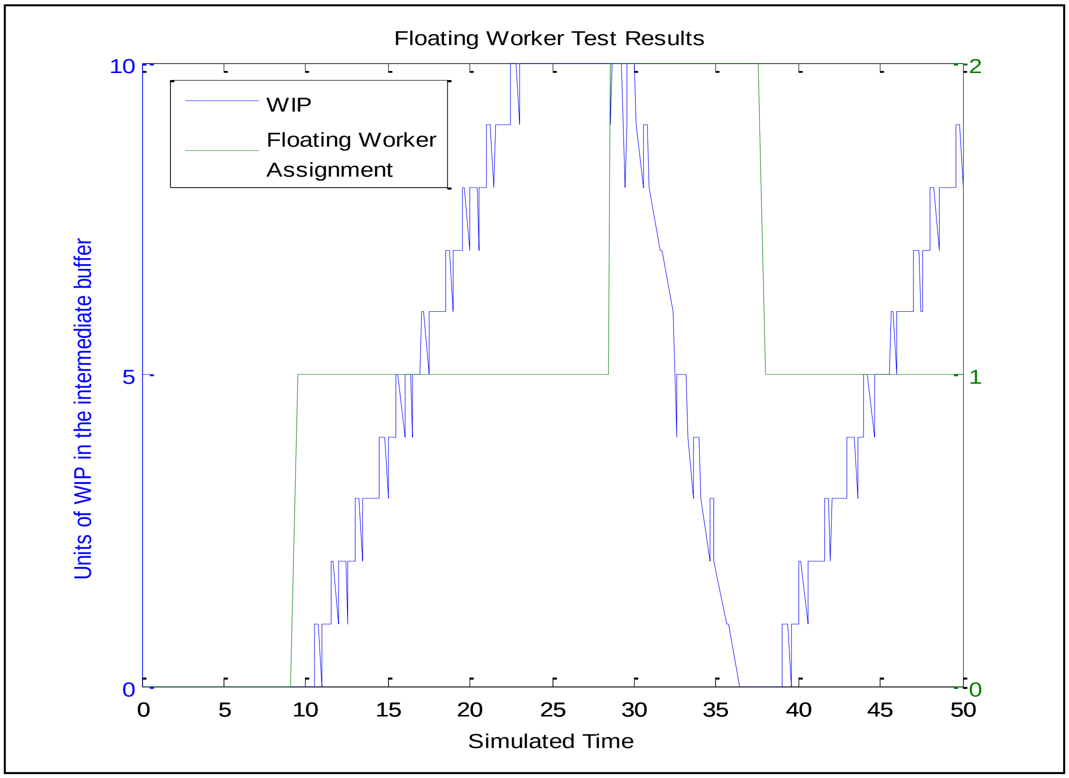

Figure 4.15*: Floating worker verification test results.*

From Figure 4.15 it can be seen that the floating worker is first assigned to workstation 1 after 9.5 units of time (which is the default). The amount of WIP in the intermediate buffer is checked every 9.5 units of time. At time equals 28.5 WIP has accumulated to the maximum buffer capacity (10 units in this case) and so the floating worker is assigned to workstation 2. The floating worker provides additional capacity to workstation 2 and so WIP depletes from the buffer. The next time the amount of WIP is checked (after 38 units of time) the buffer is empty and so the floating worker is assigned to workstation 1 again.

The floating worker was only assigned to one workstation at any given time, and was assigned using WIP as the control mechanism. This verifies that the floating worker functions properly in the simulation model.

4.2.4 Cross-training Test

To test the methods used to model cross-training in simulations a two station line was modeled in SimEvents (see Appendix A-3). Two workers rotate between workstations. Learning is included in the model. However, one worker is more proficient than the other (at either workstation). Figure 4.16 below provides the times to process a work pieces for both workers at either workstation.

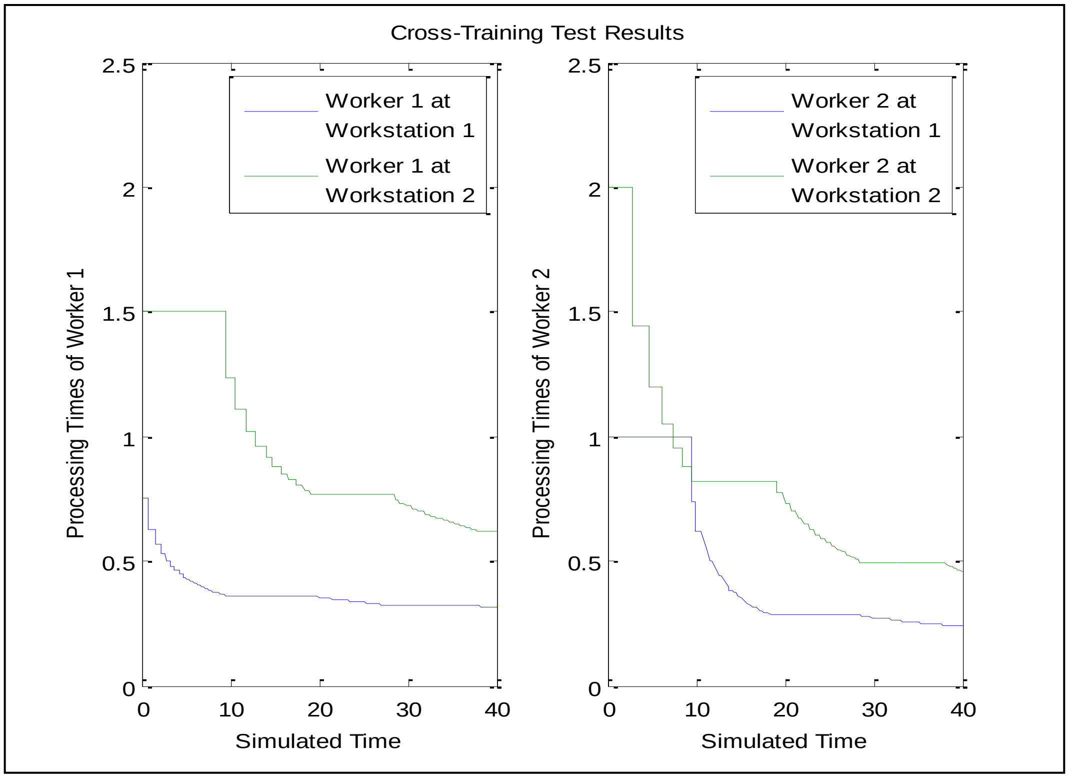

***Figure 4.16**: Cross-training verification test results.*

In Figure 4.16 the blue line are the processing times at workstation 1 and the green line are the processing times at workstation 2. Worker 1 is a worse performer, at either task, than worker 2 which has been done to allow for easier differentiation between workers. It can be seen that worker 1 starts at workstation 1 and gains experience for 9.5 units of time. Similarly, worker 2 starts at workstation 2 and gains experience at this task for 9.5 units of time. At 9.5 units of time the workers switch workstations. So worker 1 does not gain any further experience at workstation 1 and worker 2 does not gain any further experience at workstation 2. These results indicate that the methods used to model cross-training in simulations function correctly.

4.3 Phase 3 Results – Numerical Experiments and Sensitivity Analysis

The numerical experiments and sensitivity analysis phase consisted of: 1) a turnover sensitivity analysis, 2) cancelling the practice of "borrowing workers", 3) examining major changes to the system and 4) a sensitivity analysis further examining WIP capacity as a design factor.

4.3.1 Turnover Sensitivity Analysis

The turnover rate of operators is not known with high confidence and therefore simulations were performed for monthly turnover rates of 0%, 2.5% and 5% to determine how significant the effect on production capacity is. In addition, company data was available for the daily production of five production lines and so the production capacities of the five lines were compared to those predicted by simulations. The results are given below in Tables 4.23, 4.24 and 4.25 respectively and shown graphically in Figure 4.16 (error bars represent 95% confidence intervals).

Table 4.23: *Simulations with 0% monthly turnover.*

	Real Daily Production (batches/hr)			Simulated Daily Production (batches/hr)			
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI	Rel. Error
Production Line 1	**11910**	2269	882	14248	342	4	20%
Production Line 2	**15465**	1030	273	16278	123	3	5%
Production Line 3	**9930**	1014	394	10669	568	4	7%
Production Line 4	**16475**	512	364	17352	113	3	5%
Production Line 5	**6617**	1501	797	8139	497	2	23%

Table 4.24: *Simulations with 2.5% monthly turnover.*

	Real Daily Production (batches/hr)			Simulated Daily Production (batches/hr)			
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI	Rel. Error
Production Line 1	**11910**	2269	882	12434	386	374	4%
Production Line 2	**15465**	1030	273	14073	638	482	9%
Production Line 3	**9930**	1014	394	8275	565	640	17%
Production Line 4	**16475**	512	364	14027	569	420	15%
Production Line 5	**6617**	1501	797	7157	545	188	8%

Table 4.25: *Simulations with 5% monthly turnover.*

	Real Daily Production (batches/hr)			Simulated Daily Production (batches/hr)			
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI	Rel. Error
Production Line 1	**11910**	2269	882	11666	560	126	2%
Production Line 2	**15465**	1030	273	13300	849	372	14%
Production Line 3	**9930**	1014	394	8187	597	171	18%
Production Line 4	**16475**	512	364	12550	239	279	24%
Production Line 5	**6617**	1501	797	6686	565	76	1%

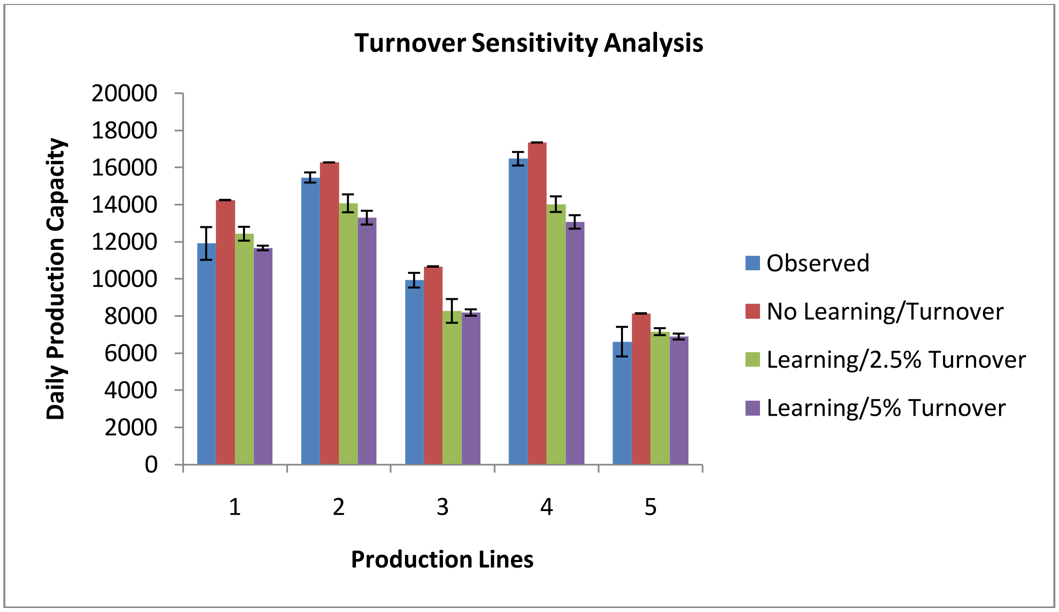

***Figure 4.17**: Simulations for 0%, 2.5% and 5% monthly turnover rates.*

In the production lines examined above a 2.5% and 5% monthly turnover rate result in average losses in production capacity of 16% and 20% respectively (significant losses). An accurate estimate of monthly turnover rate at the factory could not be confirmed. However, there is evidence (from production lines 1 and 5) that monthly turnover rate is as high as 5%. From Tables 4.23, 4.24 and 4.25 and Figure 4.17 above it can be seen that in the case where operator learning and random turnovers are ignored, simulations consistently overestimate the observed daily production capacity of assembly lines. In the case where operator learning and a 5% monthly turnover rate is used, simulations of production lines 1 and 5 predict nearly the exact daily production capacities of the observed production lines (less than 2% difference). However, the daily production capacities of the other three observed production lines were largely underestimated by simulations with learning and 5% monthly turnover which does not support the hypothesis of a 5% monthly turnover. A possible explanation is as follows: the experience of operators in the observed production lines is not known. Therefore, it is possible that the production lines that have been underestimated consisted of relatively experienced workers. Furthermore, data was collected from simulations over a period of two years. Company production records only provided a couple of weeks of data for the observed production lines. Therefore it is possible the average production capacity over a longer period is less than that observed from production lines 2, 3 and 4 over a short period of time.

Future work is required to investigate the true monthly turnover rate at the factory and whether or not monthly turnover rate varies with assembly operation and time of the year. Unfortunately, these activities were not within the scope of this study. Nevertheless, the results do suggest that learning and turnover are important components of a production line model and that the monthly turnover rate of the real system may be approximately 5%.

4.3.2 Cancelling the Practice of Borrowing Workers

The effect of cancelling the practice of borrowing workers is shown in Tables 4.26, 4.27 and 4.28 below and also in Figure 4.18 below.

Table 4.26*: Cancelling the practice of borrowing workers, no turnover.*

	Borrowing Workers			Fixed Workers		
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI
Production Line 1	14248	342	4	14184	116	2
Production Line 2	16278	123	3	16278	119	3
Production Line 3	10669	568	4	10440	120	1
Production Line 4	17352	113	3	17777	126	3
Production Line 5	8139	497	2	7092	79	2

Table 4.27*: Cancelling the practice of borrowing workers, 2.5% turnover.*

	Borrowing Workers			Fixed Workers		
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI
Production Line 1	12434	386	374	12285	427	74
Production Line 2	14073	638	482	14204	534	302
Production Line 3	8275	565	640	8584	409	155
Production Line 4	14027	569	420	13830	694	490
Production Line 5	7157	545	188	5586	382	254

Table 4.28*: Cancelling the practice of borrowing workers, 5% turnover.*

	Borrowing Workers			Fixed Workers		
	Ave.	St. Dev.	95%CI	Ave.	St. Dev.	95%CI
Production Line 1	11666	560	126	11548	393	191
Production Line 2	13300	849	372	13106	671	411
Production Line 3	8187	597	171	7805	622	329
Production Line 4	13071	1000	364	13037	725	440
Production Line 5	6893	573	160	5292	480	214

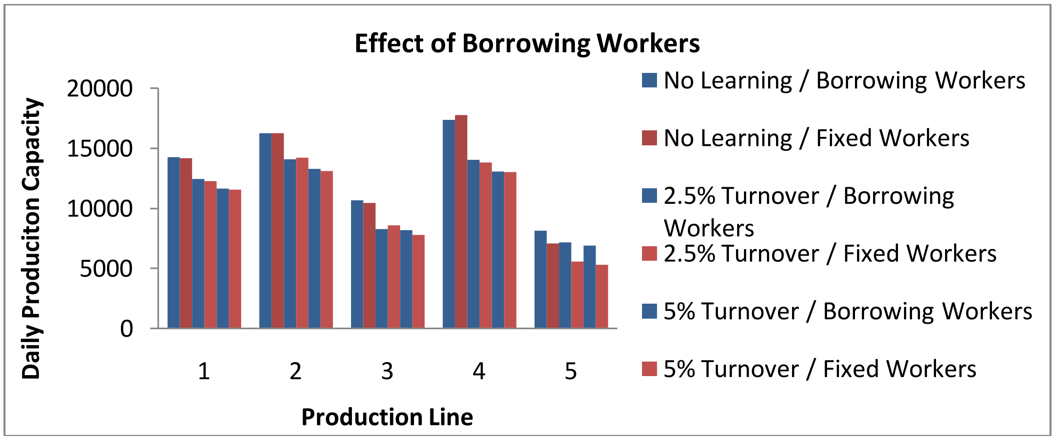

Figure 4.18*: The effect of cancelling the practice of borrowing workers.*

From the tables and figures above it can be seen that there is only a slight improvement in production capacity (4% increase on average) when borrowing workers compared to having fixed workers. And in the simulations it was assumed that additional workers are always available (though only utilized as needed). It's quite likely that there are times when a worker was borrowed in the simulation but would not have been borrowed in the real system because he/she was in greater demand somewhere else in the factory. So, in fact, it is very possible that borrowing workers does not yield any additional production capacity. Furthermore, in many cases borrowing workers only serves to increase daily production variability (on average an 85.7% increase in the daily production standard deviation). High production variability is not desirable. This results in not being able to accurately predict production capacity from day to day and increases the size of raw materials and finished goods inventory. As a result of large inventories, lead time is increased which has a negative effect on customer satisfaction. Thus, the first suggested change to the production line is to cancel the practice of borrowing workers. This is not expected to have a significant impact on production capacity (if any) and it is quite possible that the savings in raw material and finished goods inventory and the increase in customer satisfaction will outweigh any losses in capacity. The fixed worker system will serve as the base case in the following experiments examining other changes to the production line.

4.3.3 Examining Major Design Changes to the System

Time did not permit the study of all five production lines presented in the previous section. As a result only one production line was chosen to examine major changes to the system. Production line 5 is the smallest of the production lines and was chosen since it is relatively easy to implement changes and requires less computational effort when compared to larger production lines. The throughput rate, utilization and WIP results of the fractional factorial experiment examining 1) an increase in monthly turnover rate, 2) implementing cross-training, 3) utilizing a floating worker, 4) automating the folding operation and 5) an increase in WIP capacity to production line 5 are presented next.

Throughput Rate Results

Throughput rates for the 16 runs of the fractional factorial experiment are given in Table 4.29 below. Plots of the resulting throughput rates are given in Figure 4.19 for runs that involve a low or high monthly turnover rate.

***Table 4.29**: Throughput rate results.*

Run	Description Monthly turnover rate / cross-training / floating worker / WIP cap.	Throughput (batches/hr)	95% CI
4	2.5 / no / no / no / 45	6.06	0.32
15	2.5 / no / no / yes / 15	5.54	0.41
16	2.5 / no / yes / no / 15	6.59	0.18
13	**2.5 / no / yes / yes / 45**	**6.73**	**0.15**
9	2.5 / yes / no / no / 15	4.13	0.09
7	2.5 / yes / no / yes / 45	4.22	0.07
5	2.5 / yes / yes / no / 45	5.39	0.10
2	2.5 / yes / yes / yes / 15	4.77	0.10
11	7.5 / no / no / no / 15	5.20	0.19
3	7.5 / no / no / yes / 45	5.32	0.22
6	7.5 / no / yes / no / 45	5.85	0.15
14	7.5 / no / yes / yes / 15	5.75	0.23
8	7.5 / yes / no / no / 45	3.39	0.09
12	7.5 / yes / no / yes / 15	3.46	0.08
1	7.5 / yes / yes / no / 15	3.74	0.10
10	7.5 / yes / yes / yes / 45	4.71	0.09

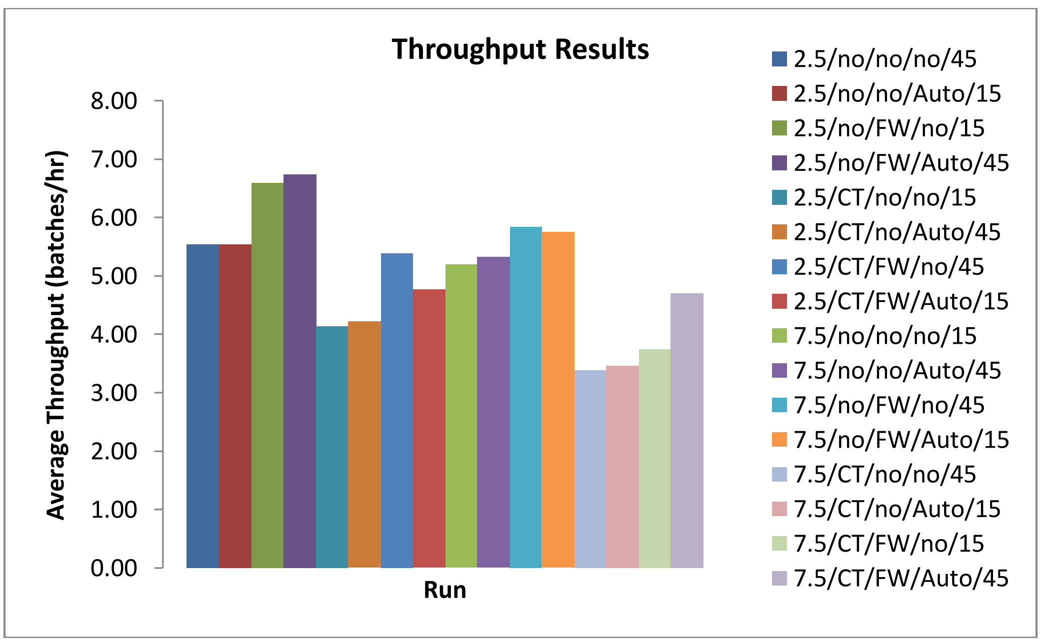

***Figure 4.19**: Throughput results.*

Run 13 achieved the highest throughput rate of 6.73 batches / hr. Run 13 involved the low monthly turnover rate of 2.5%, no cross-training, utilization of a floating worker, automated folding and the large capacity of WIP (maximum of 45 batches between workstations). To understand why run 13 achieved the highest throughput rate the main factors and two-factor interactions were examined. The main factors and two-factor interactions in a normal probability plot are shown in Figure 4.20 below where the numbers in boxes represent the factors as identified in Table 3.1 (i.e. 1 – worker turnover, 2 – cross-training, 3 – floating worker, 4 – automated folding and 5 – WIP capacity).

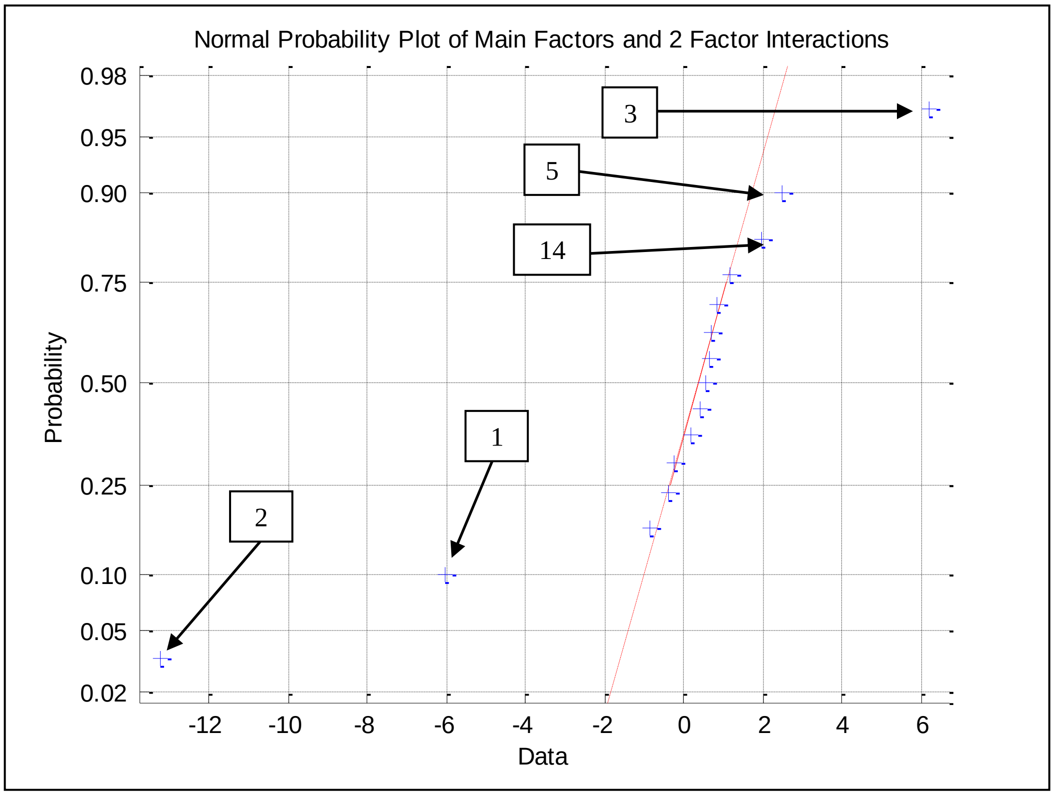

Figure 4.20*: Normal probability plot of main effects and two-factor interactions.*

From Figure 4.20, the factors that have an effect on throughput are those that do not lie on the straight line [92]. The factors affecting throughput in decreasing order are:

Utilizing a floating worker (3) shows the largest positive impact on throughput rate. The reason is that it is difficult to obtain a balanced production line since workstations can only be assigned an integer number of workers. Utilizing a floating worker helps to balance the line by having one worker spend a portion of his/her time at various workstations as needed. Furthermore, a floating worker provides assistance to a workstation when a turnover occurs while the new worker gains proficiency at the task.

An increase in WIP capacity (5) from 15 batches for each queue to 45 batches for each queue has a significant positive impact on throughput rate. This is an interesting result since a previous study including learning and random turnovers [61] concluded that WIP did not have a significant effect on throughput and suggested that this factor should not be investigated in future research. Hutchinson only found a 0.24% increase in throughput in the best case by increasing WIP capacity of each queue from 1 to 10. This study found that an increase in WIP capacity can have a significant positive effect on throughput rate, when worker learning and turnover are considered, by reducing starving and blocking of workstations. Reasons why the results of this study differ from Hutchinson's may be: 1) the WIP levels are not identical, 2) the production line in this system consists of servers in series and parallel whereas the production line in Hutchinson's study consisted only of servers in series and 3) the methods of mitigating the effect of turnover differ significantly between this study and Hutchinson's. In any case this study suggests that increasing WIP capacity may have a significant effect on the throughput rate for systems subject to worker learning and turnover, and this design factor does merit investigation in future research.

Automating the folding operation (14) does not have a significant effect on throughput by itself. What these results show is that the interaction between factor 1 and factor 4 is significant. This means that automating the folding operation only had a significant effect on throughput when turnover was high. From Figure 4.21 it can be seen that automating the folding operation had a slightly negative effect on throughput rate when monthly turnover rate was 2.5%. However, when monthly turnover rate is 7.5% there is a noticeable increase in throughput rate. The reason automating the folding operation only has a significant effect on throughput rate when turnover is high is because a large portion of workers are relatively inexperienced and still learning the assembly operation. In the case of high turnover, operators do not stay with the company long enough to become proficient at the folding task. Automated the folding operation reduces learning requirements and thus increases throughput rate. This is not the case when turnover is low since many of the operators are experienced and very proficient at the folding task.

What has been shown here is that, in addition to the known benefits of assembly automation (reduced labor requirements, consistent quality etc.), in a high turnover environment automating an assembly operation will have a larger positive effect on throughput (as a result of reducing the learning requirements) that has previously not been accounted for.

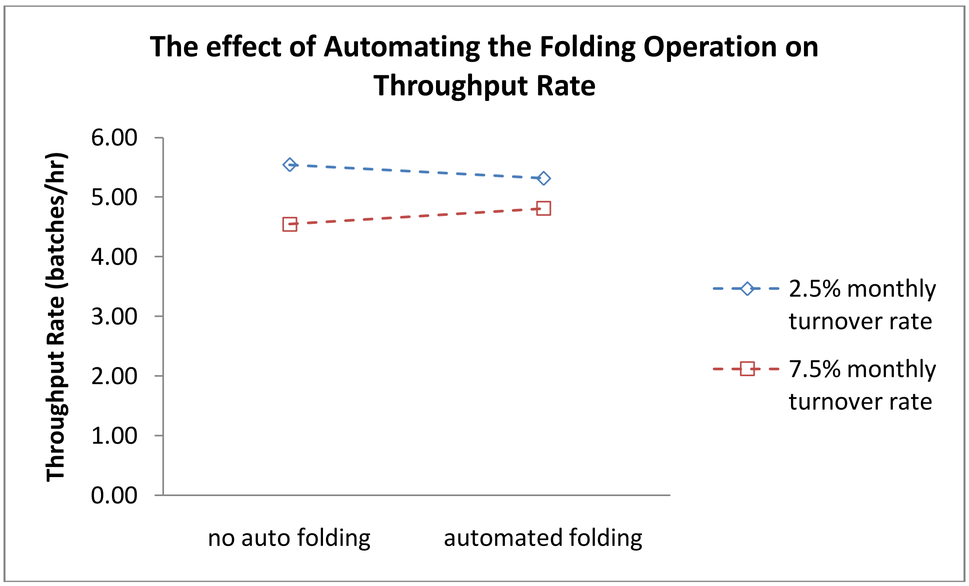

Figure 4.21*: The effect of automating the folding operation.*

There are a couple of important notes about the results given here. First, the dotted lines connecting the response data in Figure 4.21 are not necessarily linear. It's possible that the response is curved. However, the shallow slopes in Figure 4.21 suggest that the assumption of a linear response will not introduce significant errors in the result. And second, it should also be noted that the two factor interactions in the 2^{5-1} fractional factorial design of experiments are confounded with three factor interactions. In this experiment the 1-4 factor interaction is confounded with the 2-3-5 factor interaction. Thus it is also possible that the 1-4 interaction is actually partially or entirely due to the 2-3-5 factor interaction.

However, an explanation of why only a particular combination of cross-training, utilizing a floating worker and WIP capacity results in an increase in throughput rate is elusive (especially since it has been shown that the main effects of these factors are significant). Thus, the 2-3-5 interaction will be considered negligible and the 1-4 interaction considered as the contributing factor.

An increase in monthly turnover rate from 2.5% to 7.5% (1) has a significant negative impact on throughput rate. This result is expected since a high turnover rate means that a larger portion of workers are inexperienced and not as productive compared to experienced workers. However, the contribution of this result is that the losses associated with turnover have been quantified (given later in Table 4.30).

Cross-training (2): cross-training has the largest negative impact on throughput rate. The reason is that workers spend a lot of time learning all operations. Furthermore, the negative effect of cross-training seems to far outweigh any benefit of rotating heterogeneous workers. The results of this study help to quantify the negative effect of cross-training which can be used in preliminary investigation of other situations. It is important to note that this result does not suggest that cross-training should not be performed. However, a company must weigh the advantages and disadvantages of cross-training. The disadvantage is a loss in production capacity. However, many advantages of cross-training may exist. For example, cross-training across different product lines in order to compensate for product demand variability; or cross-training to reduce redundancy and increase worker satisfaction.

A summary of the effect that the above mentioned changes have on the production line is given in Table 4.30 below.

***Table 4.30**: Summary of factors affecting throughput rate.*

Factor	Result (average effect on throughput rate)
Using a floating worker.	16.6% *increase* in throughput rate
Increase in WIP between workstations.	6.3% *increase* in throughput rate
Automated folding.	5.9% *increase* in throughput rate only when turnover is high
Increase in monthly turnover rate.	13.9% *decrease* in throughput rate
Implementing cross-training of workers.	28.1% *decrease* in throughput rate

The results in Table 4.30 above are the quantified effects of the experimental factors. The factors in this study have shown to be quite significant. In fact, these results are more significant than many results from previous research. For example Hillier and Boling [51] in their historical article regarding the bowl phenomena showed that an imbalanced production line outperformed a balanced production line by approximately 0.5%. More recently, Hutchinson [61] showed that the throughput of a production line subject to operator turnover could be improved by 1 – 4% using a fast-medium-slow replacement policy and a high-medium-low workload imbalance. And two experiments performed by Munoz et al [94] showed a 4.9% and 7.4% increase in throughput when using the Bucket Brigades method. The results of this study suggest that using a floating worker can have a much more positive impact on reducing the effect of turnovers and helping to balance real production lines.

Utilization Results

The two experiment factors that had significant effects on overall system utilization were using a floating worker and implementing cross-training. However, implementing cross-training had negative effect on system utilization (average decrease of 7.2%) whereas utilizing a floating worker had a positive effect (average increase of 4.8%). The utilizations of individual workstations and overall system utilizations for all experiment runs are shown in the figures below.

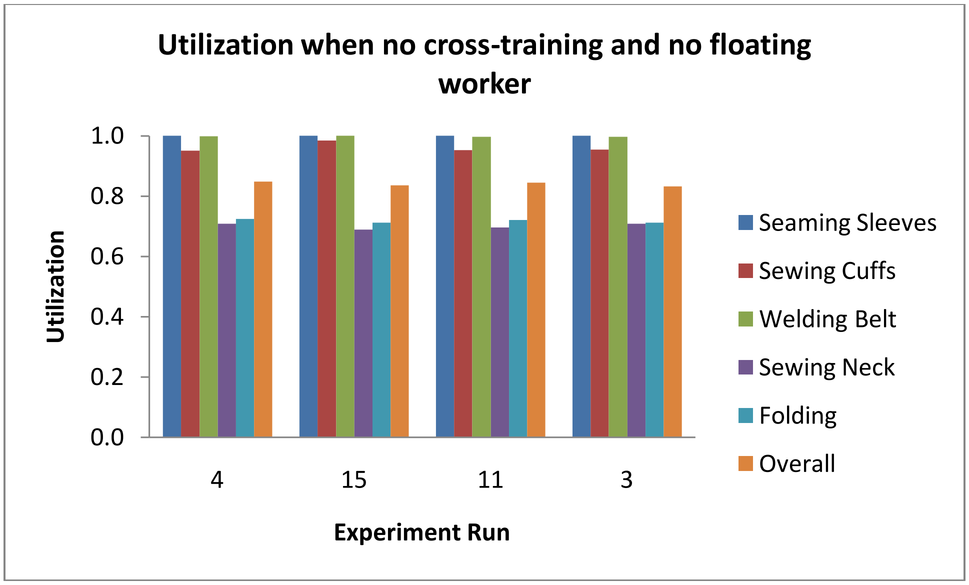

***Figure 4.22**: Utilization results for experiments where cross-training is not practiced and a floating worker is not used.*

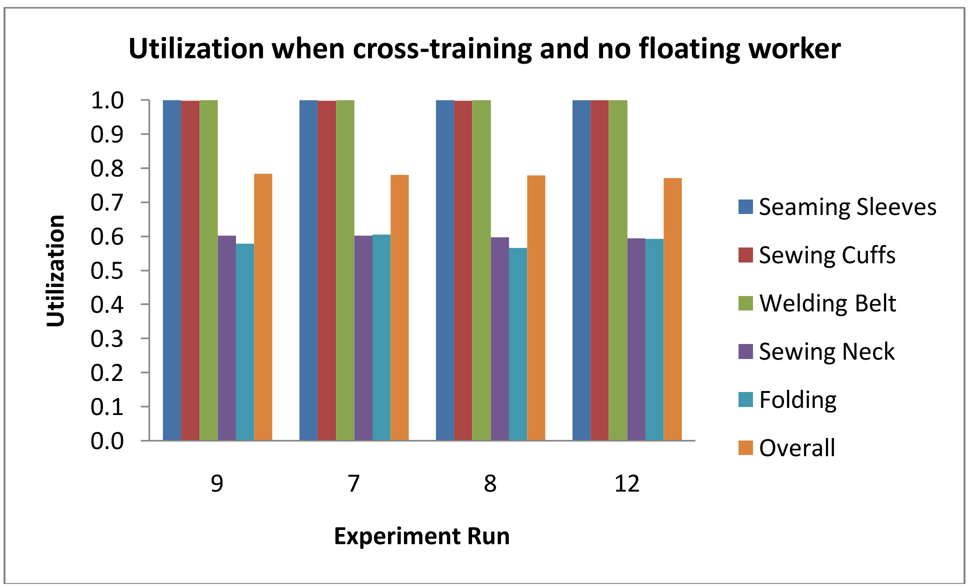

***Figure 4.23**: Utilization results for experiments where cross-training, only, is practiced.*

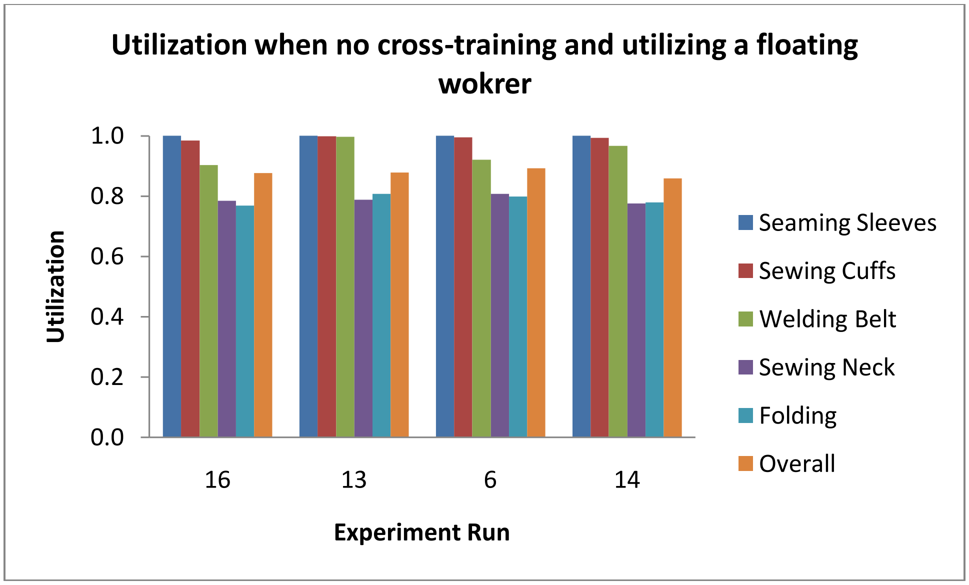

Figure 4.24: *Utilization results for experiments when a floating worker, only, is used.*

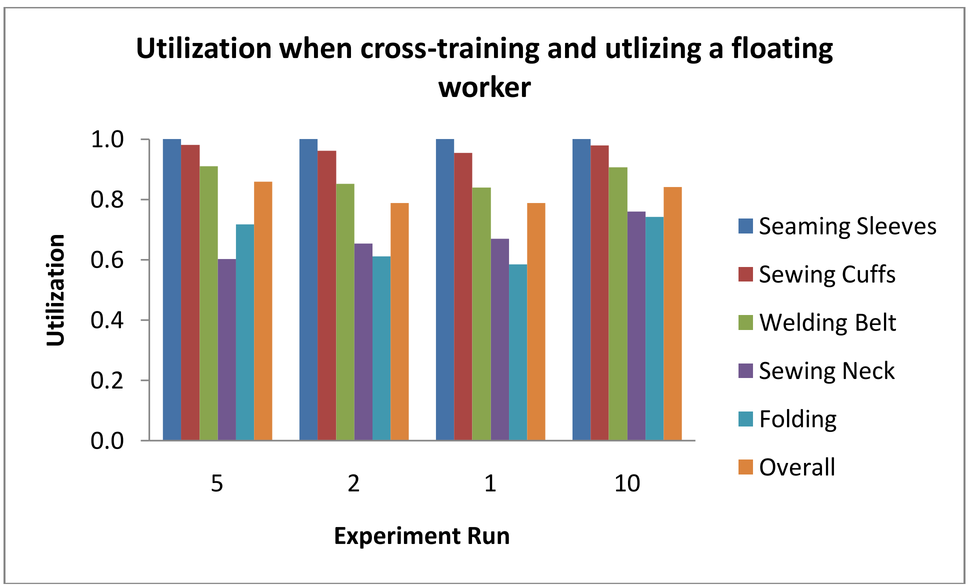

Figure 4.25: *Utilization results for experiments when cross-training is practiced and a floating worker is used.*

Comparing Figures 4.22 and 4.24 above it can be seen that using a floating worker helps to relieve workstations with high utilizations and transfer more work to underutilized workstations. Cross-training on the other hand (see Figures 4.23 and 4.25) does not provide any relief to workstations with high utilizations and decreases the amount of work transferred to underutilized workstations. This result suggests that the hypothesis that rotating heterogeneous workers will have a positive effect on system performance should be rejected. In this case it seemed to take workers an even longer amount of time to learn important operations (those with high utilizations) than to learn less important operations (the underutilized workstations). This is most likely due to the fact that in this case the bottleneck workstation only consisted of two operators whereas other workstations consisted of up to 7 operators. As a result rotating workers spent a relatively small amount of time at the bottleneck station and did not gain sufficient experience at that task. Future work may want to investigate partial cross-training where emphasis is placed on bottleneck operations.

WIP Results

Factors affecting average WIP in the system were found to be the system capacity for WIP and utilizing a floating worker. Increasing the capacity of each queue from 15 to 45 batches resulted in an 85.7% increase in the average WIP in the system. Alternatively, utilizing a floating worker resulted in a 54.1% decrease in the average WIP in the system. This is an interesting result. From Figure 4.26 below it can be seen that when utilizing a floating worker the average WIP was low even when a large capacity for WIP was provided.

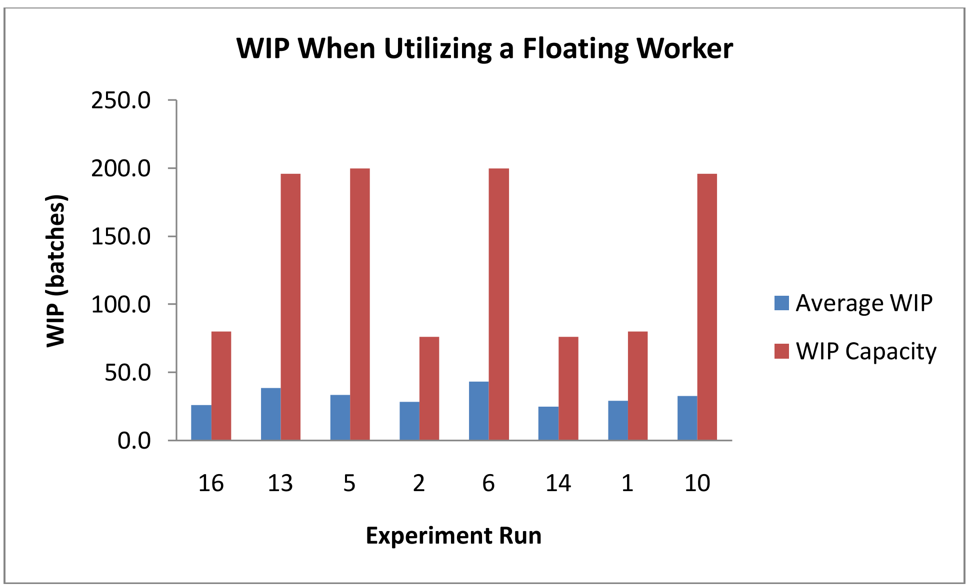

***Figure 4.26**: WIP for experiment runs that include the use of a floating worker.*

Although the average WIP in the system is low even when WIP capacity is high, this does not necessarily mean that WIP capacity should be reduced (remember the throughput rate results indicated that an increase in WIP had a positive impact on performance). The reason is that a floating worker is assigned to the most upstream workstation where WIP has accumulated in front of the workstation. The floating worker provides excess capacity to the workstation and reduces the amount of WIP in front of the workstation. Once the floating worker is removed, however, WIP may begin to accumulate in front of the workstation again and the process is repeated. So although the long run average WIP in a queue may be low the queue occupancy can vary significantly. This is supported by Figure 4.27 which plots the probabilities of finding a given number of batches in the system queues for experiment run 16.

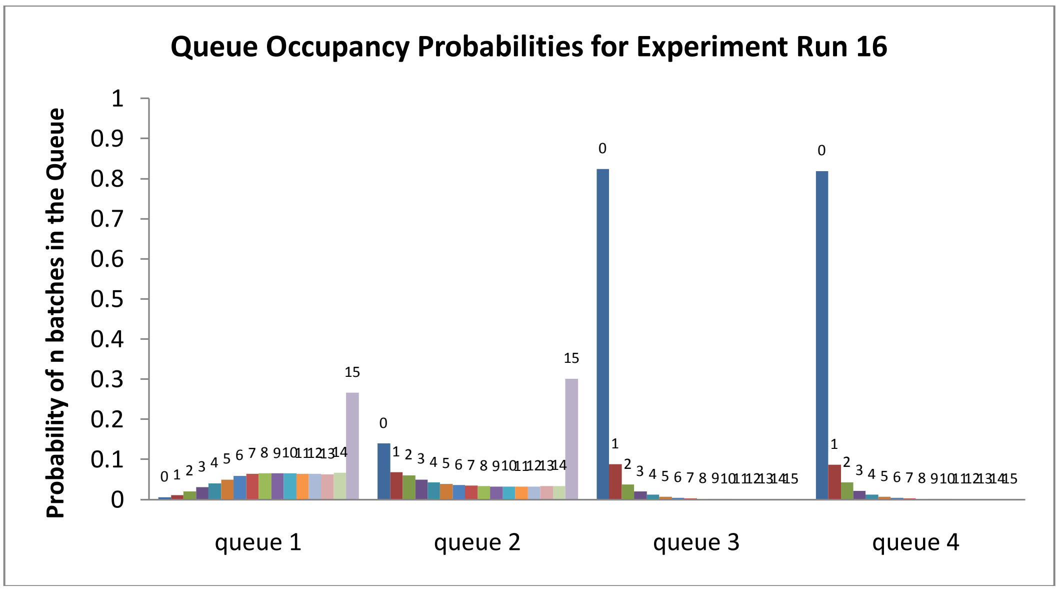

Figure 4.27: *Queue occupancy probabilities for experiment run 16 which utilizes a floating worker.*

In Figure 4.27 the numbers above each bar indicate ‘n’, the number of batches in the queue (where n = 0, 1, …, 15). The height of each bar is the probability of finding ‘n’ batches in the queue. From Figure 4.27 it can be seen that the first two queues experience full occupancy most of the time, but there is a large portion of time (approximately 70% of the time) for which there is less than maximum queue occupancy. Looking at the floating worker allocation in Figure 4.28 below it can be seen that the floating worker spends most of his/her time at the first three workstations but does not spend much time at the last two workstations. This explains why there is not the same trend of queue occupancy probabilities for the last two queues as for the first two queues.

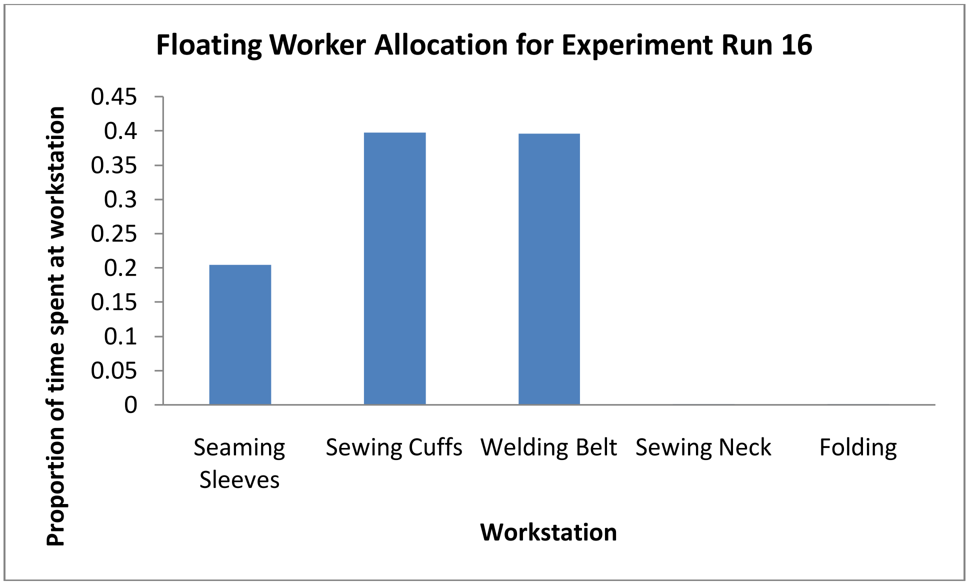

Figure 4.28: *Floating worker allocation for experiment run 16.*

Because there is a large portion of time for which the first two queues are at less than maximum occupancy the long run average WIP is reduced. Compare this to the queue occupancy probabilities from experiment run 11 (see Figure 4.29 below) which does not exercise the use of a floating worker.

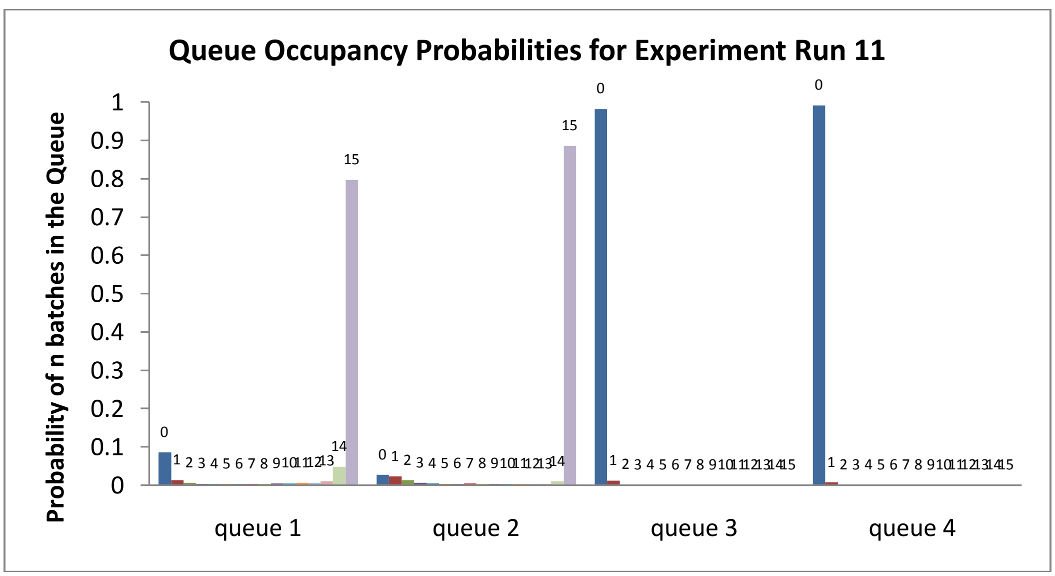

Figure 4.29: *Queue occupancy probabilities when there is no floating worker.*

From Figure 4.29 it can be seen that the first two queues (which are upstream of the bottleneck station) remain at maximum occupancy most of the time (approximately 80% - 90% of the time). In fact, it is likely that reducing the WIP capacity further will have no effect on a system that does not utilize a floating worker since the probability of emptying the buffer immediately upstream of the bottleneck workstation is small. This explanation is supported by Hutchinson's results [61] which showed little consequence of varying WIP capacity. However, when utilizing a floating worker not only is the queue immediately upstream of the bottleneck station frequently at low occupancy, so are other queues. This suggests that reducing the WIP capacity further will have an effect on the system. This is examined further in a sensitivity analysis examining the effect of changes to individual queue capacities.

From the WIP results it can be seen that utilizing a floating worker is an effective method for reducing average WIP in the system which has a positive economic impact on the system. Although, a floating worker is effective at reducing the average WIP in the system it has been shown that WIP capacity has an effect on throughput (see throughput results). Therefore, reducing WIP capacity is not recommended. However, it is possible that a more efficient allocation of WIP exists.

4.3.4 Economic Implications

The economic implications given in this section are to serve as an example. Previous experiments illustrated how system design factors can affect the performance of production lines. However, an increase in system performance can conflict with company profitability. Parameters used in the economic analysis were selected arbitrarily. However, data from simulation results needed to evaluate the operating income equation (equation 46 presented in section 3.3.4) are given in Table 4.31 so that the sponsoring company or others may repeat the analysis. It should be noted, however, that if the operating income model presented in this study is to be used it should be validated first.

Table 4.31*: Simulation results needed to evaluate operating income.*

Run	TP	N_{worker}	n_{hold}	n_{WIP}	N_{turns}
4	6.06	21	86.4	180	6.1
15	5.54	17	44.4	60	4.3
16	6.59	21	26.0	60	5.0
13	6.73	17	38.5	180	3.7
9	4.13	21	45.8	60	6.8
7	4.22	17	103.6	180	4.7
5	5.39	21	33.5	180	6.3
2	4.77	17	28.4	60	3.9
11	5.20	21	43.0	60	20.1
3	5.32	17	90.3	180	13.9
6	5.85	21	43.1	180	19.9
14	5.75	17	25.0	60	13.8
8	3.39	21	101.3	180	21.3
12	3.46	17	43.5	60	15.1
1	3.74	21	29.0	60	20.6
10	4.71	17	32.6	180	13.9

Parameters in the equation are given in Table 4.31 below and will be used to evaluate the operating income equation. Most of the parameters were selected arbitrarily. The number of hours is calculated assuming 9.5hr work days and 300 working days per year. Turnover costs are estimated using data from Globerson [45] and are calculated as a fraction of a workers monthly salary. Material costs are assumed to contribute four times as much to the COGS than direct labor.

***Table 4.32**: Parameters used to evaluate operation income.*

Parameter	Value	Units
n_{hrs}	2850	hrs
r_{sale}	406	$ / batch
c_{mat}	248	$ / batch
$c_{overhead}$	1	$ / $ labor
w_{worker}	10	$ / hr
c_{hold}	124	$ / batch
c_{WIP}	499	$ / batch
c_{sep}	760	$ / turnover
c_{sel}	2066	$ / turnover
c_{train}	7861	$ / turnover

The revenue per sale of one batch of gowns is assumed to be zero in the worst simulation case considered (Experiment Run 8 with high turnover and cross-training). The annual operating costs of the system examined in experiment run 8 are shown in Figure 4.30 below.

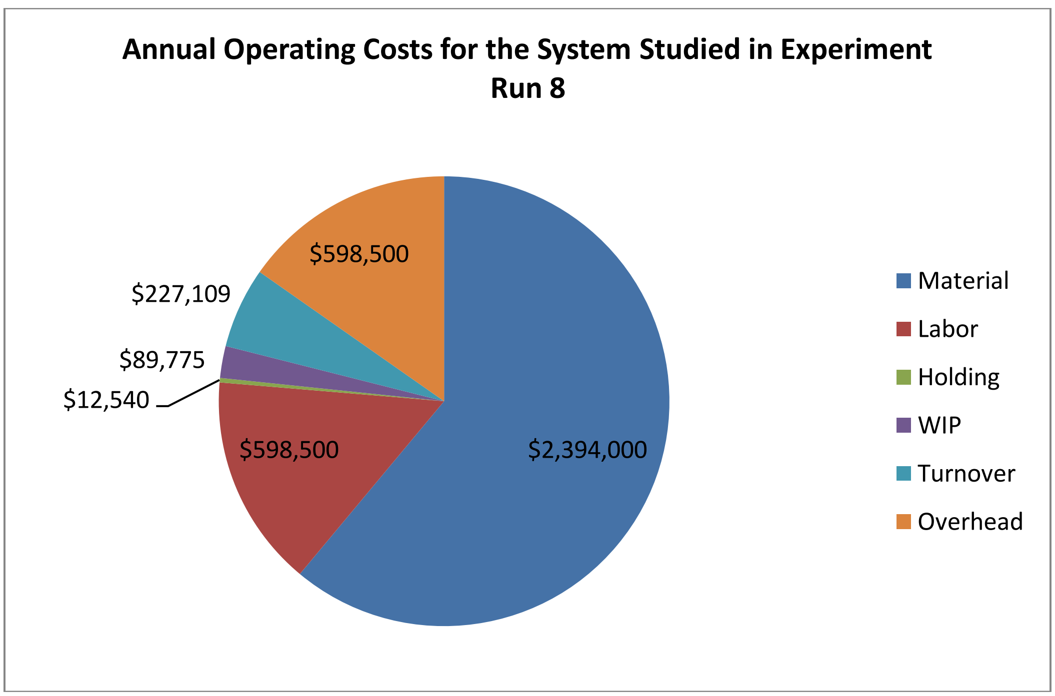

***Figure 4.30**: Annual operating costs when high turnover is experienced and cross-training is practiced.*

The operating costs of all systems examined in simulation experiments are given in Figure 4.31.

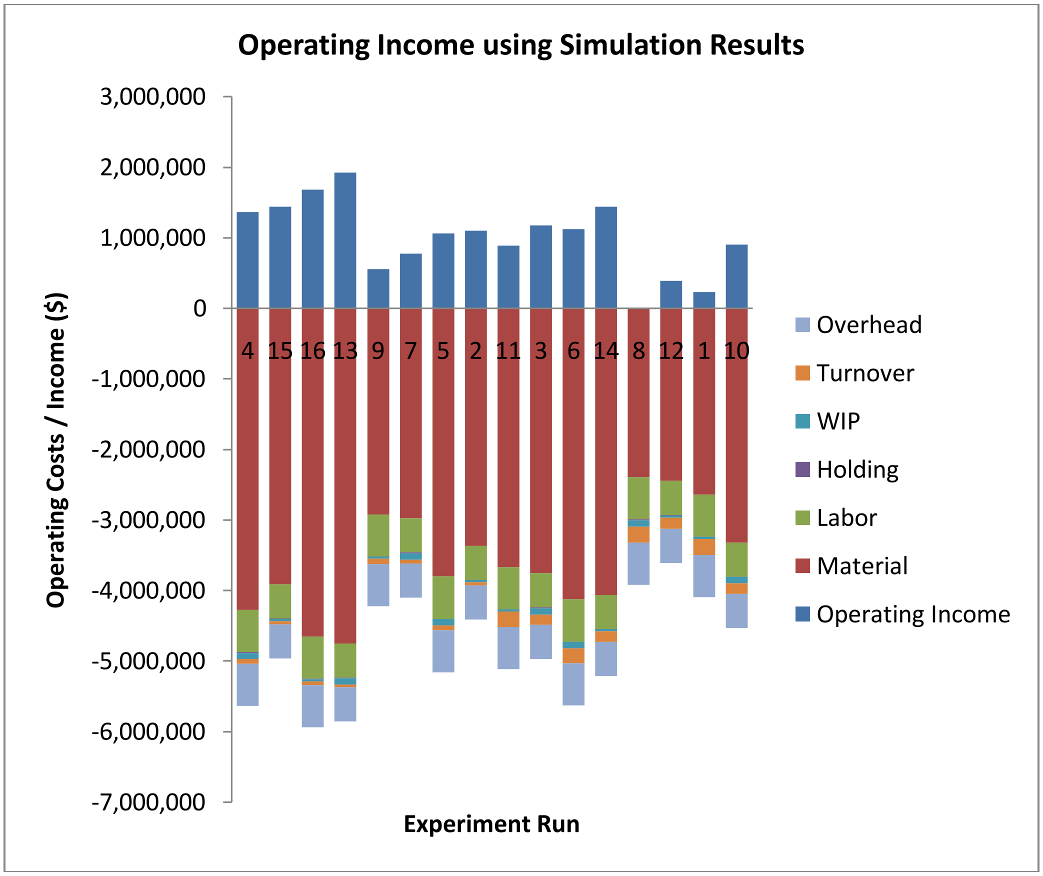

Figure 4.31: *Operating income of systems examined in simulation experiments.*

The highest operating income was achieved using the results from experiment run 13 (low turnover, utilizing a floating worker, automated folding and a large amount of WIP allowed between workstations). The largest benefit results from utilizing a floating worker causing an increase in throughput and increases revenue on average by 43.8%. Automating the folding operation reduces labor requirements and consequently reduces direct labor costs as well as turnover costs. The average effect of automating the folding operation is to increase operating income by 32.4%. In contrast, turnover and cross-training result in significant reductions in operating income. On average, moving from 2.5% - 7.5% monthly turnover and practicing cross-training result in 38% and 54% reductions in operating income respectively.

It has been shown that the changes to the system examined in this study may have a significant effect on the profitability of a company. Even though parameters in the analysis were selected arbitrarily, the results are very significant and are expected to similarly affect the profitability of the sponsoring company. However, the analysis will need to be repeated using the information provided in Table 4.31 and new values for the parameters given in Table 4.21 that correspond to the actual costs realized by the company.

4.3.5 Further Investigation of WIP Capacity as a Design Factor

Results of the fractional factorial experiment suggest that WIP capacity is an important design factor in the system – especially when a floating worker was utilized. However, in the experiment presented earlier all queues received equal amounts of WIP capacity. It's possible that a more efficient allocation of WIP capacity exists. Therefore, a series of experiments were performed in order to further investigate WIP as a design factor. The best performing system from the previous set of experiments was chosen for this set of experiments (i.e. the line utilizing a floating worker and automated folding). The intermediate value of 5% monthly turnover rate was used. A series of full factorial experiments were performed. Experiments began with a low WIP capacity of 2 batches for each queue and the effect of increasing individual queue capacities was examined. Queue capacities were increased by 8 batches in each experiment. 30 replications of each experiment run provided sufficient precision using an increase in queue capacity of 8 batches. A smaller increase in queue capacities was desired. However, the effort required to obtain sufficient precision was impractical. Figure 4.32 below illustrates how the factorial design of experiments was used to increase the capacity of queues that provided the largest increase in throughput rate using the method of steepest ascent.

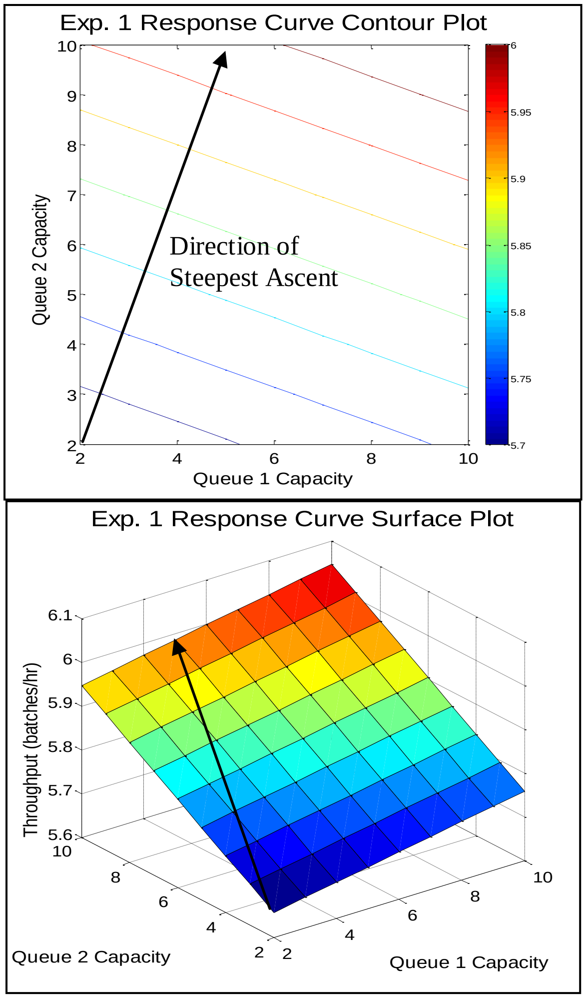

Figure 4.32. *Experiment 1 response curve contour plot (top) and response curve surface plot (bottom).*

Figure 4.32 plots the response curve which was approximated as a linear function of significant effects. The experiment from which Figure 4.32 was produced resulted in noticeable changes in throughput when the capacity of the first two queues was varied. In fact, for all experiments there were no more than two queues that significantly affected throughput by changing their capacity. As a result it is possible to graphically represent all experiments performed in the series of experiments. Figure 4.33 are surface plots for all experiments.

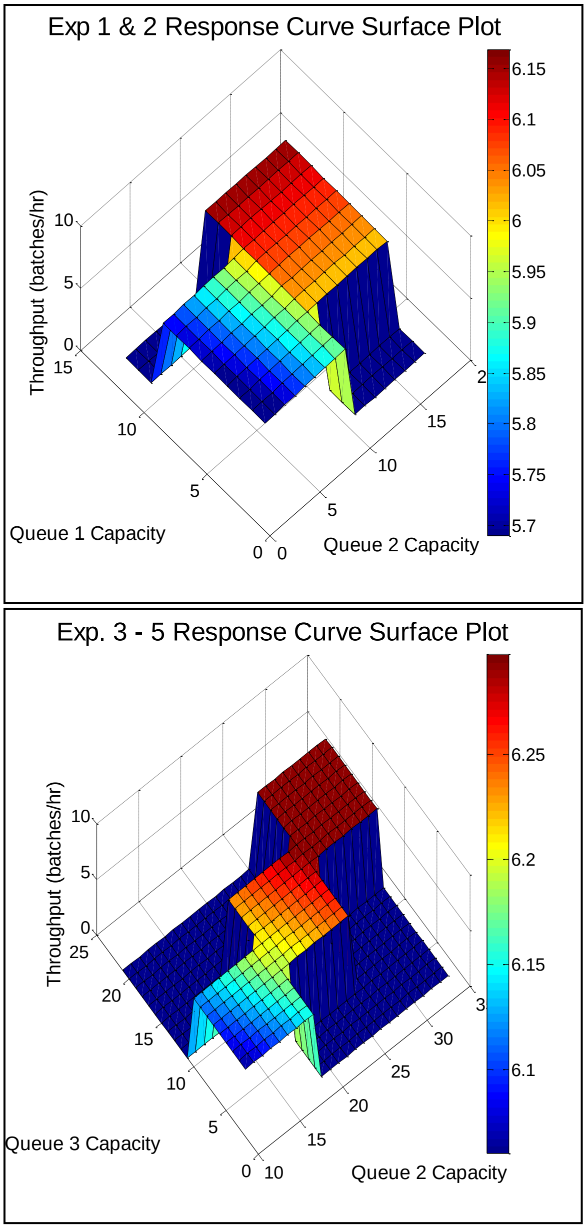

Figure 4.33: *Surface plot of all experiments. Top showing experiments 1 and 2 and bottom showing experiments 3, 4 and 5.*

The reason for two plots (top and bottom) in Figure 4.33 is that the first two experiments yielded changes to the capacity of queues 1 and 2 while the last three experiments yielded changes to the capacity of queues 2 and 3. A summary of the changes to queue capacities and the resulting effect on throughput is given in Table 4.33 below.

***Table 4.33**: Summary of changes to queue capacities.*

	Queue 1 Capacity	Queue 2 Capacity	Queue 3 Capacity	Queue 4 Capacity	Total Queue Capacity	Throughput (batches / hr)	Percent Increase in Throughput
Low	2	2	2	2	8	5.62 ± 0.11	0.0%
Expt. 1	5	10	2	2	19	5.99 ± 0.16	6.5%
Expt. 2	13	10	2	2	27	6.11 ± 0.14	8.8%
Expt. 3	13	18	7	2	40	6.18 ± 0.11	9.9%
Expt. 4	13	26	13	2	54	6.32 ± 0.12	12.4%
Expt. 5	21	34	21	10	86	6.29 ± 0.12	11.9%
High	45	45	45	45	180	6.36 ± 0.06	13.2%

From Table 4.33 it can be seen that eventually an increase in queue capacity did not result in a measureable change in throughput, at which time experiments were stopped. The allocation of WIP capacity was fairly consistent for all experiments. The largest capacity for WIP should be provided immediately upstream of the bottleneck workstation. Smaller amounts of WIP capacity can be provided to the next upstream and downstream queues. It is possible that symmetry around the bottleneck queue is advantageous. The largest measureable increase in throughput rate was achieved during experiment 4 for queue capacities of 13, 26, 13 and 2 for queues 1 – 4 respectively and yielded a 12.4% increase in throughput rate when compared to the case with low WIP capacity.

Figure 4.34 below illustrates the effect on throughput rate after each experiment. The figure suggests that throughput rate is nearing a plateau or asymptote which supports the hypothesis that further increase in WIP will not yield a noticeably higher throughput rate.

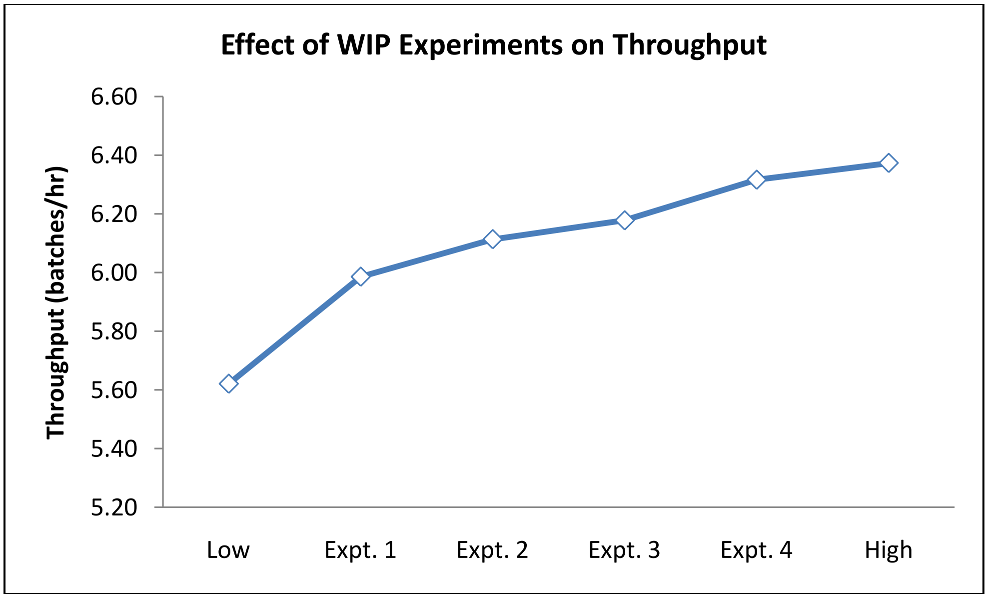

Figure 4.34: *Effect on throughput after each experiment.*

The reason that WIP has such a significant effect on throughput rate is a result of using a floating worker. Assigning the floating worker to a workstation provides that workstation with additional capacity that exceeds that of other workstations. Increased utilization of the floating worker results when there is enough supply of work in the queue upstream of the workstation to which the floating worker is assigned and enough room in the downstream queue to prevent starving and blocking respectively. This may explain why the queue immediately upstream of the bottleneck workstation requires the largest capacity for WIP. Since WIP accumulates the fastest in front of the bottleneck workstation when the floating worker is not assigned to that workstation, a large amount of WIP capacity should be provided to avoid blocking of upstream workstations.

In conclusion these results have supported the hypothesis that WIP capacity is an important consideration in the design of a production line and shown that the total system capacity for WIP can be significantly reduced by using an efficient allocation of WIP capacity. This requires the largest portion of total WIP capacity to be assigned immediately upstream of the bottleneck workstation and smaller portions of WIP capacity provided to queues upstream and downstream of the bottleneck queue (possibly in a symmetrical fashion around the bottleneck queue).

4.4 Chapter Summary

This chapter presented the results of the study. Input parameters for the simulation model were determined from time study data and company records in the first phase of the study. Assembly operation cycle times were found to be positively skewed as a result of minor quality and mechanical problems. When the processing of 100 work pieces and seeking out a new batch for processing was considered as a single event, Monte Carlo simulation verified that batch cycle times are approximately normally distributed as a result of the central limit theorem. Equipment times to failure and times to repair were found to be highly skewed and although best fitting distribution were used in this study, the use of the exponential distribution to represent times to failure and times to repair would not have resulted in significant errors. Two of the learning curve parameters were determined from company data. However, as a result of limited durations of new operator daily productions recorded, the factor of incompressibility had to be estimated. The two parameters estimated from the data were found to be relatively insensitive to a change in the factor of incompressibility.

The second phase of the study consisted of verifying the construction of the simulation model. The submodel that mimics machine failures and repairs was found to be consistent with an analytical solution of a two machine line when machine availabilities are close to those in this study. However, due to slight differences in the formulation of the analytical and simulation model a 5% error was observed when machine availabilities are low. This is not of concern in this study but is presented as a caution to other researchers. The learning and turnover submodel was tested in a deterministic case and found to function properly. And tests confirmed that a floating worker and cross-training of workers was properly modeled in simulations, which concluded the verification of the simulation model.

The third phase began by examining the effect monthly turnover rate on five production lines. This sensitivity analysis showed that including learning and turnover in the simulation model has a significant effect on the performance of the system. This hypothesis is supported by a comparison of simulation results to daily production records for the five lines. The production records suggest that not including learning and turnover results in unaccounted for losses. Furthermore, the comparison suggests that monthly turnover rate may be approximately 5%. However, further research is needed to confirm the true monthly turnover rate. After the turnover sensitivity analysis was completed the effect of cancelling the practice of borrowing workers in the five production lines was examined. It was found that borrowing workers did not provide significant increases in production capacity and in many cases only served to increase the variability of daily production (which has the disadvantage of increasing the difficulty of capacity planning, increasing raw materials and finished goods inventory and increasing lead time). The first suggested change to the system was to cancel the practice of borrowing workers. This change was implemented in one of the production lines and served as the base case for the fractional factorial experiment. Results of the fractional factorial experiment suggested that significant improvements in the throughput rate of the production line could be realized by increasing the capacity for WIP, utilizing a floating worker and automating the folding operation. And, although automating the folding operation was found only to increase throughput rate when turnover was high, automating the folding operation has a positive effect on operating income in all cases by reducing labor and turnover costs (as was verified by an economic analysis of the results). Cross-training workers and an increase in turnover rate both had a negative effect on throughput. Although cross-training showed a large negative effect on throughput rate other benefits of cross-training were not examined (such as increased flexibility and improved worker moral which can have a positive effect on production capacity and turnover).

To further improve the production line a series of experiments were performed for the case where a floating worker is used and the folding operation is automated. However, the WIP capacities of individual queues were examined in order to determine if a more efficient allocation of WIP capacity exists. It was found that the total system capacity for WIP could be reduced by more than 2/3, and have no measurable effect on throughput, if an efficient allocation of WIP capacity was used. Furthermore, an increase from a WIP capacity of 2 batches at each queue to the WIP capacities 13, 26, 13 and 2 batches resulted in a 12.4% increase in throughput rate suggesting that WIP capacity is an important design factor.

CHAPTER 5

Summary of Findings and Recommendations for Future Work

This chapter summarizes the main finding of the current study and indentifies areas that require further investigations.

5.1 Summary of Findings

The study began with problem definition for an industrial system, system description using structured analysis, and collection and analysis of data from the process during normal operations. The data set was used to characterize: assembly operations, equipment failures/repairs, human learning and turnover. The results of the data analysis were the simulation input parameters. Tests were performed to ensure that the simulation model was constructed correctly. Then, a series of numerical experiments and sensitivity analyses were performed to observe the behavior of the system and examine the effect of changes to the production line design.

System data was collected from company records and a traditional time study in order to determine operation cycle time, machine time to failure/repair, learning curve and turnover parameters. The time for an experienced operator to process a single work piece was found to be positively skewed for all operations. The positive skewness results from infrequent delays due to quality problems, minor mechanical issues, difficulty loading/unloading and more. The average coefficient of variation of cycle times was found to be 0.36. Fatigue did not affect operation cycle times throughout the day.

Machine times to failure and repair were found to be highly positively skewed. Best fitting distributions were used in simulations. The exponential distribution would not have resulted in significant errors, because this distribution provides a good fit to the data and machine availabilities were high (99.75% - 99.88%).

DeJong's equation was used to model the decrease in cycle time that results from an increase in experience, i.e., human learning. DeJong's model has the advantage of imposing a limit upon which no further reduction in cycle time is possible. Company data was used to determine the time to complete the first piece and the learning rate. The average learning rate was found to be 0.364 or a 77.7% learning curve which suggests that learning is a rapid process. The average incompressibility factor used was 0.12 suggesting that machines used in assembly operations are not a significant limiting factor on cycle time. However, the incompressibility factor (which determines the limit of improvement) was estimated since company data was limited to short durations of learning.

Limited data was available to determine the turnover rate. A combination of industry reports, company data and the turnover sensitivity analysis suggest that the turnover rate is between 2.5% and 7.5%. A stationary exponential distribution was used to describe employee duration of employment. The parameters mentioned above served as inputs into the simulation model.

The turnover sensitivity analysis compared company production data to simulation results for five production lines when monthly turnover was 0%, 2.5% and 5%. The results suggest that monthly turnover rate could be in the vicinity of 5%. In addition, learning and turnover had a significant effect on production capacity. The average decrease in capacity due to 2.5% and 5% monthly turnover was 16% and 20% respectively for the five production lines. A subsequent experiment examined the effect of some alternative production line designs when monthly turnover rate was 2.5% and 7.5%.

A fractional factorial design of experiment was used to examine the effect of five factors: an increase in monthly turnover rate from 2.5% to 7.5%, cross-training workers, cross-training a single worker who can be assigned to any workstation as needed (referred to as a "floating worker"), automating the last workstation (folding) and increasing the size of queues from 15 to 45 batches. The best performing system was one with low turnover, a floating worker, automated folding and large queue capacities.

The largest improvement in throughput (16.6% on average) was due to the floating worker. When a workstations performance is disrupted by a new worker replacing an old worker, the floating worker provides support to that workstation until the new worker becomes proficient at his/her task. In addition, the production line is difficult to balance, because only an integer number of workers can be assigned to any given workstation. The floating worker helps to balance the line by spending a portion of his/her time at several workstations. The mechanism to control the assignment of the floating worker was based on the accumulation of work-in-process. This control mechanism has several advantages: monitoring work-in-process is a known bottleneck identification method, work-in-process is an observable feature and work-in-process is required for high utilization of the floating worker.

On average increasing the queue capacities from 15 to 45 batches resulted in a 6.3% increase in throughput. However, when utilizing a floating worker the increase in throughput rate was 8.7%. Queue capacity is particularly important when using a floating worker in order to maximize the utilization of the floating worker. In general the floating worker provides additional capacity to a workstation; and thus there should be ample supply of material in the immediately upstream queue to prevent starving and ample room for material in the immediately downstream queue to prevent blocking. Later results would suggest a queue capacity allocation that could reduce the total queue capacity without incurring losses in throughput.

Automating the folding operation only resulted in an increase in throughput rate when monthly turnover rate was 7.5%. In this case an average increase in throughput rate of 5.9% was observed even though the capacity of the folding workstation with experience workers remained the same. The reason automating the folding workstation has the potential to increase throughput rate is high is because there is a reduction in skill requirements. In the case of manual folding, workers require a large amount of time to become proficient at the task. When turnover is high there can be a large number of inexperienced workers which negatively affects performance. This result supports the hypothesis that there are additional benefits to automated assembly apart from the commonly known benefits, such as reduced labor requirements. In addition, turnover costs (which are not always considered) can be significant [45] and so a reduction in labor requirements can have a significant positive impact on operating income.

This study quantified the losses associated with learning and turnover. When the monthly turnover rate of workers increased from 2.5% to 7.5% throughput decreased on average by 13.9%. This result has two important implications. First, learning and turnover significantly affects production line behavior and performance, and should be included in models of production lines. Second, a reduction in employee throughput rate can have a significant positive impact on the profitability of a company.

Cross-training workers had the largest negative impact on production line throughput. On average, cross-training resulted in a 28.1% decrease in throughput. The reason cross-training reduced production line throughput is because workers spend are required to learn all assembly operations. As a result, cross-trained workers do not acquire the same skill and proficiency as specialized workers. This study did not fully utilize the flexibility of cross-trained workers nor did it explore the relationship between job enlargement and worker satisfaction.

As mentioned earlier the best performing system was one that utilized a floating worker, automated folding and provided a large capacity for work-in-process. However, of these changes, increasing queue capacities is the only one that negatively affects operating income, as a result of the holding cost associated with work-in-process. Therefore, a series of factorial experiments were performed to determine if the queue capacities could be reduced. It was found that the total system capacity for WIP could be reduced by more than 2/3, and have no measurable effect on throughput, if WIP capacity was allocated appropriately. This requires the largest portion of total WIP capacity to be assigned immediately upstream of the bottleneck workstation and smaller portions of WIP capacity provided to queues upstream and downstream of the bottleneck queue (possibly in a symmetrical fashion around the bottleneck queue).

This study provided insight into the behavior of mass production systems when learning and turnover is considered. In addition, if the sponsoring company implements the recommended changes (i.e. use a floating worker, automate the folding operation and provide WIP capacities of 13, 26, 13 and 2 batches to queues 1 – 4) it may realize a 13.5% increase in throughput rate.

5.2 Contributions of the Present Work

Structured analysis, discrete-event-simulation, and statistical analysis were combined to conduct numerical experiments and a sensitivity analysis of a set of production alternatives, in such a way that the approach can be readily applied to other kinds of industrial systems.

Data from an actual manufacturing facility were collected to determine parameters of the simulation model, which was then used to characterize cycle times, machine failures, machine repairs, worker learning, and worker turnover. The simulation results provide further insight into the behavior of production lines when learning and random turnovers are considered. In addition, practical methods for improving production line performance were examined. Emphasis was placed on ensuring that methods proposed could be implemented in the real system.

The practical contribution is a set of analysis results that yield important useful knowledge to the sponsoring company of what strategies should be implemented to improve profitability.

The academic contribution is an extension of the works of Hutchinson [61] and Munzo [94] to include learning and turnover in a simulation model of a real production system.

5.3 Recommendations for Future Work

This study was limited in some respects. The following identifies areas that merit further investigation.

5.3.1 Worker Turnover

There was not enough empirical data to provide a high degree of confidence in the turnover rate on the production line. This is the reason that monthly turnover rate was included as an experimental factor. However, future work should examine the true turnover rate. In addition, it was assumed that the turnover distribution was stationary (i.e. not time dependent) and the same for all operations. It's possible that some times of the year experience higher turnover (e.g. before the holidays) and some operations may experience higher turnover than others due to less worker satisfaction. These possibilities should be examined since they may influence the behavior and performance of the production line.

5.3.2 Learning Curve Parameters

DeJong's equation was used to model human learning. However, only two of the three parameters of this model could be estimated from the data since only short durations of new workers performance was recorded. In addition, performance was measured by daily production which includes time for instructions, breaks and other disruptions. Future work should investigate the cycle time of new operators over a long period. This would allow all the parameters of DeJong's equation to be estimated from the data and determine the appropriateness of this model. If DeJong's model does not describe the empirical data well then there may be missing information that could merit the use of a multivariate learning model, one that includes forgetting and relearning or perhaps the assumption of homogeneous workers needs to be examined. These are areas that are beginning to receive attention in some models of production systems (such as the job shop) [72], [98] but have yet to be examined in a serial production systems.

5.3.3 Floating Worker(s)

This study indicates that a floating worker can have a substantial impact on a production line by mitigating the effects of turnover and helping to achieve a balanced production line. However, it's possible that the system would benefit further from additional floating workers. It is suspected that there is a diminishing return with an increasing number of floating workers and thus there may be an optimal number of floating workers for a given production line.

One problem may arise when using multiple floating workers is the operational control mechanism which will likely be increasingly complicated as the number of floating workers increases. Care will have to be taken to ensure that the design solution can still be practically implemented in the real system.

5.3.4 Allocation of Buffer Capacity

This study contradicts Hutchinson's [61] conclusions that buffer capacity is not a significant factor when learning and turnover is considered in models of production system. Furthermore, buffer capacity appears to be particularly important when utilizing a floating worker. This study suggests that buffer capacity should be allocated with the largest portion immediately upstream of the bottleneck station and smaller portions upstream and downstream of the bottleneck buffer (possibly in a symmetrical fashion). Further research is required in order to determine if this buffer allocation applies to other systems. A fruitful study may be one the mimics the simulation studies performed by Conway et al. [24] and Powell and Pyke [105] where the optimal allocation of buffers for: 1) a range of line lengths, 2) perfectly balanced lines and 3) lines with one bottleneck is examined. The difference being that the future study should included learning and turnover and at least one floating worker.

5.3.5 Cross-Training

This study indicated that cross-training workers to perform all five assembly operations had a large negative impact on throughput rate. On average cross-training workers resulted in a 28.1% decrease in throughput. However, there are several potential benefits of cross-training that were not examined. It's possible that cross-training will increase worker satisfaction and reduce turnover (which was shown to have a significant positive impact on throughput). In addition, cross-trained workers are highly flexible. The flexibility of cross-trained workers was not fully utilized in this study. This study was only concerned with a single production line. However, cross-trained workers may provide large benefits if they can be allocated to multiple product lines and help to compensate product demand variability. In addition, absenteeism was not considered in this study. When absenteeism is considered the flexibility of cross-trained workers could be quite valuable.

Another method that has recently emerged is known as chained cross-chaining [68, 59], and [63]. Chained cross-chaining utilizes limited cross-training. In this study workers were cross-trained in all operations and experienced a significant reduction in proficiency at a given operation. However, operator performance can be increased by limited cross-training to two tasks. This method also has the advantage of simplifying the optimization problem since it reduces the size of the solution space. Additional work in this area is required since none of the previous studies have included the learning curve in their investigations of chained cross-chaining.

5.3.6 Repair Crew Model

The current study did not include a detailed a model of the repair crew since machine availabilities were high. However, in other cases a detailed model may be necessary since queuing of machines in need of maintenance services negatively affects system performance. On the other hand an increase of maintenance personnel adds to the operating cost of the system. Thus an optimization problem presents itself. There has been some research in this area [78]; however, it seems that including the learning curve in the repair crew model may contribute to the accuracy and understanding of the effect of maintenance activities on system performance. Since mechanics are required to perform a range of troubleshooting and maintenance activities a great deal of learning is involved. Thus, a mechanics level of experience can have a significant effect on times to repair, times to failure and equipment performance. Currently, there are no studies that have considered learning in a repair crew model.

5.3.7 Variability (Sensitivity Analysis)

This study has included many sources of variability in order to obtain an accurate representation of the real system; but some sources of variability may be less significant than others. For example, the average availability of machines was observed to be 99.83% during the observation period. It's possible that the availabilities of machines is high enough that machine failures/repairs can be ignored and not result in significant errors. It may be useful to perform a sensitivity analysis of machine parameters to determine at which point machine failures/repair do or do not significantly affect the system. The same should be done for the cycle time variability.

The results may suggest that some sources of variability can be ignored which would allow for simplifications of the model. In addition, this may support the development of analytical models of production systems that include learning and stochastic turnovers. Analytical models have the advantage of providing a general solution that gives more insight into the behavior of a system and is much easier to optimize.

5.3.8 Apply Methods to Other Industries

This study has illustrated the importance of including learning and turnover in the production line of interest. Furthermore, results suggest that several changes may significantly improve the performance of the production line; however, it is not known whether other cases will experience similar improvements. Further research applying the methods proposed in this study to other cases and industries would provide evidence of the robustness of these methods.

A case that may benefit from the methods proposed in this study is the maintenance activities in the mining industry. Several important pieces of equipment are involved in mining raw materials and typically there is a dedicated maintenance crew for each equipment type; but the demand for maintenance of equipment types can vary. Furthermore, experience of maintenance crew personnel can affect equipment downtime. Having one or more “floating workers” may help to compensate for these effects and increase equipment utilization.

5.4 Conclusion

The present work involved modeling a discrete part, mass production system. These systems have received a lot of attention in previous literature; however, human learning and turnover has largely been ignored in models of production systems. The few studies that include learning and turnover in models of mass production systems suggest that it has a significant effect on the behavior and performance of these systems. The results of this study support this argument and provide additional guidelines to aid production managers in the efficient design of these systems. Since this study was concerned with a specific production system, further research is needed to determine whether similar results will be realized in other systems, and to examine other system design solutions.

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APPENDIX

A-1: Time Study Record Sheet

Operator:

Experience:

Date:

Sample No.:

Time:

File:

Observation	Clock		Cycle Time (sec)	Comment
	min	sec		
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

A-2: Matlab Code

Customhist – used to generate histograms of the data and fit distributions to the data.

```
function customhist(x,number_of_bins,length)

alpha = 0.20;

%This function takes quickly produces a
%histogram with specified width and length so that the user can
easily
%change these parameters and view the resulting histogram.

%IMPORTANT: this file has been modified to perform chi square
goodness of
%fit tests for the input data, using the specified number of bins
and
%length, against the following distributions:
%Exponential
%Gamma
%Generalized Extreme
%Lognomral
%Normal
%Rayleigh (a special case of Weibull)
%Weibull

%Input parameters:
%    numerical array of raw data (x)
%    number_of_bins as integer
%    length as double

y = x;

width = (length/number_of_bins);
edges = [(width/2):width:(length-width/2)];

%use hist(y,edges) to create the histogram.
%hist(y,edges) used the data in edge to create on-center bins
%note: histc(y,edges) creates bins at the edges (including 0).

n = hist(y,edges)
hist(y,edges)
hold on
xmin = 0;
xmax = int16(max(y));
ymin = 0;
ymax = int16(max(n)/.75);
axis([xmin xmax ymin ymax]);
hold off

edges = [0:width:length];
edges(number_of_bins + 2) = inf;
```

```
%the following is to test the data against the EXPONENTIAL
distribution
%with parameter mu (pdf(x) = 1/mu*exp(-x/mu))

%mle evaluates the maximum likelihood estimates for the
exponential
%distribution parameters. Note that Matlabs definition of mu is
not the
%same as the popular definition. In this case mu = 1 / lambda and
has units
%of time not 1 / time.
[mu mu_conf_int] = mle(x,'distribution','exponential');

%This loop calculates the expected number of counts in each bin by
taking
%the difference of the cdf evaluated at the upper and lower edge
of a bin
%and repeating the process for each bin.
for i = 1:number_of_bins
    %Notice that when using the cdf function we use 'exp' but in
the mle
    %function we have to use 'exponential' (weird???)
    expected(i) = size(x,1)*(cdf('exp',edges(i+1),mu)-
cdf('exp',edges(i),mu));
end
expected(number_of_bins+1) = size(x,1)*(cdf('exp',edges(end),mu)-
cdf('exp',edges(number_of_bins),mu));

%use the chi2gof fucntion to perform the chi square test.
[h_exp,p_exp] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',1,'alpha',al
pha);

%next test the data against the GAMMA distribution with parameters
a and b.
[phat_gam phat_gam_ci] = mle(x,'distribution','gamma');

for i = 1:number_of_bins
    expected(i) =
size(x,1)*(cdf('gam',edges(i+1),phat_gam(1),phat_gam(2))-
cdf('gam',edges(i),phat_gam(1),phat_gam(2)));
end
expected(number_of_bins+1) =
size(x,1)*(cdf('gam',edges(end),phat_gam(1),phat_gam(2))-
cdf('gam',edges(number_of_bins),phat_gam(1),phat_gam(2)));

[h_gamma,p_gamma] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',2,'alpha',al
pha);

%test the data against the GENERALIZED EXTREME VALUE distribution
with
%parameters k, mu and sigma
```

```
[phat_gev phat_gev_ci] = mle(x,'distribution','generalized extreme
value');

for i = 1:number_of_bins
    expected(i) =
size(x,1)*(cdf('gev',edges(i+1),phat_gev(1),phat_gev(2),phat_gev(3
))-cdf('gev',edges(i),phat_gev(1),phat_gev(2),phat_gev(3)));
end
expected(number_of_bins+1) =
size(x,1)*(cdf('gev',edges(end),phat_gev(1),phat_gev(2),phat_gev(3
))-
cdf('gev',edges(number_of_bins),phat_gev(1),phat_gev(2),phat_gev(3
)));

[h_gev,p_gev] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',3,'alpha',al
pha);

%test the data against theLOGNORMAL distribution with parameters
mu
%and sigma
[phat_ln phat_ln_ci] = mle(x,'distribution','lognormal');

for i = 1:number_of_bins
    expected(i) =
size(x,1)*(cdf('logn',edges(i+1),phat_ln(1),phat_ln(2))-
cdf('logn',edges(i),phat_ln(1),phat_ln(2)));
end
expected(number_of_bins+1) =
size(x,1)*(cdf('logn',edges(end),phat_ln(1),phat_ln(2))-
cdf('logn',edges(number_of_bins),phat_ln(1),phat_ln(2)));

[h_ln,p_ln] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',2,'alpha',al
pha);

%test the data against the NORMAL distribution with parameters mu
%and sigma
[phat_norm phat_norm_ci] = mle(x,'distribution','normal');

for i = 1:number_of_bins
    expected(i) =
size(x,1)*(cdf('norm',edges(i+1),phat_norm(1),phat_norm(2))-
cdf('norm',edges(i),phat_norm(1),phat_norm(2)));
end
expected(number_of_bins+1) =
size(x,1)*(cdf('norm',edges(end),phat_norm(1),phat_norm(2))-
cdf('norm',edges(number_of_bins),phat_norm(1),phat_norm(2)));

[h_norm,p_norm] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',2,'alpha',al
pha);

%test the data against the RAYLEIGH distribution with parameter b
[b b_ci] = mle(x,'distribution','rayleigh');
```

```
for i = 1:number_of_bins
    expected(i) = size(x,1)*(cdf('rayl',edges(i+1),b)-
cdf('rayl',edges(i),b));
end
expected(number_of_bins+1) = size(x,1)*(cdf('rayl',edges(end),b)-
cdf('rayl',edges(number_of_bins),b));

[h_rayl,p_rayl] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',1,'alpha',al
pha);

%test the data against the WEIBULL distribution with parameters a
and b
[phat_wbl phat_wbl_ci] = wblfit(x);

for i = 1:number_of_bins
    expected(i) =
size(x,1)*(cdf('wbl',edges(i+1),phat_wbl(1),phat_wbl(2))-
cdf('wbl',edges(i),phat_wbl(1),phat_wbl(2)));
end
expected(number_of_bins+1) =
size(x,1)*(cdf('wbl',edges(end),phat_wbl(1),phat_wbl(2))-
cdf('wbl',edges(number_of_bins),phat_wbl(1),phat_wbl(2)));

[h_wbl,p_wbl] =
chi2gof(x,'edges',edges,'expected',expected,'nparams',2,'alpha',al
pha);

%The following code is so that we can extract the estimated
parameters and
%95% confidence interval for the parameters.

estimated_parameters = [mu_conf_int(1) mu mu_conf_int(2) 0 0 0 0 0
0;phat_gam_ci(1) phat_gam(1) phat_gam_ci(2) phat_gam_ci(3)
phat_gam(2) phat_gam_ci(4) 0 0 0;phat_gev_ci(1) phat_gev(1)
phat_gev_ci(2) phat_gev_ci(3) phat_gev(2) phat_gev_ci(4)
phat_gev_ci(5) phat_gev(3) phat_gev_ci(6);phat_ln_ci(1) phat_ln(1)
phat_ln_ci(2) phat_ln_ci(3) phat_ln(2) phat_ln_ci(4) 0 0
0;phat_norm_ci(1) phat_norm(1) phat_norm_ci(2) phat_norm_ci(3)
phat_norm(2) phat_norm_ci(4) 0 0 0;b_ci(1) b b_ci(2) 0 0 0 0 0
0;phat_wbl_ci(1) phat_wbl(1) phat_wbl_ci(2) phat_wbl_ci(3)
phat_wbl(2) phat_wbl_ci(4) 0 0 0];

%Now rank the distributions by fit and print a table of the test
results

distributions = strvcat('Exp ','Gam ','GEV
','Logn','Norm','Rayl','Wbl ');

%The following ranks the distributions according to the chi-square
goodness
%of fit test results
```

```
chi2results = [p_exp h_exp 1;p_gamma h_gamma 2;p_gev h_gev 3;p_ln
h_ln 4;p_norm h_norm 5;p_rayl h_rayl 6;p_wbl h_wbl 7];

chi2results = sortrows(chi2results,-1);

fprintf('Chi-Square Test Results:\n')
fprintf('distribution      p-value       reject H0?\n')
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(1,3),:),chi2results(1,1),chi2re
sults(1,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(2,3),:),chi2results(2,1),chi2re
sults(2,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(3,3),:),chi2results(3,1),chi2re
sults(3,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(4,3),:),chi2results(4,1),chi2re
sults(4,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(5,3),:),chi2results(5,1),chi2re
sults(5,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(6,3),:),chi2results(6,1),chi2re
sults(6,2))
fprintf('%4s              %6f
%1.0f\n',distributions(chi2results(7,3),:),chi2results(7,1),chi2re
sults(7,2))

%Now add the distributions to the histogram that was called at the
%beggining of this m-file.
n_data = size(x,1);
x_values = linspace(0,double(xmax));
histarea = n_data*length/number_of_bins;

y_exp = histarea*pdf('exp',x_values,mu);
y_gam = histarea*pdf('gam',x_values,phat_gam(1),phat_gam(2));
y_gev =
histarea*pdf('gev',x_values,phat_gev(1),phat_gev(2),phat_gev(3));
y_ln = histarea*pdf('logn',x_values,phat_ln(1),phat_ln(2));
y_norm = histarea*pdf('norm',x_values,phat_norm(1),phat_norm(2));
y_rayl = histarea*pdf('rayl',x_values,b);
y_wbl = histarea*pdf('wbl',x_values,phat_wbl(1),phat_wbl(2));

hold all

plot(x_values,y_exp,'linewidth',2)
plot(x_values,y_gam,'linewidth',2)
plot(x_values,y_gev,'linewidth',2)
plot(x_values,y_ln,'linewidth',2)
plot(x_values,y_norm,'linewidth',2)
plot(x_values,y_rayl,'linewidth',2)
plot(x_values,y_wbl,'linewidth',2)
```

```
%legend('Data','Exponential','Gamma','Gen. Extreme
Value','Lognormal','Normal','Rayleigh','Weibull')
legend('Data','Exponential','Gamma','Gen. Extreme
Value','Lognormal','Normal','Rayleigh','Weibull')

hold off
```

All_dejong_nlinfit (below) – used to determine the learning curve parameters of DeJong's equation given a data set.

```
function answer = all_dejong_nlinfit(X,param0)

param1 = [param0(1) param0(2)];
A = param0(3);

%This function solves the non-linear regression problem defined in
the
%excel file 'Regression-Analysis-all-24Jan2011.xls'

%X is a 1 x m vetor of the input data
%param0 is a 1 x 3 vector of the initial guess for the parameters
t1 and b
%respectively. param0(3) is the specified value of A which is the
%the assymptote for which no further cycle time reduction is
possible. A is
%expressed in terms of the Standard, S. A = f*S where 0<f<1.

[m n] = size(X);

for i = 1:m

%in the above mentioned excel file you will find that the equation
requires
%two input variables: X1 the cumulative pieces produced at the end
of the
%previous day and X2 the cumlative pieces produced at the end of
the
%current day.
x = zeros(1,1);
for j = 1:n
    if X(i,j)~=0
        x(2,j)=X(i,j);
    else
        break
    end
end
N = size(x,2);
x(1,1) = 0;
for k = 2:N
    x(1,k) = x(2,k-1);
end

x = x';
```

```
%assume that every day a worker produces pieces for 9.5hrs (10hr
shift -
%0.5hrs for lunch)
y = 9.5*ones(N,1);

%call the function nlinfit to solve for parameters using the
Guass-Newtwon
%algorithm with Levenbuerg-Marquardt modifcations to solve the
ordinary
%least squares problem.
[params,residuals,J,COVB,mse] = nlinfit(x,y,@Tmn,param1);

param_hat(i,:) = params;
mean_square_error(i,1) = mse;

end

answer = [param_hat,mean_square_error];

%the function below is the power model manipulated to predict time
(Tmn)
%it should take to make pieces m to n.

function Tmn_hat = Tmn(params,X)

t1 = params(1);
b = params(2);

x1 = X(:,1);
x2 = X(:,2);

Tmn_hat = t1*(A/t1*(x2-x1)+(1-A/t1)/(1-b)*(x2.^(1-b)-x1.^(1-b)));

end

end
```

TwoMs (below) – used to find the exact analytical solution to two servers in series with unreliable machines and limited buffer capacity.

```
function TwoMs(mu,fail_rate,repair_rate,N)

%This function generates and solves the Chapman-Kolmogorov
equations for
%the case of two servers in series with unreliable equipment and
limited
%buffer capacity.

mu1 = mu(1);     %M1 service rate
mu2 = mu(2);     %M2 service rate
f1 = fail_rate(1);   %M1 failure rate
f2 = fail_rate(2);   %M2 failure rate
```

```
r1 = repair_rate(1);     %M1 repair rate
r2 = repair_rate(2);     %M2 repair rate
%N is the buffer capacity.

transitions = zeros(4*(N+3));

%lower boundary probabilities
A = [-(r1+r2) f1 0 0 0 0 0 0 0 0 0 0;        %P000
    r1 -(mu1+f1+r2) 0 0 0 0 0 0 0 0 0 0;     %P010
    r2 0 -r1 f1 0 0 mu1 0 0 0 0 0;           %P001
    0 r2 r1 -(mu1+f1) 0 0 0 mu2 0 0 0 0];    %P011

transitions(1:4,1:12) = A;

%interior probabilities
B = [0 0 0 0 -(r1+r2) f1 f2 0 0 0 0 0;          %P100
    0 mu1 0 0 r1 -(f1+mu1+r2) 0 f2 0 0 0 0;     %P110
    0 0 0 0 r2 0 -(f2+mu2+r1) f1 0 0 mu2 0;     %P101
    0 0 0 mu1 0 r2 r1 -(f1+f2+mu1+mu2) 0 0 0 mu2];    %P111

for i = 1:N+1
    for j = 1:N+1
        transitions((4*j+1):(4*j+4),(4*j-3):(4*j+8)) = B;
    end
end

%upper boundary probabilities
C = [0 0 0 0 0 0 0 0 -(r1+r2) 0 0 0;        %PB00
    0 0 0 0 0 mu1 0 0 r1 -r2 0 f2;          %PB10
    0 0 0 0 0 0 0  0 r2 0 -(mu2+r1) 0;    %PB01
    1 1 1 1 1 1 1 1 1 1 1 1];    %Norming Equation (replacing PB11)

transitions((4*N+9):(4*N+12),(4*N+1:4*N+12)) = C;
transitions(end,:) = 1;

b = zeros(4*(N+3),1);
b(4*(N+3)) = 1;
x = transitions\b
sumx = sum(x)

P2starv = sum(x(1:4));
P2down = sum(x(1:4:end)) + sum(x(2:4:end));
P1block = sum(x((4*N+9):end));
P1down = sum(x(1:4:end)) + sum(x(3:4:end));
TP1 = mu1*(1-P1block-P1down)
TP2 = mu2*(1-P2starv-P2down)
```

A-3: SimEvents Models

Machine Failure/Repair Model and Test

The model that was developed to test the function of machine failures/repairs is shown in Figure A-3.1 below.

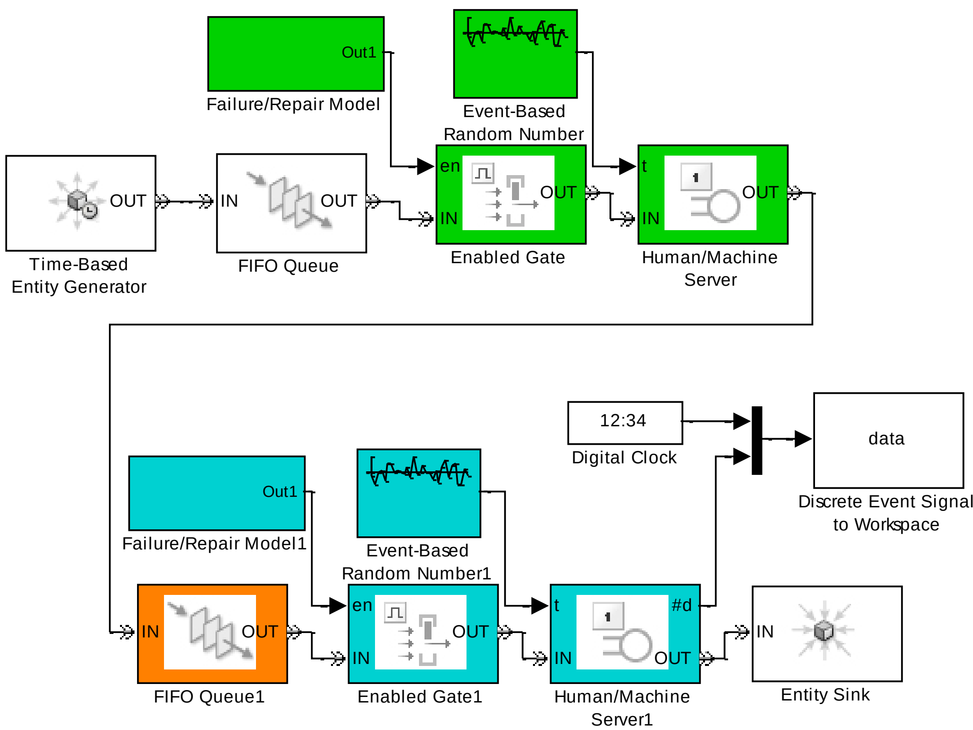


***Figure A-3.1**: SimEvents model of two servers in series with unreliable machines*

The model consists of two servers (one sever colored green and the other colored blue) in series with unreliable machines. This system was chosen since the results can be compared to an analytical solution. Entities (or work pieces) are generated by the “Time-Based Entity Generator” block. The “Enabled Gate” block prevents entities from passing when the input signal ‘en’ is less than or equal to zero. This mimics a machine in a “down” state. The “Failure/Repair” block is a submodel that determines whether the input signal ‘en’ is 0 (the machine is down) or 1 (the machine is up). The submodel is shown in Figure A-3.2 below.

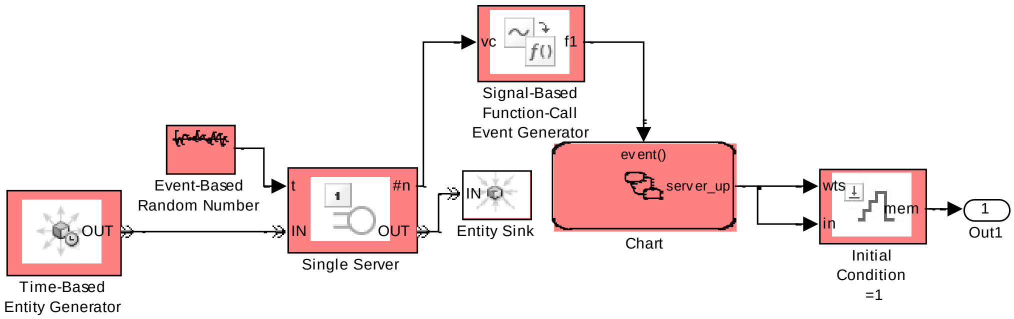


Figure A-3.2: *Failure/repair model.*

The failure/repair model generates random failures via the "Time-Based Entity Generator." The random duration of repairs is determined by the "Event-Based Random Number" block. The "Single Server" represents a repair crew member. The state of the machine is controlled by the "Chart" block which is obtained from Matlab's StateFlow software. The opened "Chart" is shown in Figure A-3.3 below.

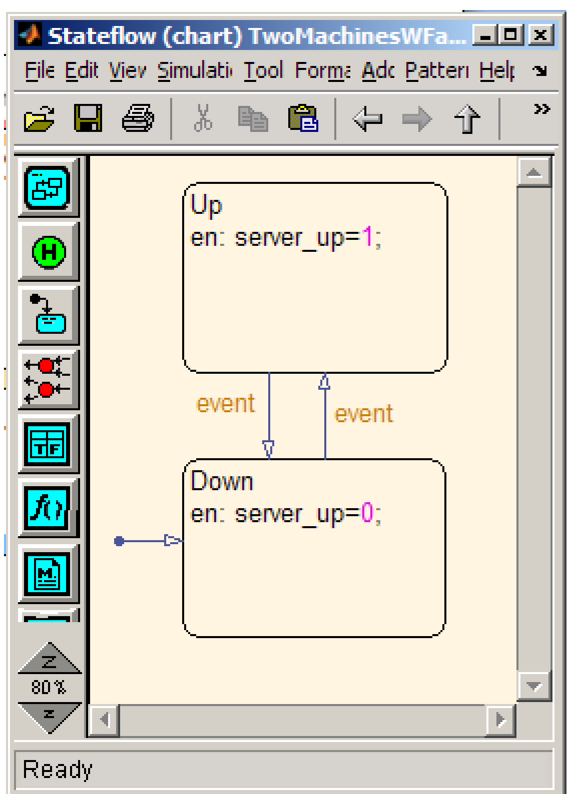


Figure A-3.3: *Machine state-flow chart.*

When the repair crew member is servicing a machine, the machine state transitions from up to down, making the output signal (defined as "server_up") zero, and engages the "Enabled Gate" in Figure A-3.3. When the repair crew member completes the service, server_up is assigned a value of one and the gate is disabled.

Single Sever to Test Turnover Model

The SimEvents model that was developed to test the function of turnovers is shown in Figure A-3.4 below.

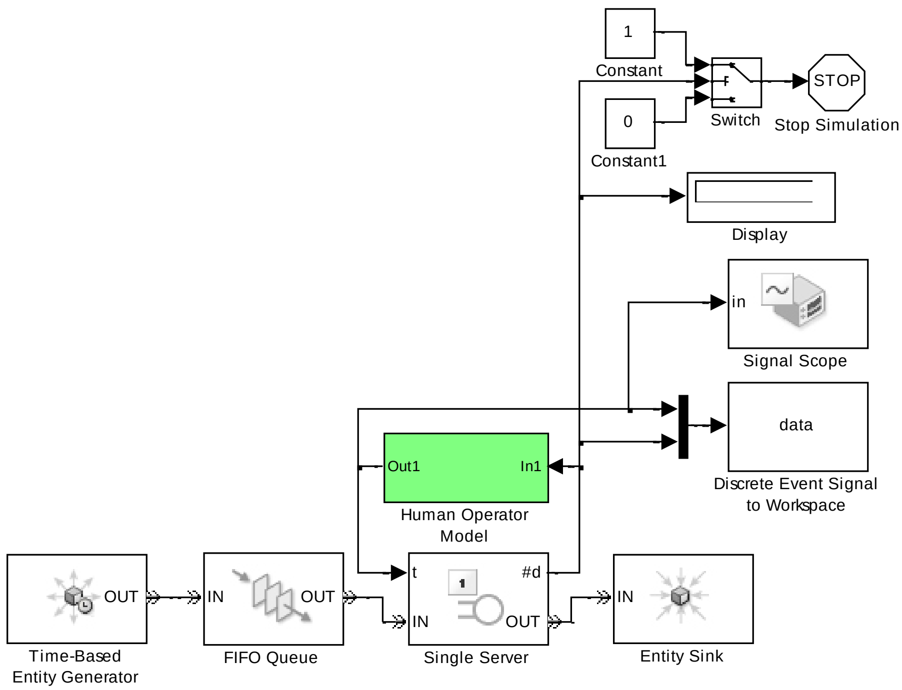


Figure A-3.4: *Single server model with learning and turnover.*

Cycle times are determined using the "Human Operator Model". Opening the "Human Operator Model" block produces the submodel shown in Figure A-3.5 below.

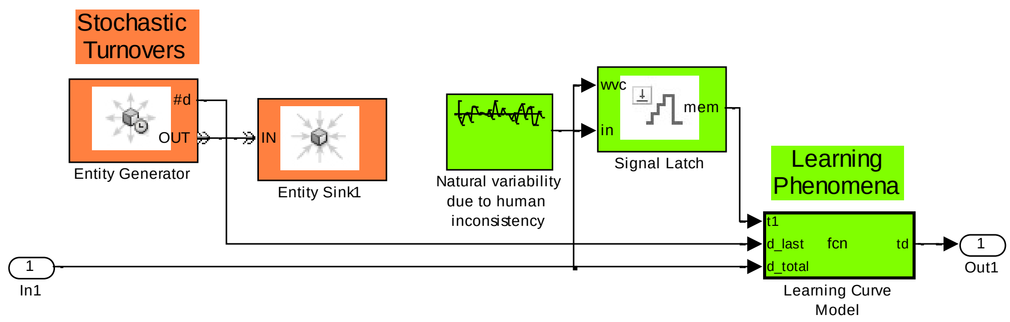


***Figure A-3.5**: Human operator model.*

The "Human Operator Model" shown in Figure A-3.5 generates random turnovers using the "Entity-Generator" block and decreases cycle time using the "Learning Curve Model." The "Learning Curve Model" block is a user defined function and is shown in Figure A-3.6.

```
function td = fcn(t1,d_last,d_total)
%This function accounts for learing where:
    %Yd - time to produce batch d (random exponential
variable)
    %t1 - random time to produce first piece
    %d - unit number

b = 0.35;        %learning factor
Y1 = 4.6;        %Observed time to produce the first piece
S = 0.8025;      %Standard taken as the observed cycle time
M = 0.85*S/Y1;   %Incompressibility factor
d = d_total - d_last + 1;
%Using the deJong learning model:
td = t1*(M+(1-M)*d^(-b));
```

***Figure A-3.7**: Learning curve model.*

DeJong's equation is evaluated in the "Learning Curve Model" block. When a turnover occurs 'd_last' is set equal to 'd_total' thereby resetting a workers experience.

Model for Testing the Floating Worker

The SimEvents model used to test methods used to model a floating worker is shown in Figure A-3.8 below.

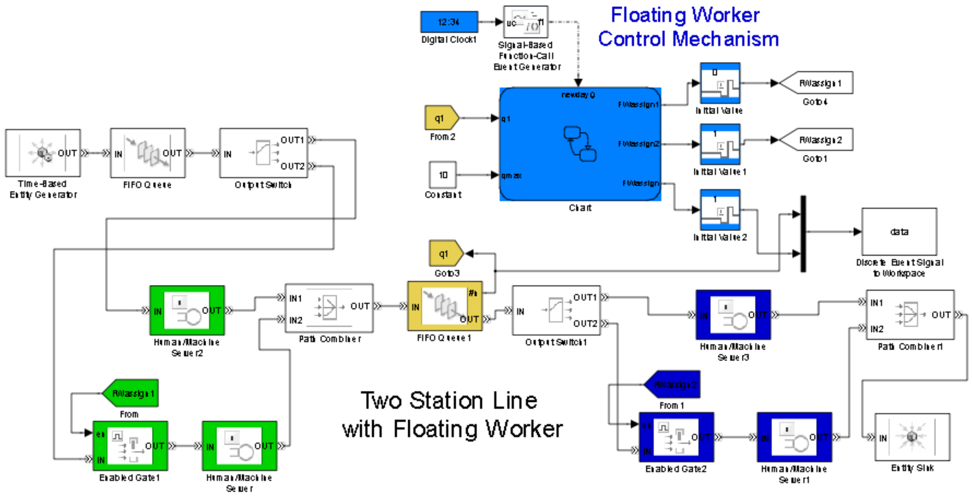


Figure A-3.8*: Floating worker model.*

A two station line is shown in Figure A-3.8. “Enabled-Gate” blocks are used to control the assignment of the floating worker. The amount of WIP in the intermediate buffer is used as the input signal to the floating worker control mechanism which is found in the top right of Figure A-3.8. The floating worker verification test confirmed that the floating worker model functions correctly.

Model for Testing Cross-Training

The SimEvents model use to verify the methods used to model cross-training in simulations is shown in Figure A-3.9 below.

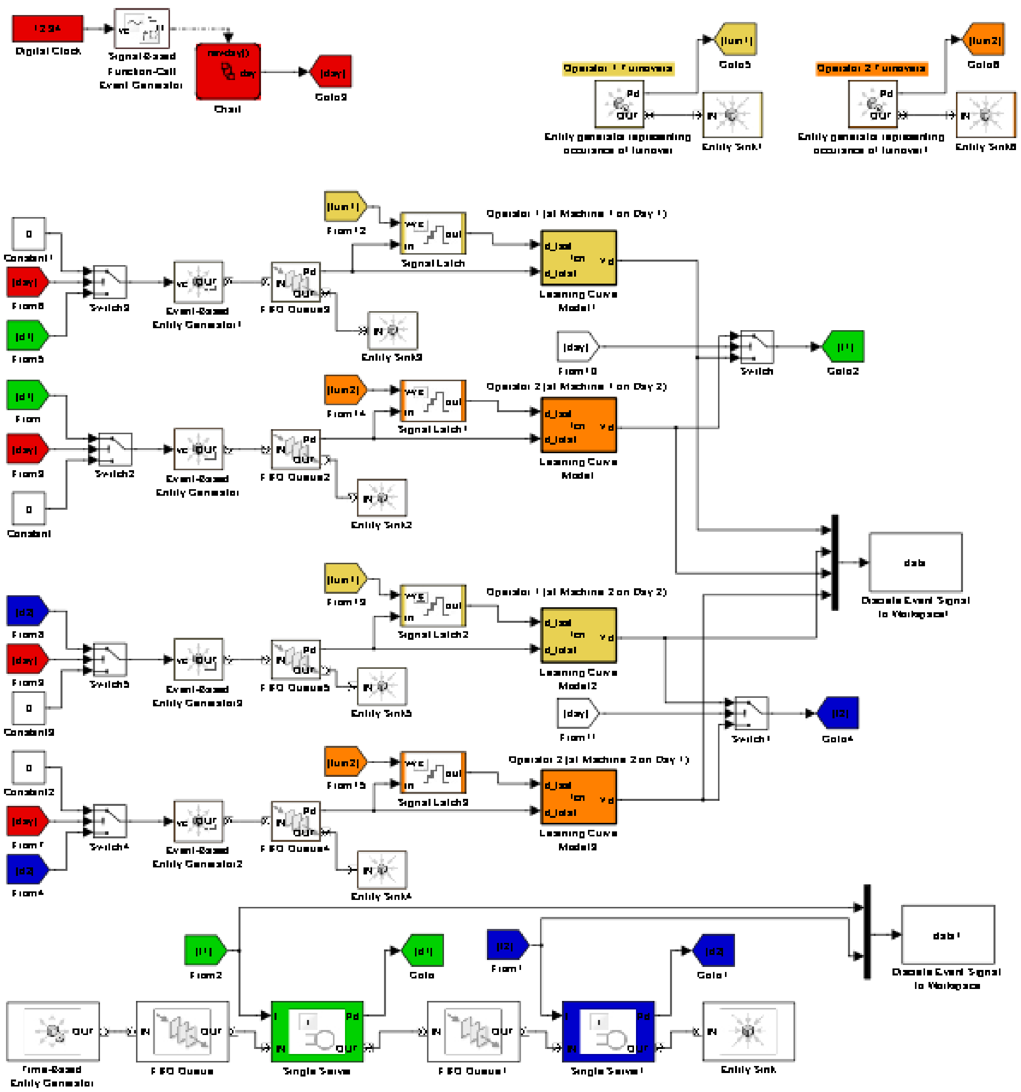


***Figure A-3.9**: Cross-training model.*

A two station line is shown in Figure A-3.9. However, the two workers rotate between workstations 1 and 2 (identified by green and blue blocks respectively). The simulated time is monitored throughout the simulation (see the red blocks at the top left of Figure 3.9) and used to control the assignment of workers. The experience of each worker, at either workstation is recorded throughout simulations. The light yellow blocks correspond to worker 1 and the orange blocks correspond to worker 2. The cross-training verification test confirmed that the cross-training model functions correctly.

Models of Existing Production Lines

Five models of existing production lines were developed in SimEvents. The models all appear as shown in Figure A-3.10 below.

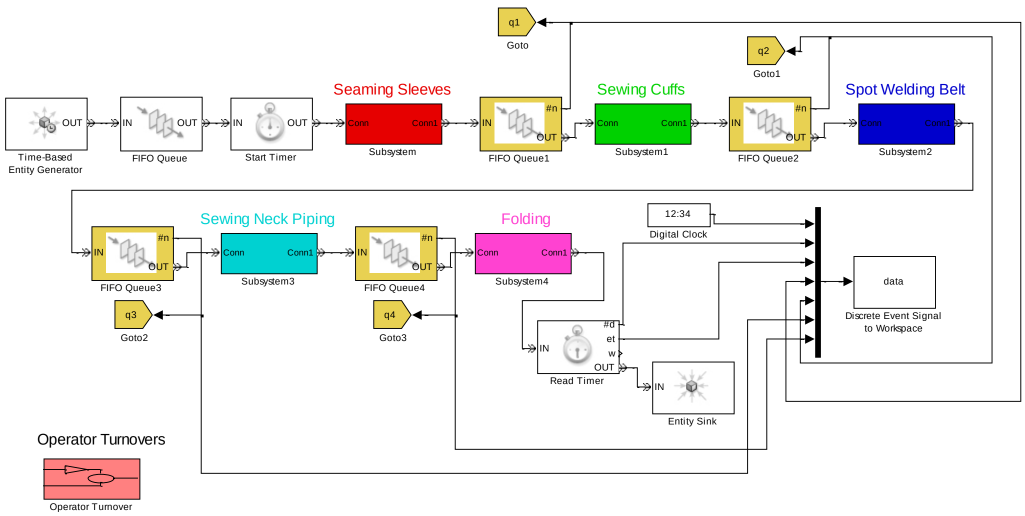


Figure A-3.10*: Model of medical garment production system.*

All five production lines consist of five workstations in series (highlighted in different colors in Figure A-3.10). Each workstation consists of multiple servers. The servers include the "Human Operator Model" and "Failure/Repair Model" presented earlier in this appendix. The difference between the five production lines is their size; so the number of servers in each workstation may be different for different lines. For example, opening the "Seaming Sleeves" block (see Figure A-3.11 below) shows that this production line has 6 servers (the 7th server is not permanently assigned to the production line), whereas other production lines may have more or less servers permanently assigned to the seaming sleeves workstation.

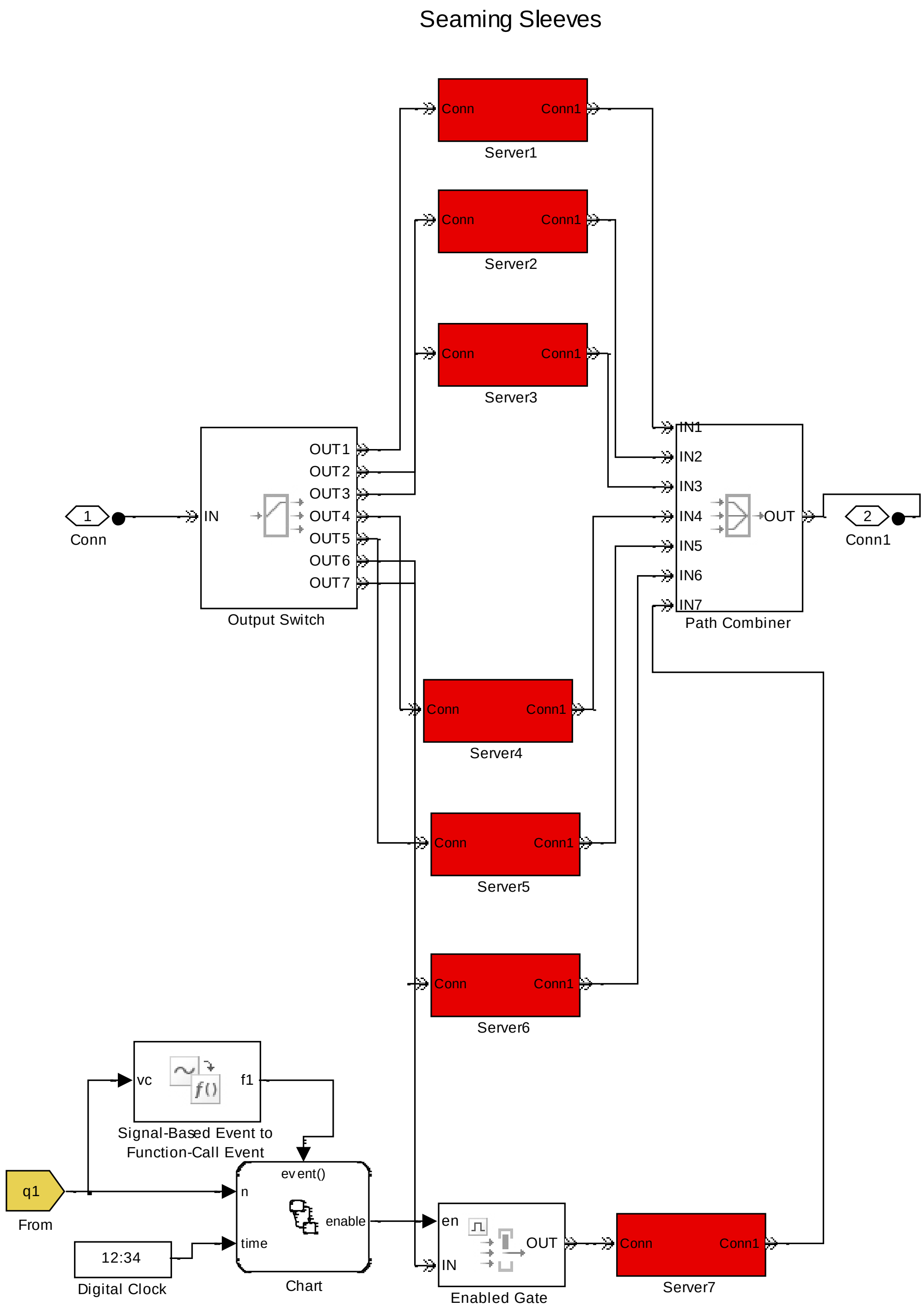


***Figure A-3.11**: Model of medical garment production system.*

The reason for "Server 7" and the additional blocks connected to "Server 7" is because the model also includes the practice of borrowing workers. In the real system when WIP accumulates upstream or downstream of workstations, additional workers are borrowed from another production line. This is modeled in simulations using signals from queues. When queue capacity is high the “Enabled Gate” shown in Figure A-3.11 is opened allowing “Server 7” to accept entities. “Enabled Gate” is controlled using the “Chart.” The Chart monitors the queue level and includes a one day delay which is to account for the fact that supervisors may not immediately notice the accumulation of WIP.

Implementing Changes to Production Lines in SimEvents

Five changes to production lines were implemented in SimEvents: an increase in monthly turnover rate from 2.5% to 7.5%, cross-training workers, utilizing a floating worker, automating the folding operation and increasing queue capacities. Details of these changes are described below.

Increasing Monthly Turnover Rate:

From Figure A-3.12 it can be seen that operator turnovers were all placed in a separate submodel. This was done so that operator turnover parameters could be modified quickly and easily. Opening the “Operator Turnovers” block in Figure A-3.10 produces the submodel shown in Figure A-3.12 below.

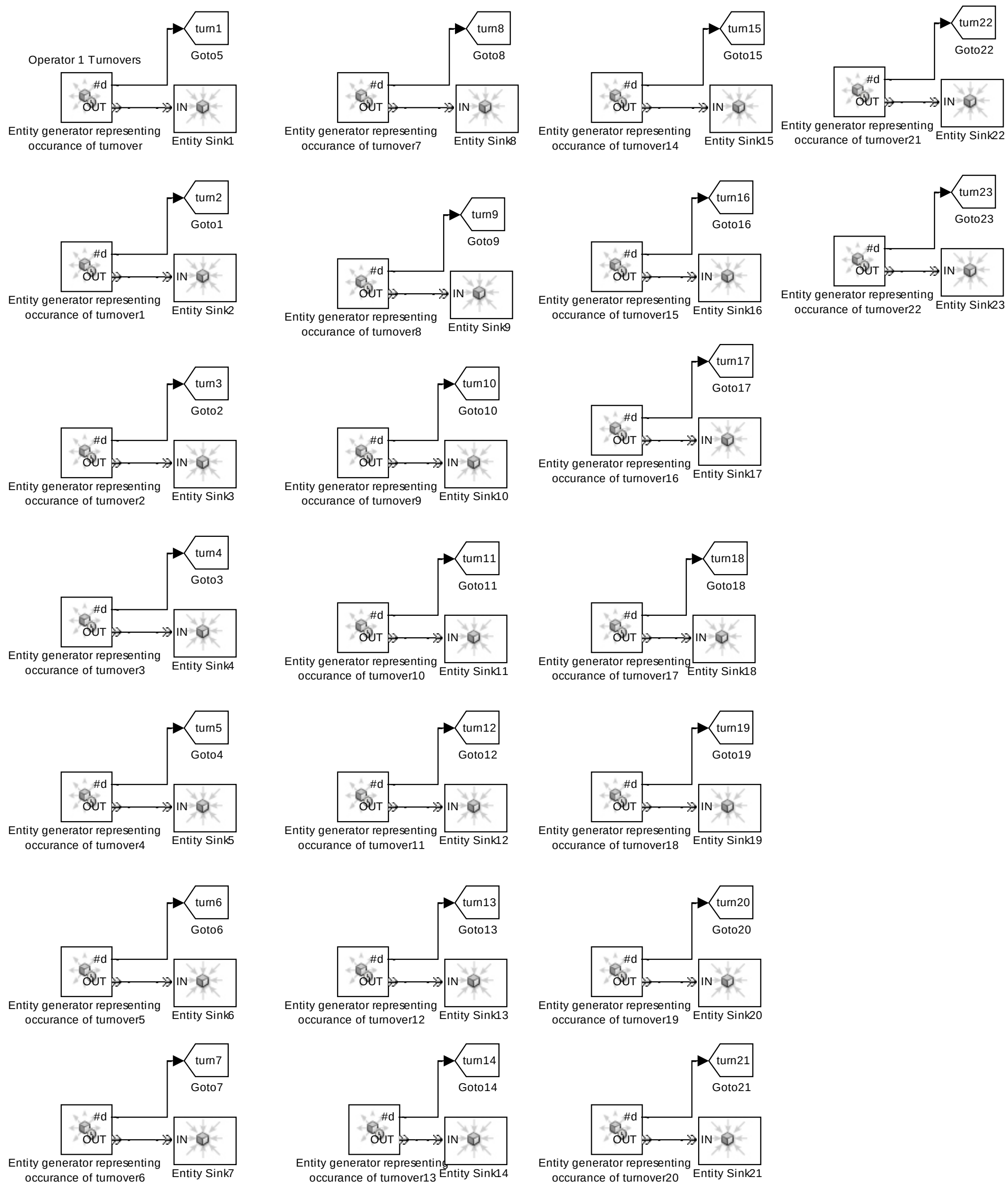


Figure A-3.12: *Operator turnovers.*

Each operator requires an "Entity-Generator" block responsible for generating turnovers for each worker. The signal is sent to the appropriate server using "Goto" blocks.

Cross-Training Workers

Cross-training workers was the most difficult change to implement in simulations. Each person rotates through each workstation to gain experience at all assembly operations. Therefore, the position of each worker needs to be constantly monitored and controlled and the experience of each worker needs to be recorded for all assembly operations. The model that was created is shown in Figure A-3.13 below.

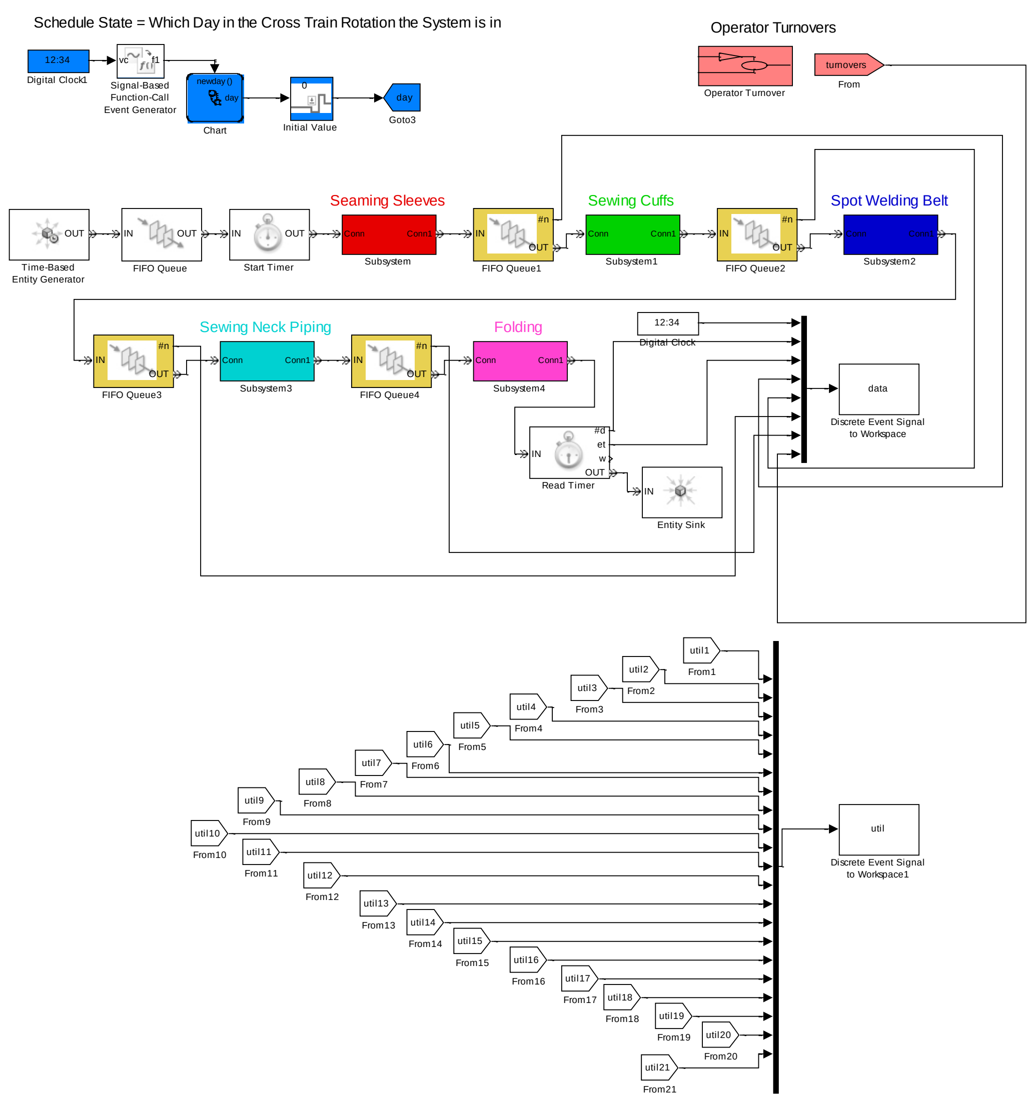


Figure A-3.13:*SimEvents model with cross-trained workers.*

The solution to model cross-training in simulations was to create a human operator model for each person that would visit a machine – for all machines in the system. An example of for one machine is shown in Figure A-3.14 below. Using this method all human operator models exist but only one is active at any given time. The experience of active human operator model increases while the experience of inactive human operators does not change. Simulated time is monitored and used to activate/de-activate human operators each day.

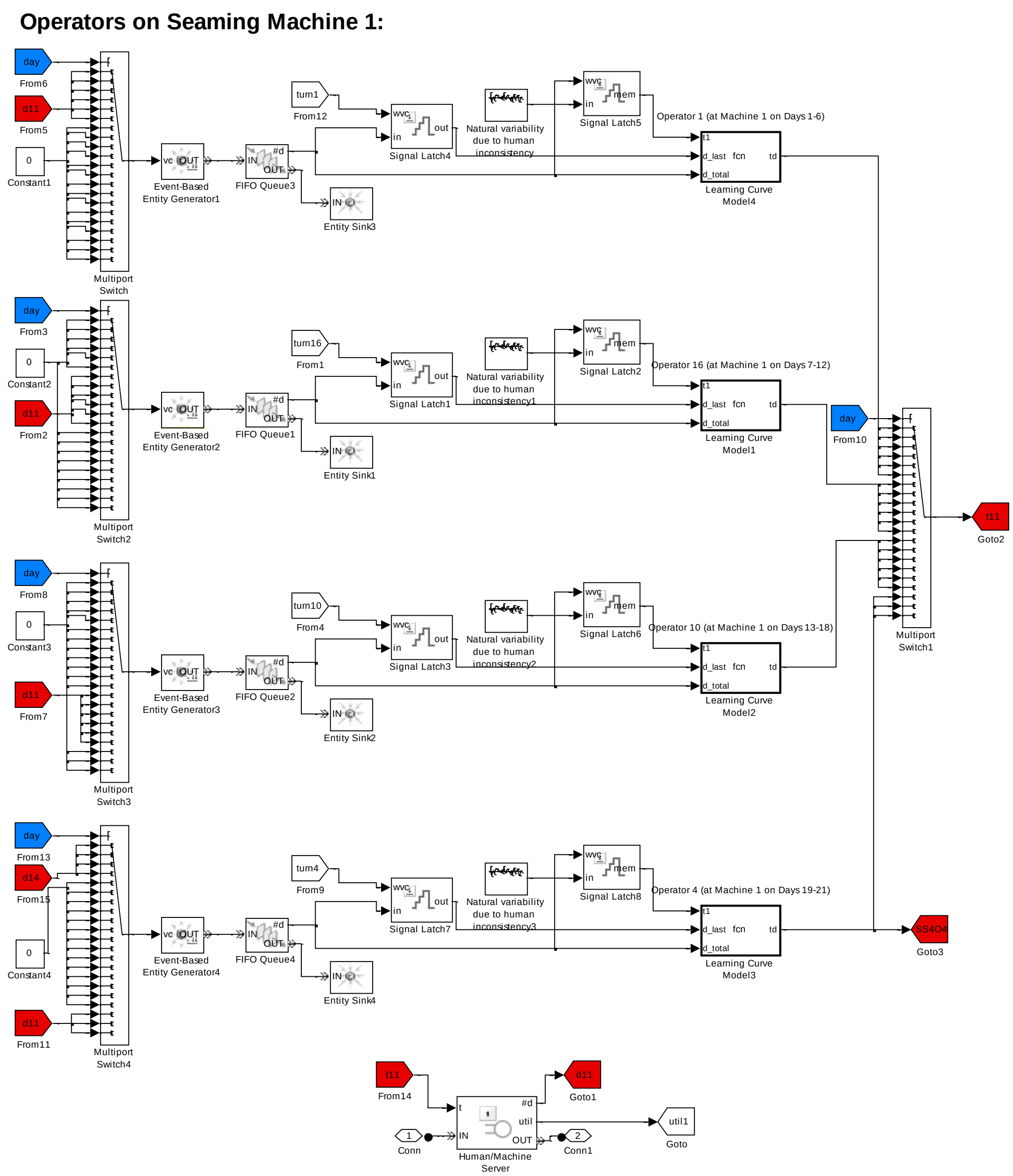


Figure A-3.14*: Multiple Human operator models at a single server.*

Utilizing Floating Worker

Utilizing a floating worker in SimEvents was relatively easy. A floating worker was modeled similar to how "borrowing workers" was modeled (see Figure A-3.11); however, the control mechanism was modified. In the case of the floating worker an additional server was only allowed to process entities at one workstation at any given time. A floating worker control model, shown in Figure A-3.15, was developed to control the assignment of the floating worker.

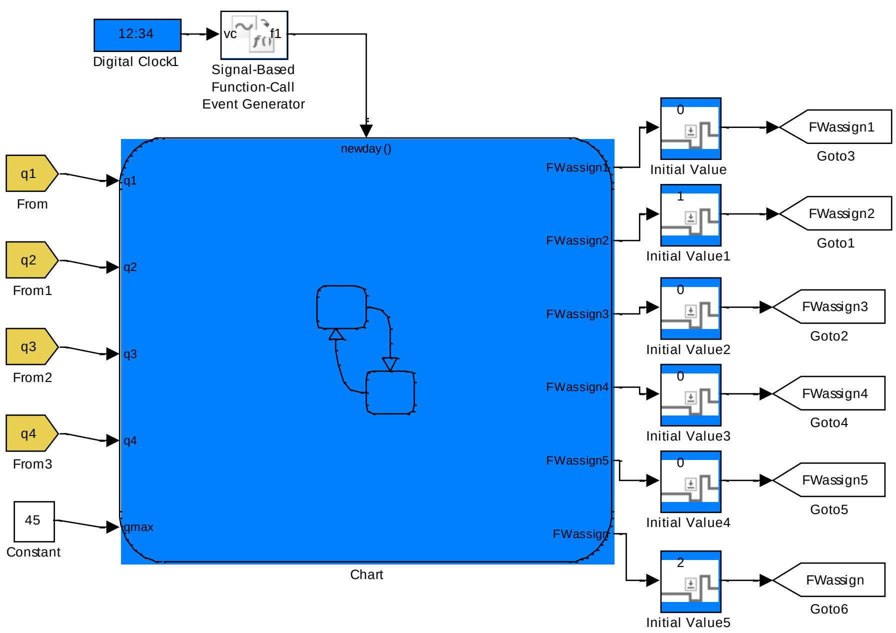


Figure A-3.15*: Floating worker assignment control.*

The model shown in Figure A-3.15 monitors the level of all queues and assigns the floating worker to the most upstream workstation with near maximum queue occupancy upstream and less than near maximum queue occupancy downstream of the workstation.

Automating the Folding Operation

The automated folding workstation, in SimEvents, is shown in Figure A-3.16 below.

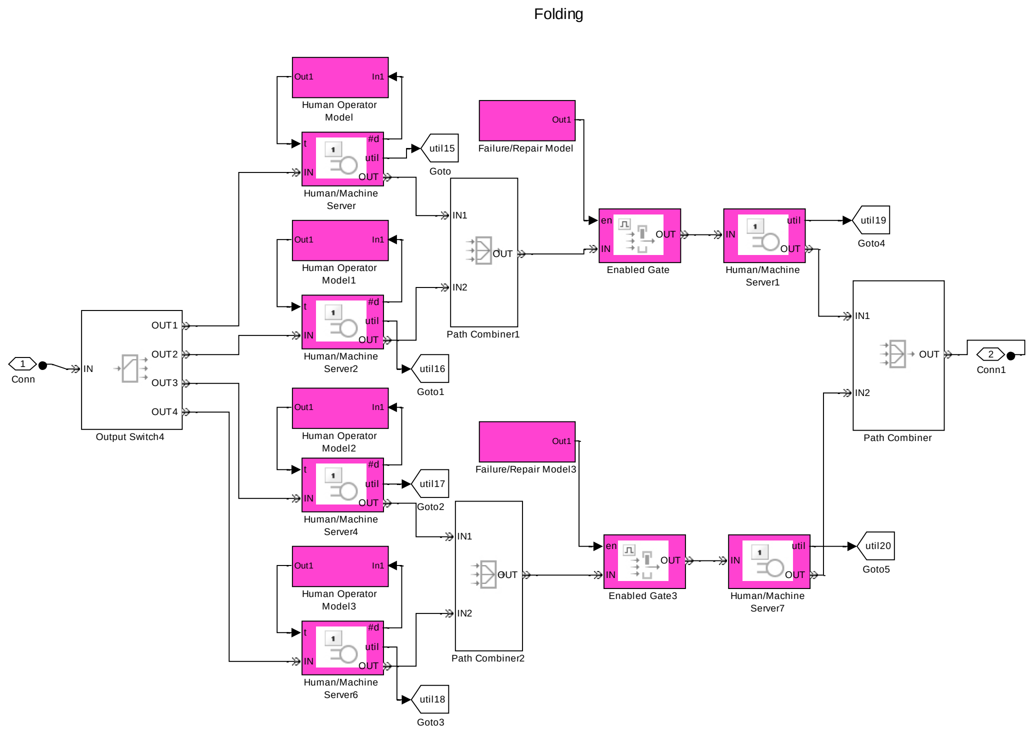


Figure A-3.16: *Automated folding in SimEvents.*

The automated folding workstation consists of two operators tending to a single machine. The reason that two operators are assigned to one machine is that the manual portion of the semi-automated operation was estimated to be twice the machine cycle time. In order to achieve high machine utilization more than one operator is required. From Figure A-3.16 it can be seen that the each operator includes a “Human Operator Model” (but no “Failure/Repair Model”) while the folding machine only includes a “Failure/Repair Model.”

A-4: Limited Repair Crew Problem

This study assumed unlimited maintenance resources. However, real production systems have limited repair crews that are required to service many pieces of equipment as shown below.

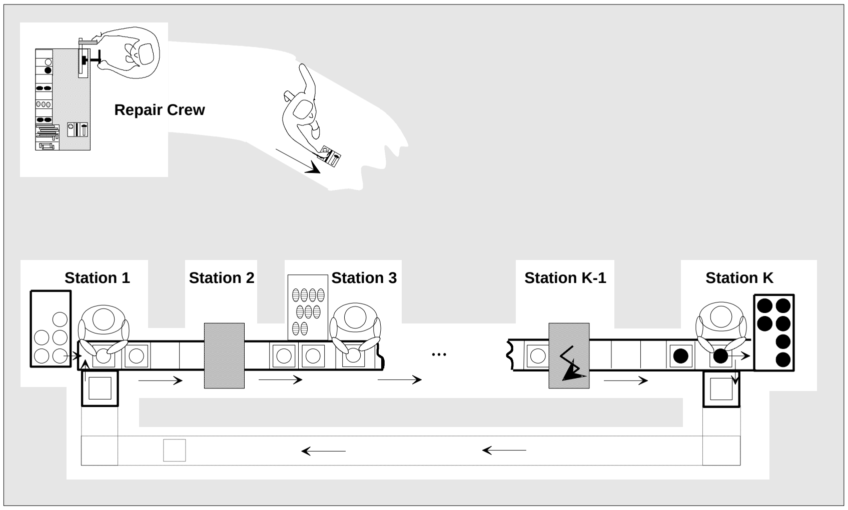


Figure A-4.1*: Limited repair crew. Permission to reproduce image obtained from Professor Heinrrich Kuhn (see Appendix A-6).*

This leads to the possibility that equipment in need of repair has to wait for maintenance service. If this occurs often it can significantly affect performance. Below is a method that can be used to determine whether or not the assumption of unlimited maintenance resources is appropriate.

In the case of homogeneous equipment, a homogeneous repair crew, exponential times to failure and exponential times to repair a Markov model can be used to analyze a finite source queueing system (such as the case with a limited repair crew). Given the size of the number of machines, M, the number of repair crew persons, n, the average failure rate, λ, and the average service rate μ the probability of n machines in the maintenance queuing system is calculated using

$$p_n = \begin{cases} \binom{M}{n} r^n p_0 & (1 \le n < c) \\ \binom{M}{n} \frac{n!}{c^{n-c}-c!} r^n p_0 & (c \le n \le M) \end{cases}$$

and the norming equation

$$\sum_{i=0}^{n} p_n = 1$$

Then if there is a small probability that there are more machines in need of repair than there are repair crew persons (i.e. $P\{n>M\} \leq \delta$) the assumption of unlimited maintenance resources is appropriate.

A-5: Analysis of Two Servers in Series with Unreliable Machines and Limited Buffer Capacity

The analysis of two servers in series with unreliable machines and limited buffer capacity is an important result since provides insight into the behavior of a simple production line the explicitly considers machine failures. Furthermore, it is used in several approximate numerical methods that allow for the analysis of longer lines and assembly systems (e.g. the David-Dallery-Xie decomposition method and the Meerkov aggregation method). However, the solutions provided in the literature are either difficult to apply or plagued with errors. In addition, the derivation of the solution is not provided making corrections and alternative methods difficult. For these reasons the Markov model of the system shown below is provided.

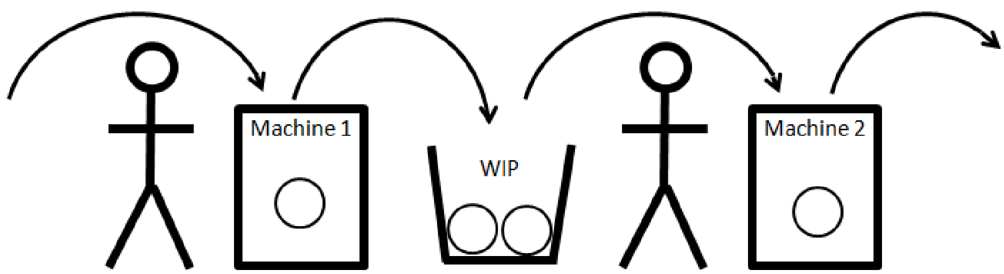


Figure A-5.1*: Two servers in series with unreliable machines and limited buffer capacity.*

The state of the system is denoted by $p(n,m_1,m_2)$ where n is the number of work pieces in the system (not including the work piece at station 1), m_1 is the state of machine 1 (0 – down or 1 – up) and m_2 is the state of machine 2. The model assumes exponential service times, times to failure and times to repair. In addition, the first server is never starved and the second station is never blocked.

The transition rate diagram is given below where

mu1 is the service rate of station 1

mu2 is the service rate of station 2

f1 is the failure rate of machine 1

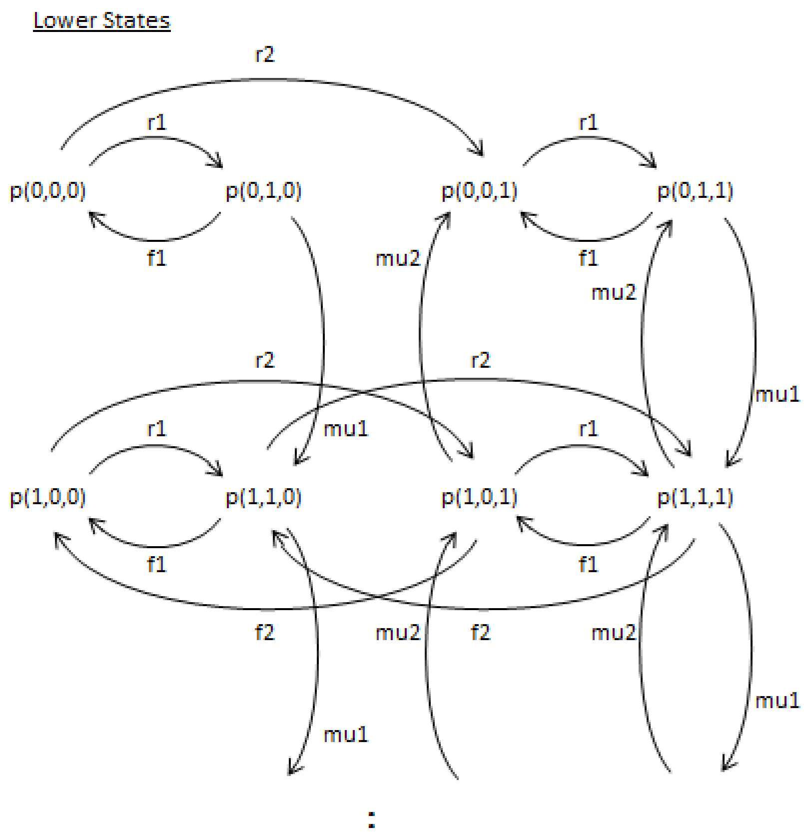
f2 is the failure rate of machine 2

r1 is the repair rate of machine 1

r2 is the repair rate of machine 2

N is the buffer capacity

and b denotes the “blocked” state.



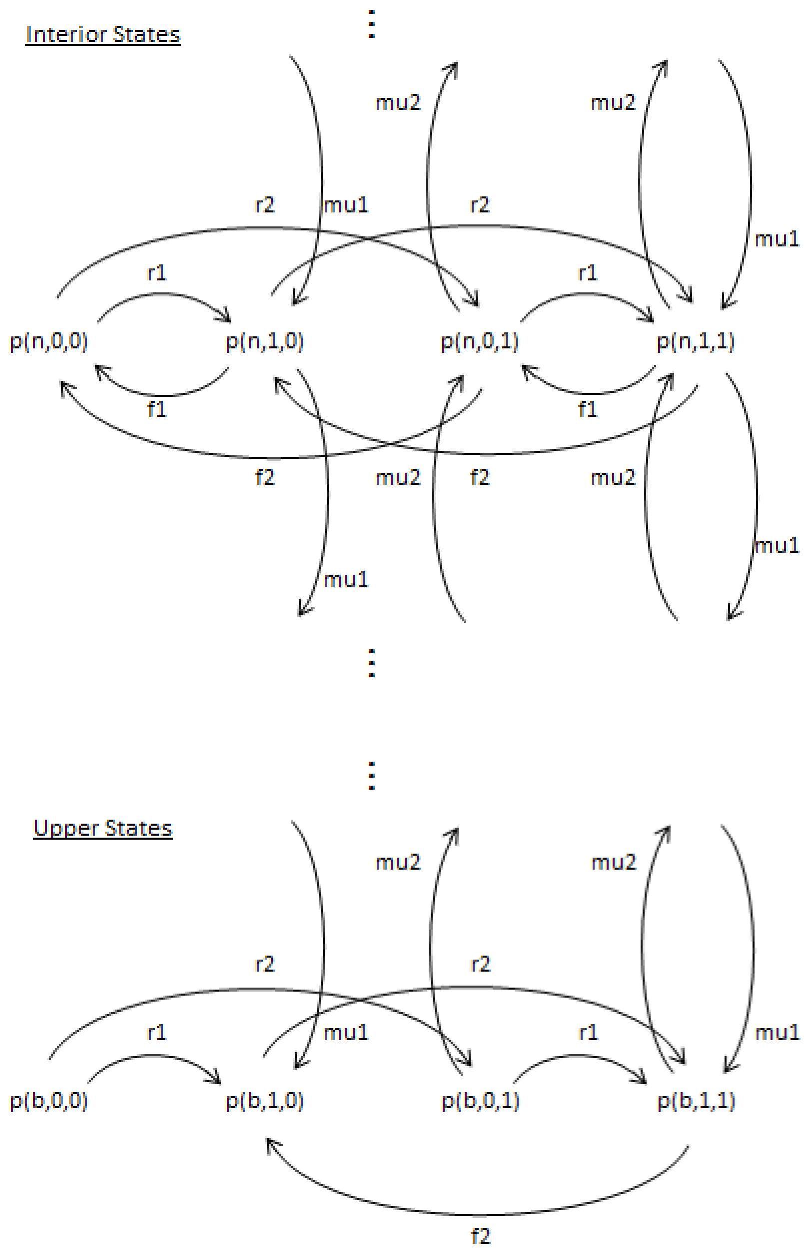


Figure A-5.2*: Transition rate diagram.*

Then the Chapman-Kolmogorov equations are determined using state-flow balance approach at each state which gives:

Lower States

p(0,0,0): $0 = -(r1+r2)\cdot p(0,0,0) + f1\cdot p(0,1,0)$

p(0,1,0): $0 = -r1\cdot p(0,0,0) - (mu1+f1+r2)\cdot p(0,1,0)$

p(0,0,1): $0 = r2\cdot p(0,0,0) - r1\cdot p(0,0,1) + f1\cdot p(0,1,1) + mu1\cdot p(1,0,1)$

p(0,1,1): $0 = r2\cdot p(0,1,0) + r1\cdot p(0,1,1) - (mu1+f1)\cdot p(0,1,1) + mu2\cdot p(1,1,1)$

Interior States (n = 1, 2, …, N+1)

p(n,0,0): $0 = -(r1+r2)\cdot p(n,0,0) + f1\cdot p(n,1,0) + f2\cdot p(n,0,1)$

p(n,1,0): $0 = mu1\cdot p(n-1,1,0) + r1\cdot p(n,0,0) - (mu1+mu2+f1)\cdot p(n,1,0) + f2\cdot p(n,1,1)$

p(n,0,1): $0 = r2\cdot p(n,0,0) - (mu2+f2+r1)\cdot p(n,0,1) + f1\cdot p(n,1,1) + mu2\cdot p(n+1,0,1)$

p(n,1,1): $0 = mu1\cdot p(n-1,1,1) + r2\cdot p(n,1,0) + r1\cdot p(n,0,1) - (mu1+mu2+f1+f2)\cdot p(n-1,1,1) + mu2\cdot p(n+1,1,1)$

Upper States

p(b,0,0): $0 = -(r1+r2)\cdot p(b,0,0)$

p(b,1,0): $0 = mu1\cdot p(N+1,1,0) + r1\cdot p(b,0,0) - r2\cdot p(b,0,1) + f2\cdot p(b,1,1)$

p(b,0,1): $0 = r2\cdot p(b,0,0) - (mu2+r1)\cdot p(b,0,1)$

p(b,1,1): $0 = mu1\cdot p(N+1,1,1) + r2\cdot p(b,1,0) + r1\cdot p(b,0,1) - (mu2+f2)\cdot p(b,1,1)$

All $p(n,m_1,m_2)$ can be found using the above equations and the norming equation and all performance parameters can be determined (as shown in 'TwoMs' in Appendix A-2).

Appendix A-6: Permission to Reproduce Images

Email Conversation Granting Permission to Reproduce Image in Figure 2.4:

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Thank you,

--
Nathan Starchuk
MSc Candidate, University of Alberta
Mechanical Engineering, Engineering Management Mechanical Engineering Building, Rm 6-29
Mobile: 780.405.5903
E-mail: nls@ualberta.ca

from **Lutz Walter** Lutz.Walter@euratex.eu   hide details Aug 3 (5 days ago)
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Best regards,
Lutz Walter
===================================
Lutz Walter
Head of R&D, Innovation and Projects Department
EURATEX – The European Apparel and Textile Confederation
24, rue Montoyer - Box 10
B-1000 Brussels
Ph. +32-2-285.48.85
Fax: +32-2-230.60.54
E-mail: lutz.walter@euratex.eu
WWW: http://www.euratex.eu

from**Ulla Schütte** u.schuette@moll.ac hide details 2:13 AM (5 hours ago)
to nls@ualberta.ca

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What is your thesis about? Can you give me a short abstract?
Best regards,
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Email Conversation Granting Permission to Reproduce Image in Figure A-4.1:

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--
Nathan Starchuk
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Mechanical Engineering, Engineering Management
Building, Rm 6-29
Mobile: 780.405.5903
E-mail: nls@ualberta.ca

from **Prof. Dr. Heinrich Kuhn** heinrich.kuhn@ku-eichstaett.de hide details 2:54 AM (4 hours ago)
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Dear Mr. Starchuk,

Of course this will be ok, if you accordingly cite the figure.

Good look for your thesis.
Best regards,
Heinrich Kuhn