Discrete Event Simulation and Production System Design for Rockwell Hardness Test Blocks

By
David Eliot Scheinman

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Signature of Author: ______ Department of Mechanical Engineering
August 18 2009

Certified by: ______ Jung-Hoon Chun
Professor of Mechanical Engineering
Thesis Supervisor

Accepted by: ______ David E. Hardt
Chairman, Committee for Graduate Students

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Submitted to the Department of Mechanical Engineering on August 18, 2009 in partial fulfillment of the requirements for the Degree of Master of Engineering in Manufacturing.

Abstract

The research focuses on increasing production volume and decreasing costs at a hardness test block manufacturer. A discrete event simulation model is created to investigate potential system wide improvements. Using the results from the simulation a production work-cell is proposed that will allow a single worker to operate 7 machines at a rate that exceeds existing production rates. This results in the workforce being reduced by a factor of four while reducing product lead-time by 30% and increasing throughput by 50%.

Thesis Supervisor: Dr. Jung-Hoon Chun

Title: Professor of Mechanical Engineering

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Chapter 1: Introduction

This thesis is sponsored by Wilson Instruments. It is focused on improving the productivity and throughput of the production line dedicated to manufacturing metal calibration blocks used to calibrate Wilson's Rockwell hardness testing equipment. Over the course of a 7-month internship, we have analyzed and improved the production process of the calibration blocks.

1.1 Corporate Background

Wilson Instruments, a subsidiary of Illinois Tool Works (ITW), has been a pioneer in hardness testing equipment and standards. The company was founded by Charles H. Wilson. In 1920, Charles Wilson collaborated with Stanley Rockwell to produce the first commercially available Rockwell hardness testing machines. The Rockwell Hardness standard has become the prominent hardness testing standard for metals. Since their original success with Rockwell hardness testers, Wilson Instruments has continued to be a market leader in hardness testing with an expanded instrument line including micro hardness and Brinell hardness testing equipment.

1.2 Rockwell Hardness Testing Background

The Rockwell hardness scale is used to define the indentation hardness of metals. There are multiple Rockwell scales. For this project we are focused on the Rockwell-B (HRB) and Rockwell-C (HRC) scales.

The Rockwell hardness test uses a calibrated machine to apply a known force to a diamond or tungsten-carbide indenter in accordance with ASTM E18-08a. In order to calibrate the testing machine, a material of a known hardness is tested, and the machine is adjusted so that it reads correctly. The specifications of the blocks are described in ASTM E18-08a. According to the standard, Rockwell hardness testing machines shall be verified on a daily basis by means of standardized test blocks. These test blocks are manufactured and calibrated in accordance with ASTM E18-02 as shown in Appendix D. The Rockwell test blocks provide an easy and inexpensive way to verify the machine. These blocks are used as a standard reference to verify the hardness tester. Due to the destructive nature of the Rockwell indentation test, each time a calibration block is used a small indentation is left on the block. This means that each block can only be used 100-200 times before it must be replaced. As a result, Wilson Instruments manufactures the calibration blocks in large quantities and sells them as consumables.

1.3 Manufacturing Process

The Rockwell test blocks are circular discs approximately 2.5" (63.5mm) in diameter and 0.25" (6.35mm) thick. The Rockwell test blocks are made from two different materials to provide a full range of hardness. Cartridge brass is used for test blocks ranging from HRB30 to HRB90, while O-1 tool steel is used for harder materials up to HRC-60. The test blocks are physically identical, regardless of material, except for the varying hardness. However, the manufacturing processes are slightly different for each material. Figure 1 shows the manufacturing process of both types of Rockwell test blocks.

Wilson manufactures the test blocks at Instron's machine shop in Binghamton, New York. The manufacturing process is as follows:

1. Brass test blocks are rough cut from 0.350" (8.89mm) brass plates by water jet. Steel blocks are rough cut with a band saw from round bar stock. Both steel and brass cutting processes are outsourced and then shipped to the Binghamton facility.

2. At the Binghamton facility a CNC lathe is used to cut the final diameter, face the blocks, and chamfer the edges. This is performed in two setups. The machined blocks are then roll stamped with a unique serial number on the circumference.

3. The test blocks are then sent out for heat treatment. The blocks are heat treated to full hardness and then annealed down to the desired hardness level.

4. When the blocks return from the heat treating facility they have a scaled finish. The blocks are bead blasted to remove this surface. The blocks are then manually buffed to remove any sharp edges.

5. The steel blocks are surface ground to ensure proper parallelism.

6. All the blocks are lapped and polished to ensure proper parallelism, surface flatness, and surface finish.

7. After passing dimensional quality control the blocks are sent to Instron's Norwood facility.

8. At the Norwood facility the hardness of every block is tested and recorded. The blocks are then packaged and shipped out.

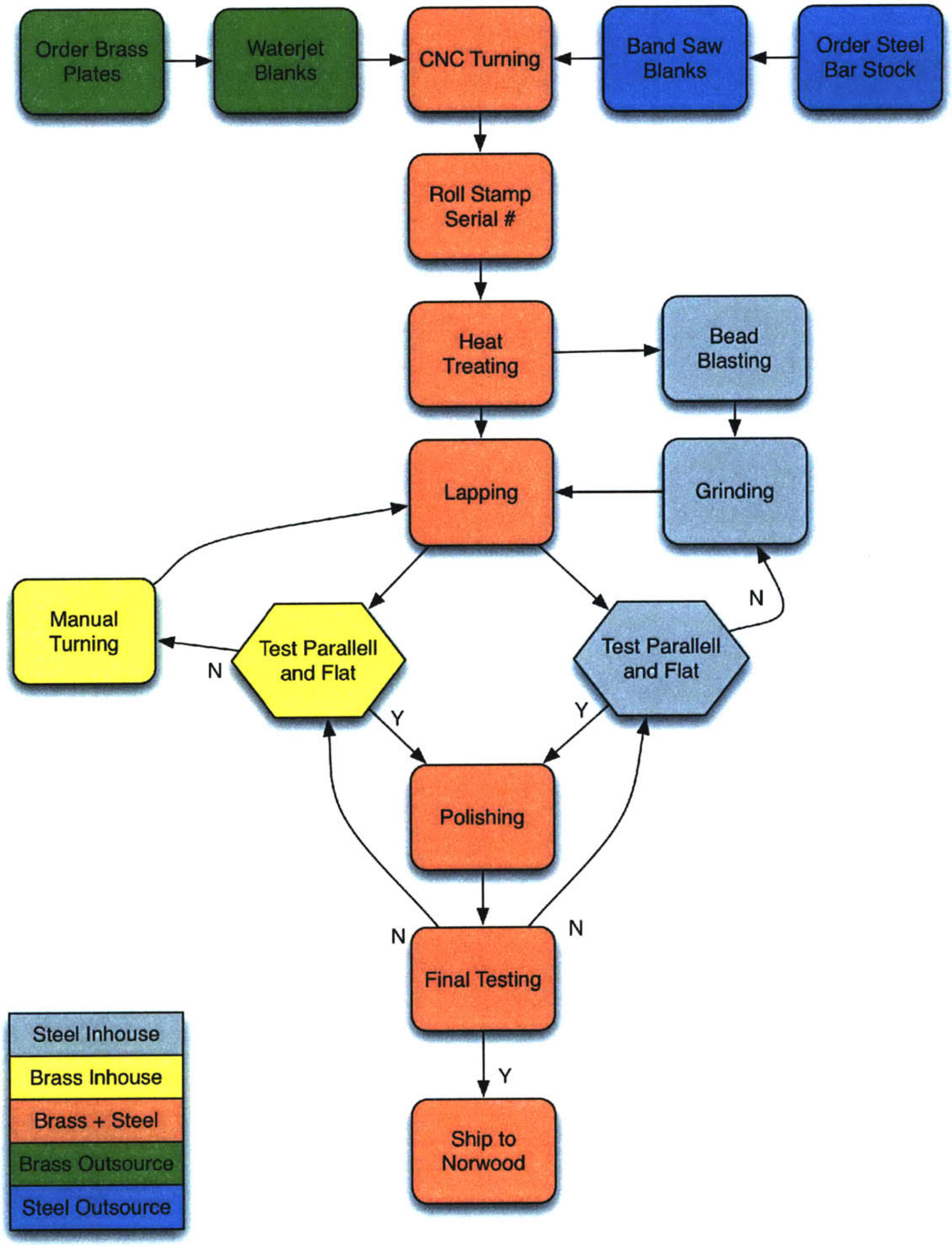


Figure 1: Test Block Manufacturing Process Flow Chart

1.4 Problem Statement

Many of the steps involve high rates of rework, parts often fail final QC due to unknown causes, and training new workers has been difficult as many of the processes are not properly understood or documented. Instron wants to investigate the entire manufacturing process to find ways to streamline the process in order to improve productivity by reducing costs, lead time, and expanding the potential manufacturing capacity to allow for future increased demand.

During our first month of work we visited the calibration and packaging facility in Norwood, the production facility in Binghamton and key outside vendors. We interviewed and observed as many people as possible who were involved with producing the test blocks. Throughout this process we noticed several reoccurring themes and problems.

The most striking problem we noticed is that the later stages of the manufacturing line, polishing and lapping, have substantially higher rework rates than the other stages. Both operators and management complained that cycle times are very inconsistent at these stages. Parts are often scratched during polishing or lapping, which requires them to be sent back several steps in the sequence as shown in Figure 1. Some operators are able to produce consistent, high quality parts while other operators struggle to produce any good parts. We concluded that the polishing and lapping processes were poorly understood and poorly defined. Mohammd Imani Nejad has dedicated his efforts to improving the polishing and lapping processes. [5]

While the majority of defects become apparent in the final steps of lapping and polishing, there were many signals indicating the defects were not necessarily caused by the actual lapping and polishing processes. Latent defects created during turning, heat-treating, and grinding were going undetected until late in the production process when rework is more difficult and costly. Jairaj Vora has dedicated his efforts to discovering and quantifying the sources of variation caused during all steps preceding lapping. [8]

Vincent Tan focused on reducing the rate of rejected parts at the final stage of the test block manufacturing by identifying the significant factors from the heat treatment process that affect the mean hardness and uniformity of the test block. He has also dedicated his efforts to improving the current sampling methods to provide a better understanding of the mean hardness and hardness ranges at different stages of the production line. [7]

In the larger picture, the entire production process appears to be rather disorganized. Human resources are sparsely distributed across several machines causing some of the machines to often sit idle. This thesis will focus on creating a simulation model to explore strategies for organizing and distributing the limited machine and human resources to meet the demand in the most cost effective way possible. The model will also be used to explore the system wide impacts of the findings of Jairaj Vora's, Mohammad Imani Nejad's, and Vincent Tan's thesis.

Chapter 2: Literature Review

The goal is to create an accurate model of the entire production system, starting with the turning processing and ending with the polishing process. Avrill Law presents critical decisions to make when selecting a model type [2]. It is proposed that the ideal solution would be to run tests on the actual system, unfortunately due to cost time restraints this is not feasible. Short of that, creating a physical model or a closed form analytical model would also be preferred but are also not feasible due to time, money, and complexity constraints. With the realm of simulation models we are interested in a model that will account the dynamic and stochastic nature of the system.

Within the realm of dynamic, stochastic simulations there are two main types: continuous time and discrete time simulations. The hardness test block production lends itself well to a discrete event simulation. The information we are interested in from the simulation is discrete by nature: the completion of a parts at all production stages, the length of the queues for workers and machines, the time it takes an order to propagate through the system, and the total number of parts in the system at any given time.

Chapter 3: Simulation Model

3.1 Model Design

A discrete event simulation was selected to simulate the production process. Several software simulation packages were considered. The open source SimPy Python library was selected to implement the simulation. "SimPy is an object-oriented, process-based discrete-event simulation language based on standard Python"[6]. SimPy allows for a flexible discrete event simulation to be quickly programmed in Python. SimPy will be used to manage the event list and system resources while the system layout and mechanics are programmed in Python.

The production process was modeled as a network of queues. Each node of the network represents a step in the production process. When a part arrives at a node it proceeds through the following steps[1]:

1. The part will queue for the machine at that node. The machine's queue is prioritized so that the oldest parts will receive the highest priority. This allows reworked parts to catch up with their batch.
2. When a part reaches the front of the machine's queue it then queues for an operator to load it into the machine. Each machine is assigned to a worker pool with the *workpool* variable in the data file. Each worker pool contains one or more workers, which are responsible for servicing parts at one or more nodes. The number of workers in each worker pool is defined with the *workcap* variable in the data file.
3. When the part reaches the front of the worker's queue it is then loaded into the machine. The amount of time it takes to be loaded is defined in the data file with the *loadtime* variable.
4. Once loaded into the machine the parts wait until the machine is full. The capacity of the machine is defined in the data file with the *maccap* variable.
5. Once the machine is at capacity it will either immediately start operating, or, if an operator is required to run the machine it will queue for an operator. Weather a machine needs an operator is defined in the data file with the *needop* variable. The processing

[1] See Appendix C for a list of all variables.

time of the machine is modeled as an exponential distribution with the mean value defined in the data file with the *means,* for steel blocks, and *meanb*, for brass blocks.

6. When the operation is complete the parts then queue for an operator to unload it from the machine. The amount of time it takes to be loaded is defined in the data file with the *unloadtime* variable.

7. Once unloaded the parts are then sent to the next node. The parts transition to the other nodes with the probabilities defined in the data file by the *Ps* and *Pb* transition matrices for steel and brass, respectively. The row of the transition matrix is the current node. Each column represents the probability of transitioning from the current node to that node.

8. The previous 7 steps are repeated at every node until the part reaches the final node, which represents a successfully completed part.

Figure 2 depicts the general structure of the network of queues. When a part completes processing at a given node it proceeds to the next node based on the probabilities defined in the *Ps* or *Pb* matrix. For example, if a part is at Node 1 it will return to Node 1 with the probability defined in row 1, column 1 of the *P* matrix (P1,1). It will proceed to Node 2 with probability P1,2 and return to Node 0 with probability P1,0.

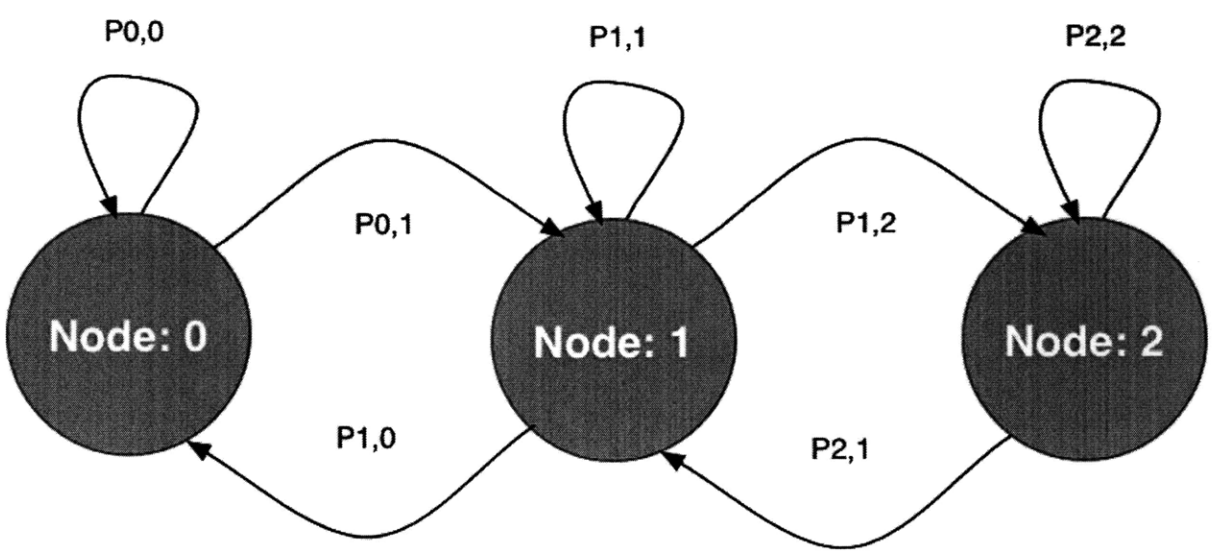


Figure 2: Node structure utilized to simulate the production process.

The demand for blocks is modeled as an exponential distribution with a mean arrival rate defined in the data file with the *os* variable. When a demand hits the system, the type of block ordered must first be determined. The number of block types is defined with the *types* variable. The probability of each block type is defined with the *typedist* variable. The *matdiv* variable defines the division between steel and brass blocks. Blocks of a type greater than *matdiv* are treated as steel blocks and will use the *means* and *Ps* values, while types less than or equal to *matdiv* will use *meanb* and *Pb*.

After the type is determined one lot is pushed out of the buffer, at Node 2, and another lot is pushed into the beginning of the line, Node 0 (CNC Turning). Node 2 of the system is unique node as it represents the buffer that exists after the lengthy heat treating stage. In this buffer, one lot of each part type is kept.

If the buffer at Node 2 is empty, the next batch of the appropriate type will not be put into the buffer but continue on to the next node. The location of the buffer is defined with the *buffernode* variable. The size of a batch is defined in the data file with *os* variable.

3.2 Data Acquisition

The production of the test blocks consists of eight sequential processes as described in Section 1.3. Each process requires an operator to load and unload the parts. Many of the processes also require an operator to run the machine. When the parts are finished an operator quickly inspects them to determine if they are ready for the next process, need to be reworked on the current process, or set back up the production line to a previous process. In order to properly model the entire production process it was necessary to accurately characterize each production process.

In order to accurately characterize each production, process data was needed to describe each step of the process. Initially, production workers, supervisors and managers were interviewed. They were asked about their expectations for production rate, shift throughput, and rework rates for each process based on their experience. Everyone felt that the earlier processes in the chain rarely presented a problem. However, polishing and lapping were highly erratic and often required multiple rounds of rework.

Each processes was closely monitored with a stopwatch. This reinforced what we had been told. Production rates at the earlier stages, most notably turning and grinding, were very consistent. Both of these processes are automated and require minimal operator interaction. The last two stages, which are entirely manual, are very erratic. Nearly half the parts are sent for rework at the current process or back to a previous process. A large amount of operator judgment is required to determine when parts are finished or what to do if there is a problem. Decision making varies among operators. One operator may deem a part acceptable another would send the same part 3 stages back in the production process for reworking.

Finally, production records were harvested. Each batch of parts has a paper "traveler" that stays with the batch from beginning to end of production. The traveler records the date, time, and operator at each process when it arrives. Any required rework is also recorded on the traveler. Unfortunately, the actual data recorded on the traveler is also highly dependent on the operator. Some operators meticulously record every last detail about the production process while others record nothing more than the date and lot size of each batch when they start work on it.

These three data sources were aggregated to create a baseline set of data to be used in the simulation. Table 1 shows the final aggregated data. Note that the loading time, unloading time, and operating time are consolidated into one time value while the actual simulation uses all 3 values. Also, when parts need reworking they are reworked on the current process or sent to a previous process. The listed rework rates include all the rework consolidated into one value while the simulation uses the specific rework rates and locations.

Table 1: Aggregated production and rework rates for each process. (s) denotes steel parts, (b) denotes brass parts.

Process	Load Size	Time(min)	Rework(%)
Turning(b)	1	1.8	0
Turning(s)	1	2.8	0
Heat Treating	200	3600	0
Bead Blast	50	50	0
Grinding	100	300	5
Buffing(b)	1	2.2	10
Buffing(s)	1	1.1	10
Lapping(b)	20	10	30
Lapping(s)	20	10	20
Polishing(b)	10	15	50
Polishing(s)	10	19	30

3.3 Model Validation

With data based on the observations of the real system, the outputs from the model were compared to the outputs from the actual system. The primary metric used to validate the model is the production lead-time. To find the actual lead times we are able to look at the production logs, which are hand written logs updated by the operators of each machine as the parts pass through their stations. Because the production logs are hand written it was not possible to record the lead times from all the records so a sampling was required. 40 production logs from the past 9 months were sampled to determine the typical lead times. The sampling of production logs indicate a mean lead time of 16 days (7680 minutes) with a standard deviation of 7 days (3300 minutes.) The simulation produced an average lead time of 15.5 days (7400 minutes) with a standard deviation of 8 days (3,840 minutes).

Figure 3 shows a sample lead time from a simulation. Some of the part types have a lower demand so orders are always fulfilled from the post heat treating buffer, this can be seen with part types 0,1,8, and 14.

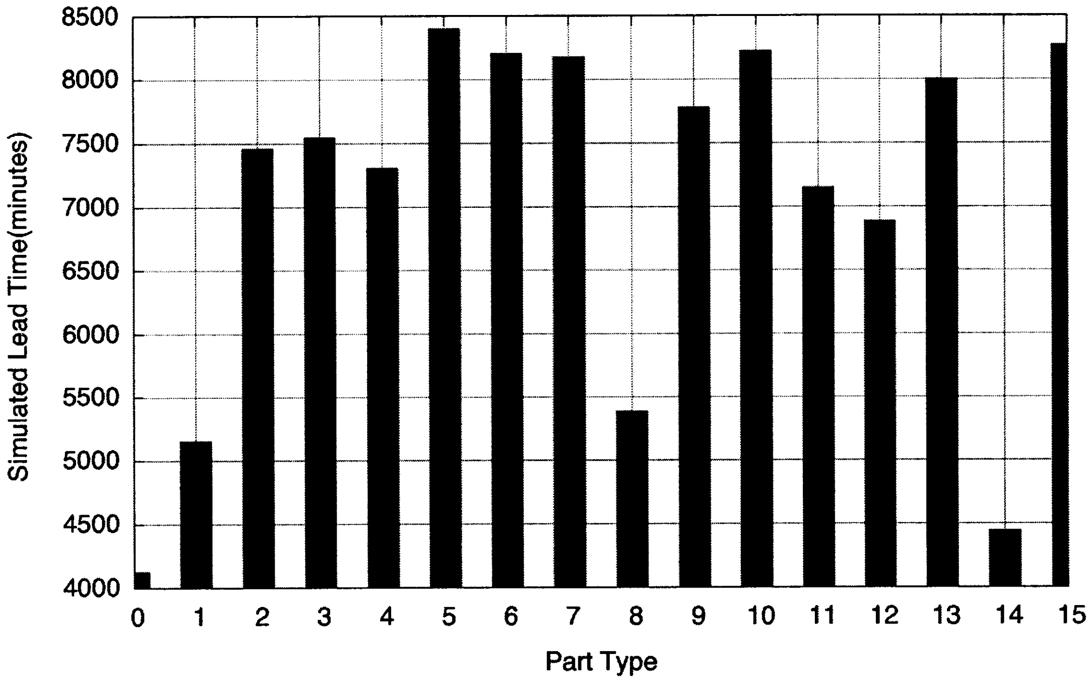


Figure 3: Sample lead time by part type of the existing system. Parts Types 0-7 represent brass parts while 8-15 represent steel parts.

The results of the simulation can also be compared to what can be observed on the factory floor. Most of the machines tend to sit idle, with the exception of the lapping and polishing machines that have perpetually backed up queues of parts waiting to be processed. Figure 4 shows the simulated queue length for the steel polishing machine. It can be seen that the machine is continually backed up reaching as many as 1200 parts. At a nominal production rate of ~21 parts per hour this equates to seven days of backlog. Unfortunately, there is not solid data beyond visual observations to quantify the actual amount of inventory in the real world queues.

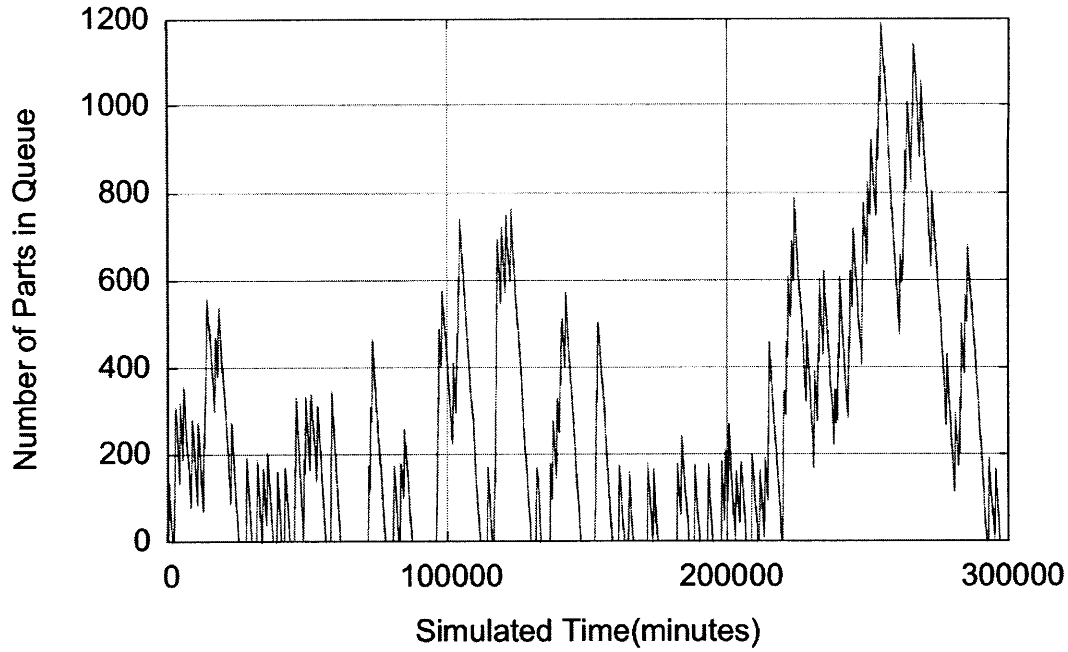


Figure 4: Queue length of the steel polishing machine.

Chapter 4: Results

4.1 Existing System

The model was used to answer several hypothetical questions about the behavior of the production system. The first question to answer was to determine the maximum theoretical production rate of the existing system. Currently, Instron produces roughly 15,000 parts per year. By increasing the demand rate of the simulation we are able to find the maximum production rate to be about 24,000 parts per year. This is comparable to what is expected based on the polishing rates from Table 1. When load/unload time is taken into account a simple hand calculation indicates the polishing throughput should be around 26,000 parts per year. Figure 5 shows the total system output at a demand rate of 30,000 parts per year. Early on in the simulation the system has still not reached a steady state, which is why the production rate is initially erratic. Once the system reaches a steady state the production rate more or less stabilizes. At peak output, when demand exceeds the production rate, it becomes clear that polishing is the rate limiting process. The queue lengths for the steel and brass polishing operations can be seen in Figure 6 and Figure 7, respectively. These queue lengths are growing unbounded because the incoming arrival rate exceeds the production rate.

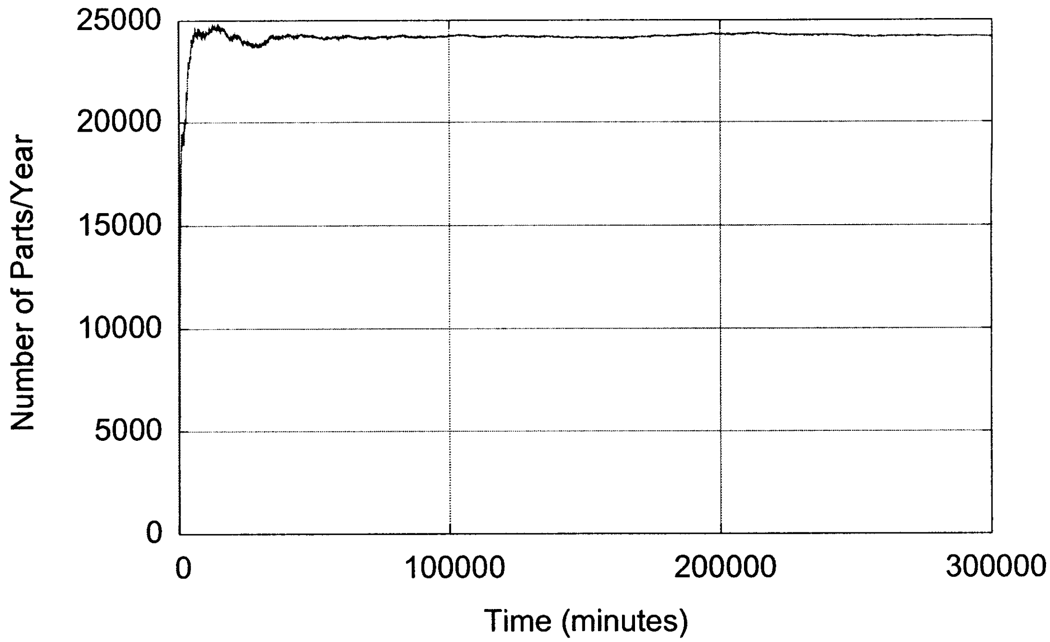


Figure 5: Production rate over time of the existing production system. Demand rate is 30,000 parts per year.

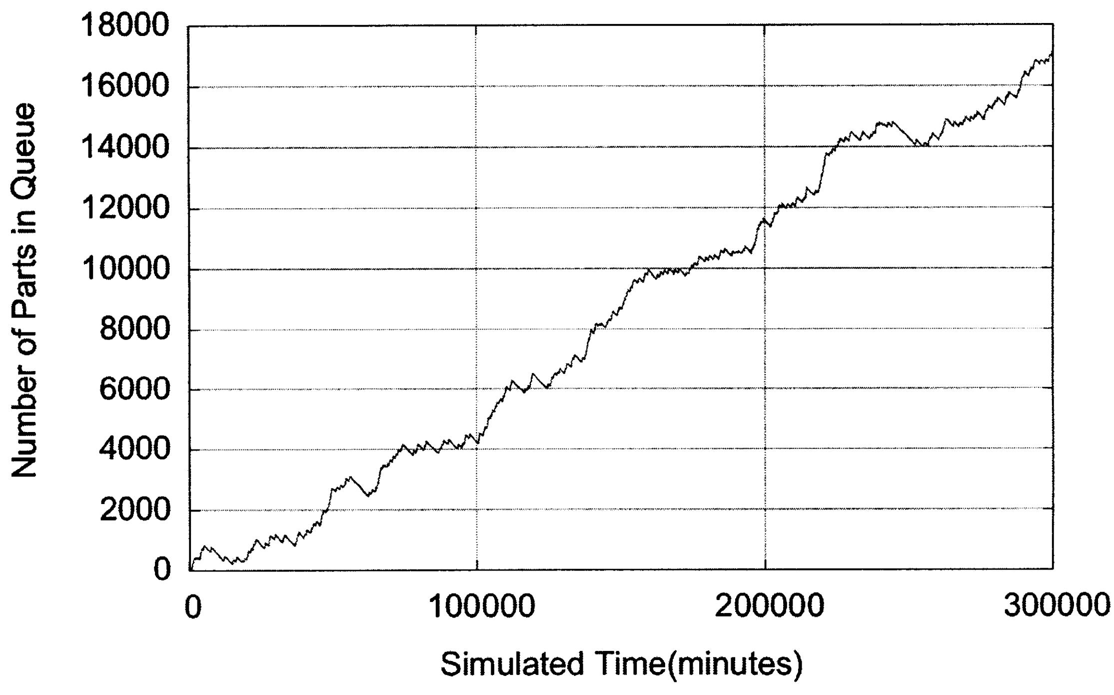


Figure 6: Queue length for the steel polishing node at a demand rate of 30,000 parts per year.

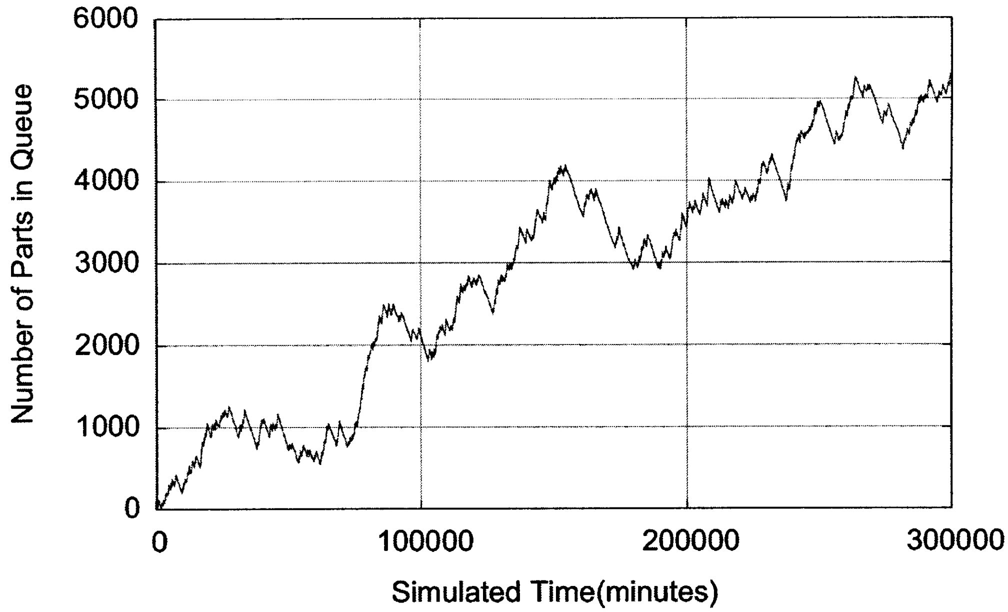


Figure 7: Queue length for the brass polishing node at a demand rate of 30,000 parts per year.

4.2 Polishing Improvements

Mohammad Imani Nejad was able to improve the polishing process. The improvements allowed the lapping stage to be completely removed, the processing time of the polishing machines to be reduced from 15 minutes per 10 parts for both steel and brass to 4 minutes for steel and 1 minute for brass. The rework rate was improved from nearly 50% to less than 5% [5]. Using these modified rates the simulation predicts a peak output in excess of 40,000 parts per year given the existing workforce of 4. Figure 8 shows the system output exceeding 40,000 parts per year with a demand rate of 48,000 parts/year.

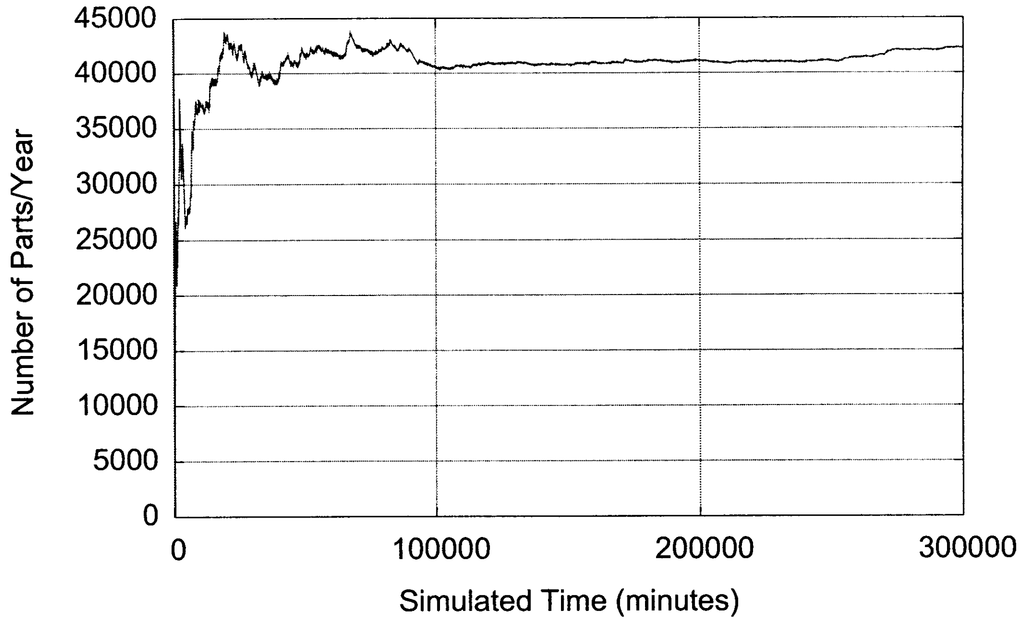


Figure 8: Production rate over time with the proposed improvements to the polishing process. Demand rate is 48,000 parts/year.

At 40,000 parts per year the polishing process is not a system bottleneck. Figure 9 shows the average queue length for the brass polishing node at a demand rate of 48,000 parts per year. The length of the queue is not growing overtime and never exceeds 140 parts. However, as shown in Figure 10, the length of buffing node queue is growing unbounded which indicates that this node is now the system bottleneck.

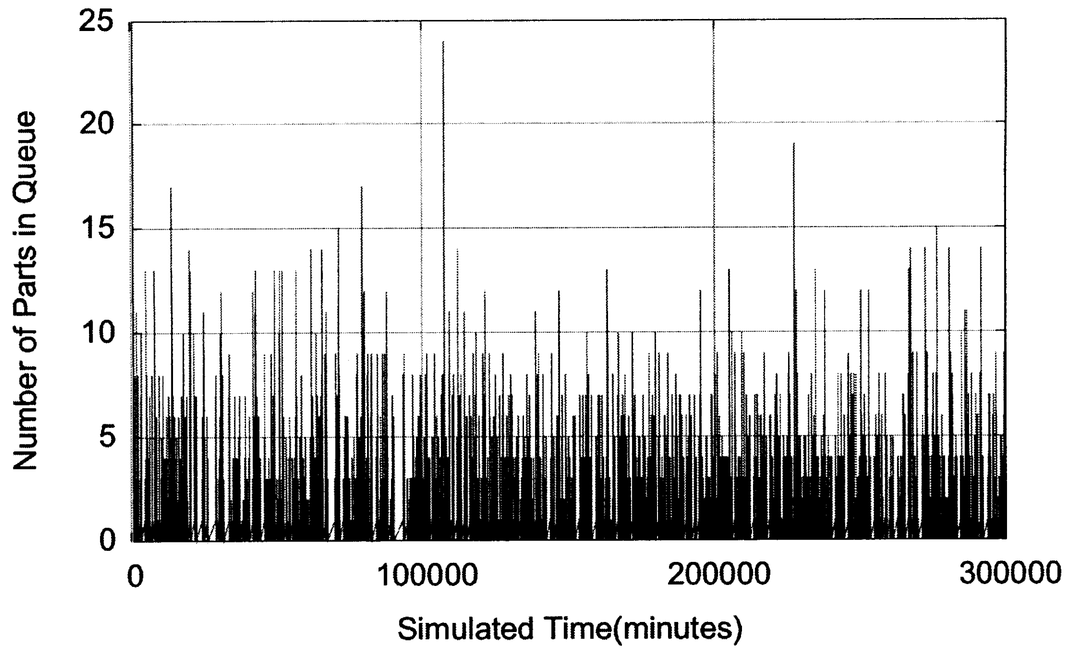


Figure 9: Queue length over time for the bras polishing node at a demand rate of 48,000 parts per year.

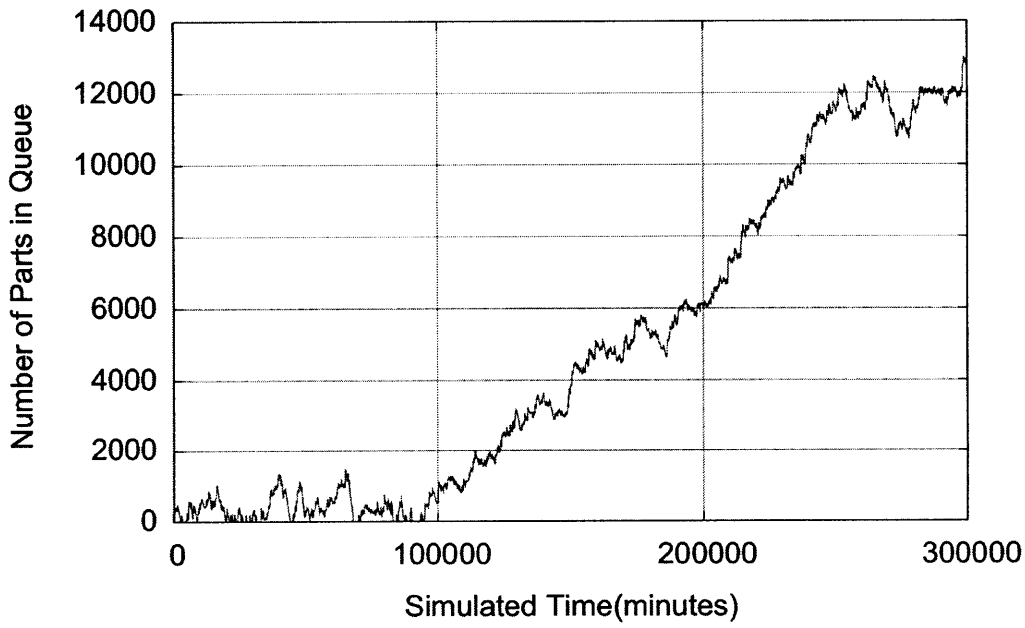


Figure 10: Queue length over time for the grinding node at a demand rate of 48,000 parts per year.

4.3 Maximizing Efficiency at Expected Demand Levels

While a peak throughput of 40,000 parts per year is a substantial increase over the initial peak rate of just 24,000 parts per year, this production volume far exceeds excepted demand of ~20,000 parts per year. We are interested in maximizing the efficiency of the total system at production levels slightly higher than the existing level of 15,000 parts per year. With Instron's existing production setup, 4 workers are assigned to operate the 7 machines to meet the demand. Instron is interested in minimizing the required workforce to meet existing and expected future demand. Running the simulation with just one worker to service all machines we can validate that it is in fact possible to do this. Figure 11 shows the production rate of the entire system with one worker to operate all of the machines. It can be seen that the production rate tops out at about 22,000 parts per year.

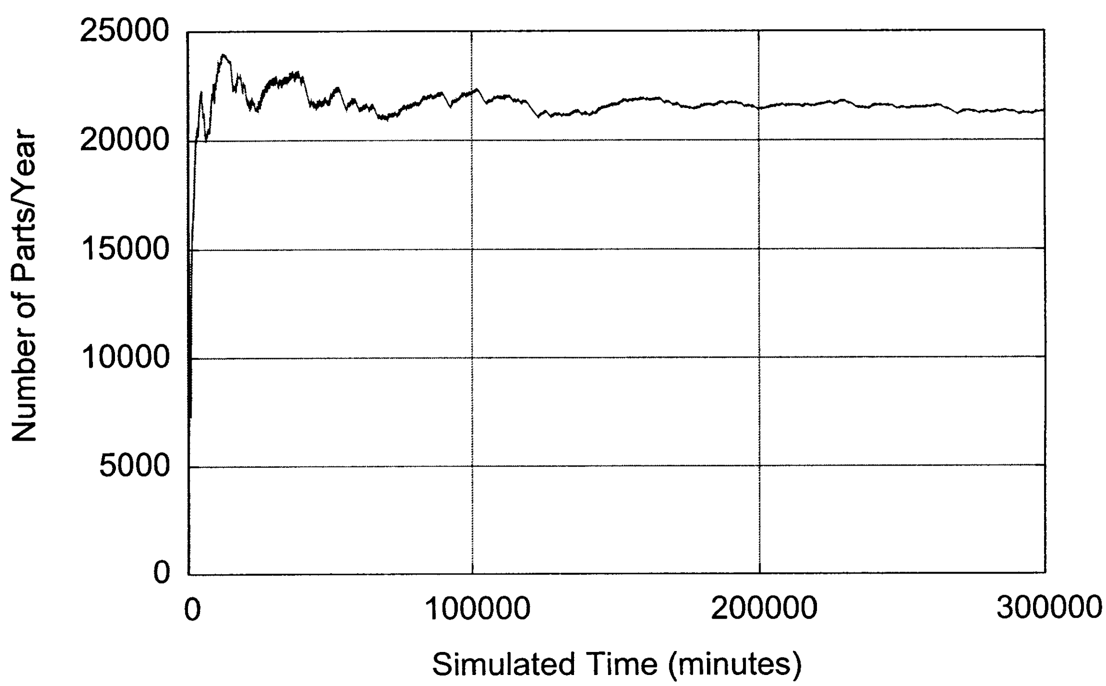


Figure 11: Production rate vs. time with proposed polishing improvements and a single worker with a demand rate of 25,000 parts per year.

While the simulation is helpful to validate the concept of a single worker it is not feasible to implement a single worker with current machine layout. With Instron's current setup, machines are distributed throughout the large production facility at Binghamton despite the fact that most of the machines used for the production of test blocks are dedicated to this task. It would be ideal to consolidate all the machines required for production into a work-cell that can be easily operated by one worker. The grinding and polishing machines do not need an operator while running. However, it is important that the operator remain close to the machines in case there is a problem.

A structured work schedule designed around a consolidated work-cell will address the coordination issues associated with the single worker production. A full grinding cycle consists of 15 minutes of setup, 2 hours of unattended operation, 30 minutes of cleaning and setup to turn the parts over, 2 hours of operation, followed by 15 minutes of cleaning and removal for a total cycle time of 5 hours. During a single 8 hour shift one full batch of 100 parts can be produced on the grinder. If the grinder is run every other workday, 125 days per year, it can have an annual throughput of 12,500 parts per year. 100 steel blocks every two days will be the takt time for steel blocks. Historically, demand for brass blocks is slightly less than steel so it will have a takt time of 80 parts every two days. This results in a total annual output of 22,500 parts per year. Table 2 shows a proposed schedule to achieve the combined production rate of 22,500 parts per year.

Table 2: Proposed production schedule for up to 22,500 parts per year with a single worker.

	Parts per Day	0:15 – 8:00 (15-minute intervals)
Day 1:		
Bead Blast Steel	105	
Grinding Steel	100	
Polishing Steel	100	
Polishing Brass	100	
Turning Brass	82.5	
Buffing Brass	83	
Day 2:		
Buffing Steel	100	
Turning Steel	100	

Worker Occupied
Machine Operating Unattended

With the proposed schedule on Day 1 the worker will remove 100 steel blocks from the existing buffer of completed heat treated parts. It will take the worker 1:45 to buff all 100 blocks. After buffing the worker will spend 15 minutes loading all 100 parts into the grinder. Once the grinder is started he will simultaneously polish brass and steel blocks. It will take 1 hour to polish 100 steel and 100 brass blocks using the improved polishing procedure. Once polishing is finished the worker will start turning and roll stamping brass blocks. While turning blocks, the worker will have to spend 30 minutes reloading and cleaning the grinder so the second side of the blocks can be ground. The next day, the worker will spend their day turning steel parts and buffing brass parts to complete a full cycle of 100 steel blocks and 80 brass blocks.

This aggressive schedule demonstrates the limits of what is possible with the existing machinery. If such an aggressive schedule were actually implemented several precautions would have to be taken in order to ensure reliable production. Primarily, such a system relies on a continuous flow of materials. All stages of the production process, except heat-treating, are performed in house and can be closely controlled. Ensuring a continuous flow of parts from the heat-treater will require close coordination and a carefully arranged supply agreement.

It was previously demonstrated that with a single worker and running at capacity the buffing processes is the bottleneck of the system. As a result, the total system throughput is sensitive to variations in this stage. If the rework rate triples from 5% to 15% the total system capacity is reduced by nearly 20%. Figure 12 shows the system throughput with a 15% defect rate in the buffing stage. The system is not as sensitive to increased rates of failure at other stages. Figure 13 shows the total system throughput with a 25% rework rate (nominally 5%) at the polishing stage. Total system throughput is unchanged. The turning, bead blasting, and grinding stages have less negative impacts.

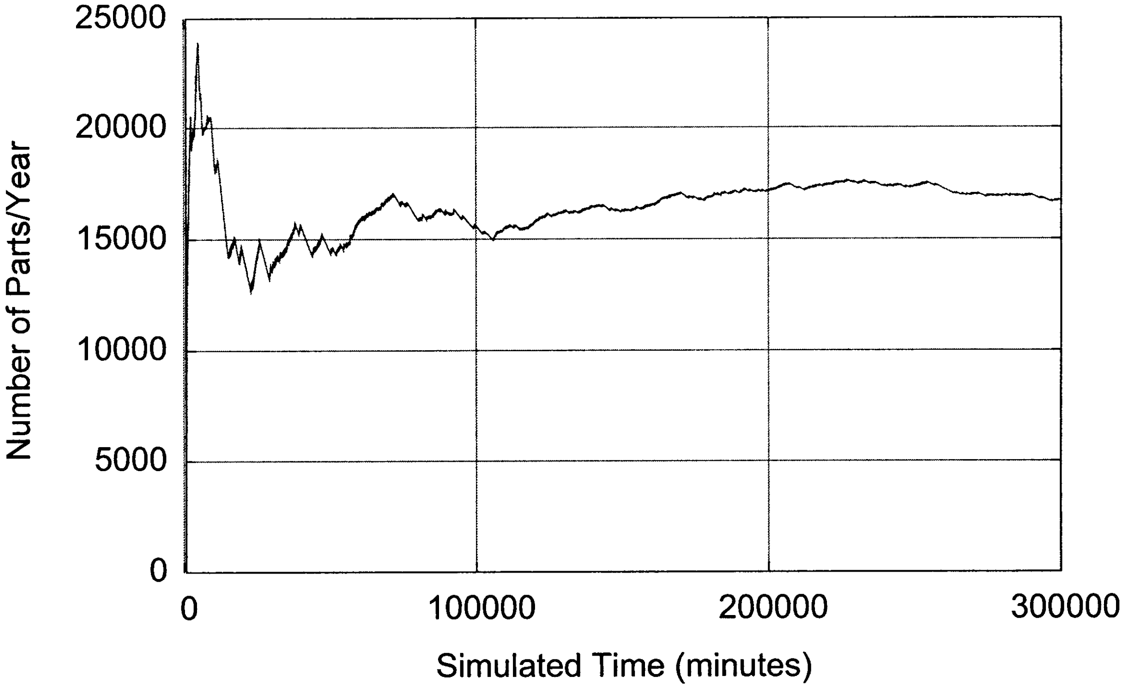


Figure 12: System production rate with a 15% rework rate at the buffing stage.

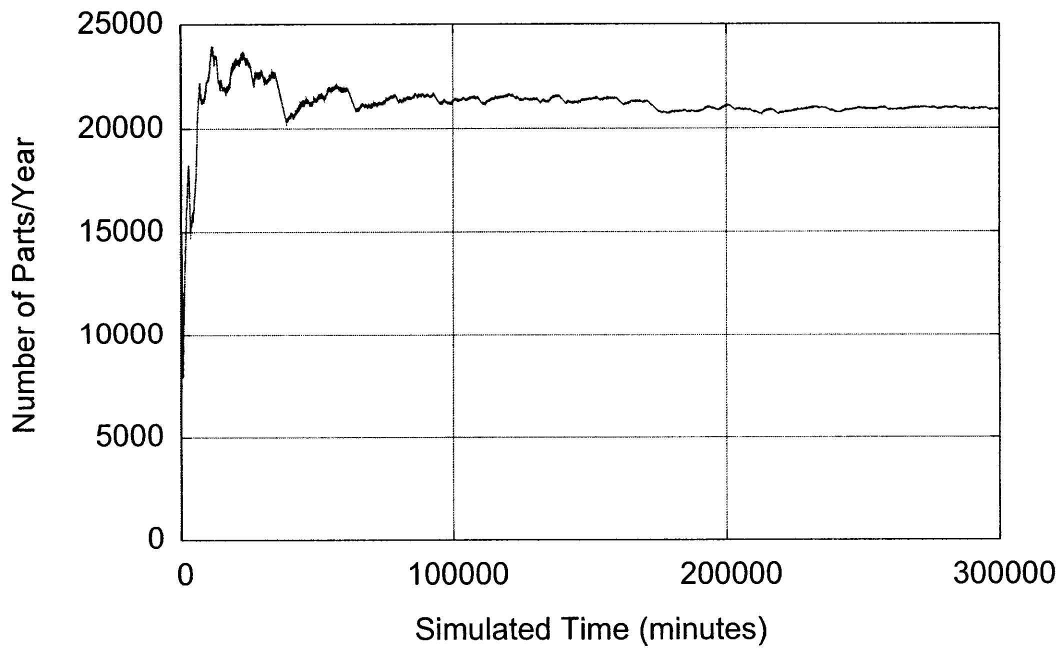


Figure 13: System production rate with a 25% rework rate at the polishing stage.

In addition to the degradation in throughput due to variations in the buffing stage, it was recognized that nearly half of the worker's time is spent operating the CNC lathe during the initial rough turning operation. Jairaj Vora has presented potential improvements to the rough cutting and CNC turning processes that can reduce the worker's time spent operating the lathe. Vora has proposed using a centerless grinder to turn the raw steel barstock to minimize the lathe time spent turning parts to the final diameter. He has also proposed to add a bar-feeder to the CNC lathe so it can be run unattended [8]. These two improvements have the potential to reduce cycle times in the CNC lathe by as much as 50% and eliminate the need for the operator to continuously tend to the machine. Figure 14 shows the effect of these improvements on the simulated single worker production system. Peak throughput has been increased from 22,500 to 27,000 parts per year, a 20% improvement.

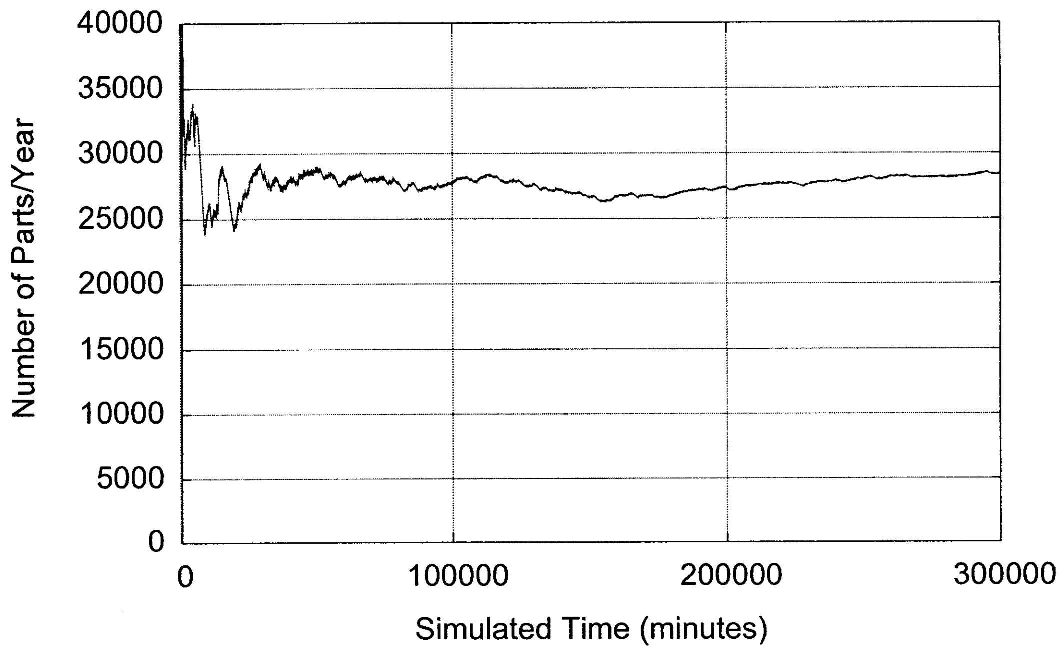


Figure 14: Single worker production with proposed improvements to the initial turning processes.

Chapter 5: Conclusions and Recommendations

Using Python and freely available libraries, an accurate discrete event simulation model of Instron's Rockewell hardness test block production line was created. This model was effective at predicting the limits of Instron's existing production line. The model was also effectively used to predict the overall production line performance when improvements are made to the polishing process. Using the model the limits of the existing production system have been demonstrated. The proposed improvements to the polishing process are shown to more than double the potential production rate without any other improvements. The simulation model is a helpful tool for predicting system behavior.

A production schedule and organization methodology, based on the findings uncovered by the model, has been demonstrated to allow a single worker to produce over 20,000 parts per year. In addition to reducing the required workforce, the proposed production method also reduces order lead time. However, care should be taken when implementing such a system as it is shown to be extremely sensitive to variations in the buffing stage.

Based on the results of the simulation it is clear that improving the polishing process and eliminating the lapping stages provide substantial improvements in the overall system throughput. Furthermore, the proposed production system, which utilizes these improvements, allows a single worker to produce at levels exceeding current production volumes. When implementing the production system it would be advisable to start at a lower production rate than the peak capacity of 22,500 parts per year. If the grinder is operated every third day and the other two days used to perform the other tasks an annual production rate of 15,000 parts per year can be achieved. If higher production rates are desired, it has been shown that improvements to the CNC turning process can allow annual production rates as high as 27,000 parts per year.

While working with the current production workers it became clear that when rework of materials is required it is often unclear what process should be utilized to fix the defective parts.

As a result, workers tend to "pass the buck" to another production process. As a result excessive rework often occurs, workers will send parts upstream to previous production processes unnecessarily. By moving to a single worker responsible for all stages of production it is plausible that the amount of unnecessary rework will be reduced as the individual worker will have no where to "pass the buck."

As previously mentioned, the proposed production system is dependent on a continuous flow of materials. Future work should investigate the sensitivity of the system to machine breakdowns, heat treating delays, outsourced cutting delays, and stock out of raw materials.

It is apparent that tight coordination with the heat-treating supplier will be required. Additionally, accurate demand forecasting will go a long way to ensure minimal lead times. A standard inventory model, such as a base stock model, can be implemented to place orders into the system in order to consistently produce the desired parts. Such an inventory model should be used to control inventory across the entire product line and production facilities. With the current setup, disjointed inventories are kept at the Binghamton and Norwood facilities. It seems unnecessary to keep finished goods inventory at both locations. If these inventories can be unified, total inventory volume can be further reduced.

Appendix A: Simulation Code

Usage:

Attached below is the Pythong code used to create the simulation used in this thesis. It was run using Python 2.5.1 on MacOS 10.5.7. The following python libraries are also required:

SimPy 2.0.1
Numpy 1.3.0
Gnuplot.py 1.8

#python simulation.py [simulation duration] [data file name/path] [demand rate]

Usage Notes:

- The demand rate argument is optional. If omitted the demand rate specified in the data file will be used.
- This script will create several output files in a folder called *runs*. Please create this folder before running the script. The files will be placed within *runs* in a new folder named with the current date and time.
- While running, the provide a continual system update to the user. Every time a new order is added to the system the time and number of parts in the system will be printed.
- If the demand rate substantially exceeds the production rate the number of parts in the system will grow unbounded. On a 2.5ghz dual core CPU with 4GB of RAM systems with more than 25,000 parts run too slow to be useful.

Code:

```
from SimPy.Simulation import *
#from SimulationGUIDebug import *
import random as ran
import shutil, csv, sys, Gnuplot, datetime
import os as OS
from SimPy.SimPlot import *
from collections import deque
from numpy import *
import gc

execfile(sys.argv[2])
random.seed(1)
rate = int(sys.argv[3])

class Part(Process):
	def execute(self,i,pri,type,P,mean):
		self.pri = pri;
		while i < len(mean):
			global cpmon, compparts, st, myQ, wm, buffernode, outfile, inflight, sstock

			if i == buffernode:
				if bufferdebt[type] == 0:
					buffer[type].append(self)
```

```
                        #printbuff()
                        #print "buffer" + str(type) + ": " + str(len(buffer[type]))
                        yield passivate, self
                else:
                        bufferdebt[type] -= 1
                        #printbuff()
        if i <> 1:
                mqtime = now()
                yield request,self,mac[i],pri           #queue for desired machine
                w = workpool[i]
                mmon[i].observe(now()-mqtime)
                wqtime = now()
                yield request,self,work[w],pri          #queue for worker to load into machine
                wmon[w].observe(now()-wqtime)
                yield hold,self,loadtime[i]
                yield release,self,work[w] #release worker who loaded

        if(len(myQ[i]) < maccap[i]-1):          #passivate if machine is not at capacity
                myQ[i].append(self);
                yield passivate, self
        else:                                   #if machine is at capacity, activate all items in myQ
                for x in myQ[i]:
                        reactivate(x);
                myQ[i] = [];

                st[i] = ran.expovariate(1.0/mean[i])
                if needop[i]:                   #if node needs operator last part into node will q for
op
                        wqtime = now()
                        yield request,self,work[w],pri
                        wmon[w].observe(now()-wqtime)
                        wm[i] = pri             #wm[i] is the process holding operator
        yield hold, self, st[i]

        if i <> 1:
                if (wm[i] == pri):              #release worker if this was the holding process
                        yield release,self,work[w]
                        wm[i] = None

                wqtime = now()
                yield request,self,work[w],pri          #unload part
                wmon[w].observe(now()-wqtime)
                yield hold,self,unloadtime[i]
                yield release,self,work[w]
                yield release,self,mac[i]


        i = choose2dA(i,P)                      # choose next node to go to
compparts += 1
cpmon.observe(compparts*120000/now())
pendord[type][0]["num"] -= 1
inflight -= 1
ifmon.observe(inflight-sstock)
if pendord[type][0]["num"] == 0:
        #print(str(now() - pendord[type][0]["start"]))
        pendord[type][0]["end"]=now()
```

```
                    pendord[type][0]["tottime"]=now()-pendord[type][0]["start"]
                    compord[type].append(pendord[type][0])
                    #print "compord: " + str(compord[type][-1]) + "\n\n\n"
                    #printbuff()
                    pendord[type] = pendord[type][1:]

def choose2dA(i,P):                                    #from node i chooses next node j based on matrix P
    U = ran.random()
    sumP = 0.0
    for j in range(len(P[i])):
        sumP += P[i][j]
        if U < sumP: break
    return(j)

class Demand(Process):
    def execute(self,rate):
        global outfile,os,types,buffernode,demparts,inflight,sstock
        self.count=0
        for i in types:
            type = i
            for j in range(0,os):
                inflight +=1
                #ifmon.observe(inflight)
                self.count += 1
                p = Part(self.count)
                if type < matdiv:
                    P = Ps
                    mean = means
                else:
                    P = Pb
                    mean = meanb
                activate(p,p.execute(i=buffernode,pri=-self.count,type=type,P=P,mean=mean))
            sstock = inflight
        while True:
            type = choose2dA(0,typedist)
            gc.collect()
            pendord[type].append({"num":os,"size":os,"start":now()})
            inflight += os
            ifmon.observe(inflight-sstock)
            print str(now()) + " : " + str(inflight)


            demparts += os
            if now() > 10000:
                rpmon.observe (demparts * 120000.0/now())
            for i in range(0,os):
                self.count += 1
                p = Part(self.count)
                if type < matdiv:
                    P = Ps
                    mean = means
                else:
                    P = Pb
                    mean = meanb
                activate(p,p.execute(i=startMac,pri=-self.count,type=type,P=P,mean=mean))
                if len(buffer[type]) == 0:
```

```
                                        bufferdebt[type] += 1
                                else:
                                        reactivate(buffer[type].pop())
                        yield hold,self,ran.expovariate(1.0/rate)

def printbuff():
        outfile = open("bufferfile","w")
        for type in types:
                outfile.write(str(type) + ": start: " + str(compord[type]["start"] + "\n"))
        outfile.close()

initialize()
inflight = 0
sstock = inflight


buffer = {}
bufferdebt = {}
pendord = {}
compord = {}
leadtime = {}
for type in types:
        buffer[type]=[]
        bufferdebt[type]=0
        pendord[type]=[]
        compord[type]=[]
        leadtime[type]=[]

mac = []
work = []

#register(Demand,name="Demand")
wmon = {}
mmon = {}
ifmon = Monitor()
cpmon = Monitor()
rpmon = Monitor()

st = {}                 #st defines work time at each node, changes with each batch
myQ = []                  #myQ keeps track of items waiting in machine before machine is full
wm = []                  #wm keeps track of which process is holding the operator
compparts = 0
demparts = 0

for x in range(len(means)):
        myQ.append([]);
        wm.append([]);

for x in range(len(means)):
        mac.append(Resource(name="Machine%d"%x,capacity=maccap[x],qType=PriorityQ,monitored=True))
        #register(mac[x])
        mmon[x]=Monitor()

for x in range(len(workcap)):
        work.append(Resource(name="Worker%d"%x,capacity=workcap[x],qType=PriorityQ,monitored=True))
        #register(work[x])
```

```
		wmon[x]=Monitor()

simendtime = float(sys.argv[1])
g = Demand("Demand")
activate(g,g.execute(rate))
simulate(until=simendtime)
print "done!"

leadtime = {}
rowlist = ["type","leadtime"]
ttimes = []
for type in types:
	sum = 0
	for x in compord[type]:
		sum += x["tottime"]
		ttimes.append(x["tottime"])
	if len(compord[type]) == 0:
		leadtime[type] = 0
	else:
		leadtime[type] = sum / len(compord[type])

dirname='runs/'+(str(datetime.datetime.utcnow())[:-5])+'/'
OS.mkdir(dirname)
shutil.copy(sys.argv[2],dirname+sys.argv[2])

print mean(ttimes)
print std(ttimes)

def plotmonitor(mon,x,y,title,xtitle,ytitle,color=1):
	global dirname
	if len(mon) == 0:
		return
	x1 = []
	y1 = []
	for z in mon:
		x1.append(z[x])
		y1.append(z[y])
	g = Gnuplot.Gnuplot()
	d = Gnuplot.Data(x1,y1, with='l lt '+str(color))
	g('set grid')
	g.title(title)
	g.xlabel(xtitle)
	g.ylabel(ytitle)
	g.plot(d)
	g.hardcopy(filename=dirname+title+'.pdf',terminal='pdf')

drate = 200*2000*60/rate
plotmonitor(ifmon,0,1,'Items in Flight: '+str(sys.argv[2]),'Time (minutes)','Items in Flight Minus Buffer Stock')
plotmonitor(cpmon,0,1,'Production Rate vs Time ('+str(drate)+' pts yr)', 'Time (minutes)','Parts/Year')
plotmonitor(rpmon,0,1,'Demand Rate vs Time ('+str(drate)+' pts per yr)', 'Time (minutes)','Parts/Year')

#macact = []
#i = 0
#total = 0
#for x in mac:
#	if x[i] <> 0:
```

```
#               macact[i] = x[i]
#               if i <> 0:
#                       total += macact[i][1]
#                       macact[i].append(total)
#                       macact[i].append(total/macact[i][0])
#               else:
#                       total = macact[i][1]
#               i += 1

#print macact[8]

i = 0
for x in mac:
        if i <>1:
                plotmonitor(x.waitMon,0,1,'Machine '+str(i)+' Q Length','Simulation Time(minutes)','Items in Q')
                plotmonitor(x.actMon,0,1,'Machine '+str(i)+' Activity','Simulation Time(minutes)','Items in Q')
        i += 1

plotmonitor(work[1].waitMon,0,1,'Worker'+str(i)+' Q Length','Simulation Time(minutes)','Items in Q')

g = Gnuplot.Gnuplot()
d = Gnuplot.Data(leadtime.keys(),leadtime.values(), with='boxes fs solid lt 1 lw .5 ')
g('set grid')
g.title('lead time by part type')
g.ylabel('lead time (Simulation Minutes)')
g.xlabel('part type')
g.plot(d)
g.hardcopy(filename=dirname+'leadtime.pdf',terminal='pdf')
```

Appendix B: Example Data File

```
from SimPy.Simulation import *
#from SimulationGUIDebug import *
import random as ran

types = range(0,16)
typedist = [[ 0.05, 0.05, 0.05, 0.10, 0.10, 0.05, 0.05, 0.05, 0.05, 0.10, 0.10, 0.05, 0.05, 0.05, 0.05,
0.05]]
buffernode = 2
matdiv = 7

#Overall Setup
os = 200                        #batch size
rate = 1600.0                   #demand rate, overridden if specified at runtime
startMac = 0                    #starting node

Ps =    [[0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0,0.05, 0.0,0.95, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.2, 0.0, 0.8, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.3, 0.0, 0.5, 0.2]]

Pb =    [[0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0,0.05,0.95, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.2, 0.0, 0.8, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.3, 0.0, 0.5, 0.0, 0.2],
         [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]]

#machine setup
means =     [2.6, 3600, 0.0001,40.0, 240.0, 1.8, 0.0, 10.0, 0.0, 15.0]          #mean
processing time per batch each node
meanb =     [1.6, 3600, 0.0001, 0.0,  0.0, 0.7, 10.0, 0.0, 15.0, 0.0]           #mean
processing time per batch each node
```

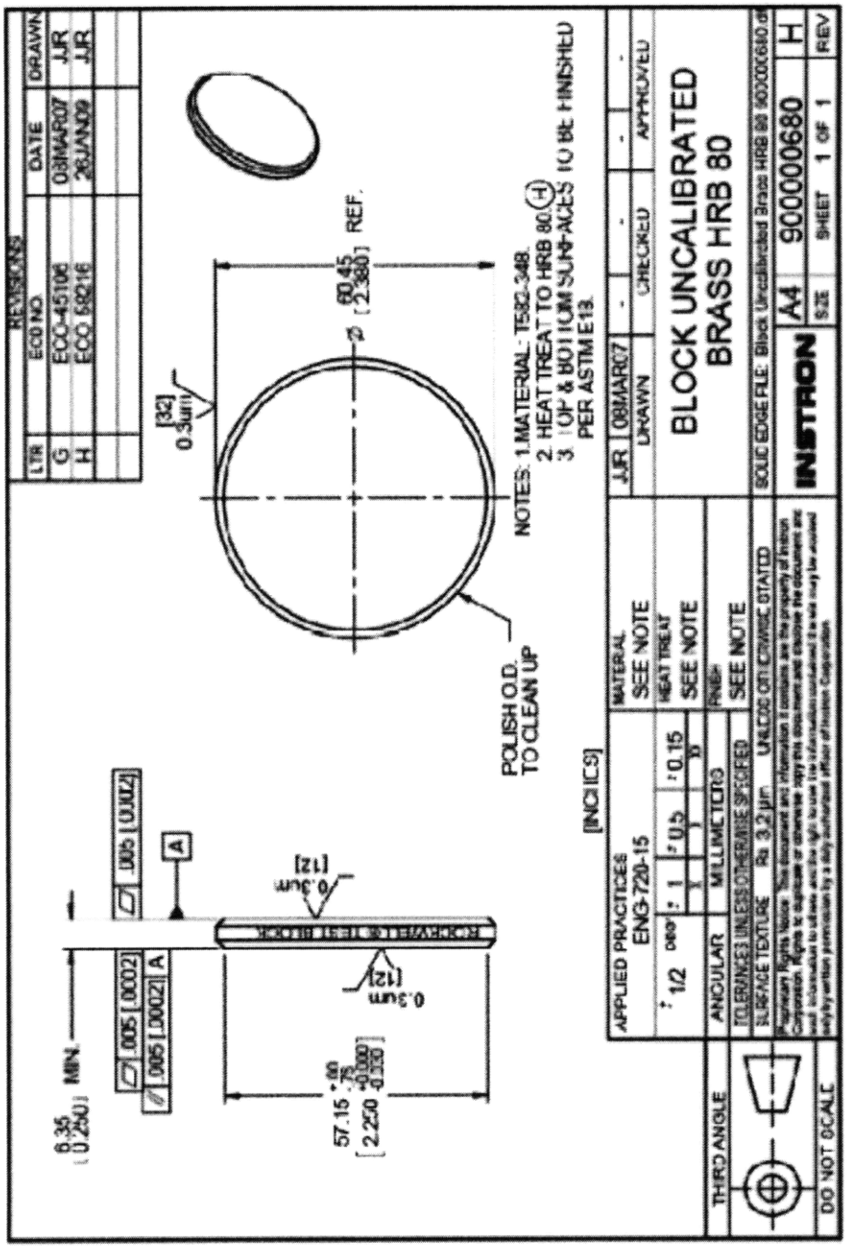
loadtime = [.1, 0, 0.0001, 0.1, 0.14, 0.01, 0.2, 0.2, 0.2, 0.2] #load time per part at each node
unloadtime = [.1, 0, 0.0001, 0.1, 0.6, 0.01, 0.2, 0.2, 0.2, 0.2] #load time per part at each node
maccap = [1, os, 1, 50, 100, 1, 20, 20, 10, 10] #machine capacity

#worker setup
workpool = [1,0,0,2,2,2,3,3,4,4] #which worker pool is needed at node i
needop = [1,0,0,1,0,1,1,1,0,0] #boolean to define if a continuous operator is required
workcap = [99999,1,1,1,1] #number of workers available in each worker pool

Appendix C: Variables

Variable	Type	Description
types	int range	total number of part types
typedist	vector double	probability of demand for each part type
buffernode	int	node of buffer
matdiv	int	number of brass part types
os	int	number of parts in 1 order
rate	double	demand rate, can be overridden at runtime
startMac	int	first node of the system
Ps	matrix double	transition matrix for steel parts
Pb	matrix double	transition matrix for brass parts
means	vector double	mean processing time for steel
meanb	vector double	mean processing time for brass
loadtime	vector double	loading time for each machine
unloadtime	vector double	unloading time for each machine
maccap	vector int	machine capacity
workpool	vector int	which worker group is assinged to each machine
needop	vector bool	weather a machine needs an operator while running
workcap	vector int	the number of workers in each group

Appendix D: ASTM E18-08a



Thickness	>6mm (0.236in)
	<16mm (0.630in)
Test surface area	<2600mm^2 (4in^2)
Flatness	< 0.005mm (0.0002in)
Parallelism	<0.0002 mm per mm (0.0002in per in)
Roughness	<0.003 mm (12µin)

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