APPLICATION OF INTELLIGENT-OBJECTS SIMULATION TO MANUFACTURING PROCESS EFFICIENCY ANALYSIS: A CASE STUDY

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APPLICATION OF INTELLIGENT-OBJECTS SIMULATION TO MANUFACTURING PROCESS EFFICIENCY ANALYSIS: A CASE STUDY

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In this study, intelligent objects-based simulation methodology is applied to the analysis of efficiency of a human-robot hybrid assembly cell in the SRG Global Morehead manufacturing facility. Intelligent objects-based simulation software technology, particularly the Simio simulation software suite, is tested for its viability as an everyday tool for engineers in an industrial setting to work toward the maximization of efficiency of manufacturing processes. The human-robot hybrid assembly cell selected for this study assembles automobile grilles. The methodology used in this study involves collecting data from the human-robot hybrid assembly cell, developing models to simulate the actual cell layout and production, and ultimately experimenting with the developed simulation models to test for possible solutions to address inefficiencies observed within the cell. The production data that was collected and analyzed from the assembly cell included an in-depth time study, throughput analysis, and recording cell downtime and scrap data. Using this data, a simulation model of the assembly cell was built and subsequently validated. Next,

potential cell layout modification scenarios were developed to increase the throughput of the cell. These solution scenarios were then ran as experiments against the current process model, testing against a response variable that was a key process indicator in production level. Finally, the results of these experiments were analyzed and summarized to determine the best scenario for actual implementation.

Accepted by: ______________________, Chair

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Chapter 1: Introduction

1.1 General Area of Concern

In any manufacturing industry, the process time is very important. With every process and every product, the more quickly and efficiently a product can be made the more profitable that product can be. This equates to a better manufacturing system and a more profitable business model. Methodologies such as Six Sigma and Lean Manufacturing have put an emphasis on efficiency and quality in manufacturing in recent decades, but in most cases, these techniques have their limitations and can only go so far in maximizing the process efficiency. It is difficult to experiment with a running production line due to the fear of lost time and resources. The need for continuous product supply and short timelines does not offer a succinct way to allow for the time and effort that would be needed to hone a manufacturing process to greater heights of efficiency. This dichotomy runs against most every credence and principle of manufacturing. According to Feld (2000), lean manufacturing encompasses continuous improvement of processes. But with manufacturing being the time-oriented business as it almost always is, that improvement can sometimes be lost in the shuffle. While this is not to say that efficiency is completely forsaken, it could definitely be emphasized more if there were a way to be able to study a process closely enough to work toward maximizing efficiency without disrupting production.

However, there may be a solution to address this dichotomy. With recent advances in computer and software technology, there is enough cheaply attainable processing power available commercially to be able to utilize specially built software suites that can build a manufacturing process digitally through simulation.. A full scale simulation of even complex manufacturing processes is possible to build to real life specifications and run thousands of times spanning the course of days, weeks, or years. And no work stoppage is required to experiment with the simulated model by changing different variables. Because of this, computer simulation could be a key tool for manufacturing organizations now and in the future if utilized correctly. The modern era of simulation began in earnest in the early 1950s with the use of early computer assembly languages and the use of slow and expensive early computers (McHaney, 2009). With greater processing power and highly specialized simulation software however, simulation can be done more quickly and effectively today than at any other time.

Computer simulation holds a myriad of uses in the manufacturing field. From the setup and projection of the capacity of an entire new facility to the analysis of a single manufacturing cell that needs to be improved, there are a number of benefits to be experienced. Without even shutting down for a minute, a production line or assembly cell could be analyzed in detail. Data could be derived and validated and from that evidence for the viability of effective changes could be had. More often than not, a decision for a sizeable proposed change to a manufacturing process will not be made based solely on an educated guess. Far too much lost production would be at stake to gamble making a change that may prove to hurt production rates rather than help them. With a simulation, many proposed changes can be synthesized and rigorously tested in a model for validity before being considered. This way, any change that is proposed would have already proven effective before any real physical change to the process is done. This provides much more help to management personnel who must not only make decisions rooted in engineering but also in finances.

1.2. Problem Statement

In this study, a medium-sized manufacturing assembly cell at SRG Global in Morehead, KY assembling the grille for the F-150 pickup truck will be simulated with an advanced computer simulation program in efforts to find, and ideally generate ways to address, any inefficiency in the process and try to create ways in which to increase the overall throughput of the cell. This will be done by first building a simulation model of the current assembly cell using current production data and cycle times in order to have a baseline to begin from. After building this model and testing its validity, possible ideas for increasing process efficiency will be trialed using a custom-built simulation model for each idea. Each of those models will then be run a minimum of one month of simulated production within the simulation software to see if the average cycle times and production rates differ in any way. In addition to focusing on the time facet of the process, minimizing movement of both material and people will be focused on. The data obtained from the baseline simulation model as well as the potentially improved models will then be analyzed statistically in order to attempt to glean some root causes of inefficiencies within the process.

It is hypothesized that the main areas where improvement could be gained within the assembly cell would be within either the operations manned by human workers or in the material handling system that brings raw parts into the cell and takes finished products out. Based on a preliminary analysis, these areas are where the most variance appears to be within the whole cell in terms of production rate and cycle time and could stand to improve markedly with some change.

1.3. Objectives

The objectives of this study are listed below:

1. Collection of production data (including cycle times, scrap data, machine availability, and downtime) on assembly cell.

2. Modeling current assembly cell using a simulation software to establish the baseline model.

3. Developing potential viable solutions that could improve process efficiency through analysis of current process and data available.

4. Building individual unique simulation models for each potential solution in order to gauge the effectiveness at increasing process efficiency.

5. Analyzing simulation results in order to determine which solutions, if any, would boost process efficiency enough to be considered for actual implementation.

6. Preparing an implementation plan and timeline.

1.4. Assumptions

The assumptions of this study are:

1. The process and the sequence of operations in it will not change for the different product variants produced within the assembly cell.

2. The process will not change in its fundamental design and/or purpose throughout the length of the study.

3. All production data used within the simulation will be indicative of the current process in use.

4. Any rise of the production rate or lowering of the cycle time within the simulation will indicate a positive result.

5. The baseline production data and simulation results will be that data that is gleaned from the currently running assembly cell and be considered the control.

1.5. Definition of Terms

Lean Manufacturing- Manufacturing methodology that focuses on the removal of waste and the maximization of value of the production of a product to the end customer.

Six Sigma- Quality performance measurement methodology based in continuous improvement toward reducing quality defects.

Simulation- Analogous representation of a particular process or event through the use of a scale model.

Injection Molding- Manufacturing process where molten material (most usually plastics) are forced under pressure into a multi-piece hollow mold in order to shape the material into a desired figure.

Flexible Cell- Manufacturing term referencing a collection of material handling and work equipment that can be quickly altered in order to meet a versatile set of manufacturing needs

Simio- Simulation software suite based on Intelligent Objects Simulation format

Intelligent Objects-Based Simulation- Simulation where focus of simulation is on the building of intelligent logic-programmed 'objects' which represent the different components of a simulation model (Pegden, Intelligent Objects: The Future of Simulation, 2010).

Transfer Time- Time taken to transfer a material from one place or station to another.

Work In Process (WIP)- Any product that has received value-added input but is not fully finished.

Material Handling- The act of moving a raw, WIP, or finished product within a manufacturing facility.

Cycle Time- The time taken to complete one part or product within a manufacturing process

Scrap- Any product deemed not usable to the customer through defective workmanship, materials, or quality rejection.

Scrap Percentage- The percentage of parts from an entire 'run' of parts that were deemed as scrap.

Downtime- Any time within a specified production time period in which production equipment are not running due to an unforeseen issue or cause.

Availability- The ratio of actual machine runtime to the full amount of allotted runtime, usually depicted as a percentage.

Operation- Name for each individual workstation whose purpose within the manufacturing cell is unique and non-redundant.

Production Data- Data such as cycle time, availability, downtime, and scrap percentage that give an accurate portrayal of the production rate of a particular manufacturing process.

Efficiency Analysis- An analysis on the efficiency of a process with emphasis on those areas where the most inefficiencies are located and their root causes.

Rework- Any part that must be subjected to more work than the normally specified amount in order to ensure compliance with customer tolerances.

Robot-Human Hybrid Cell- Manufacturing cell where both humans and robots work in tandem to perform specific tasks (J. Kruger, 2009).

Triangular Distribution- Probability distribution based around a normal distribution where values fall around a most likely value and disperse between a minimum and maximum.

Chapter 2: Background and Review of Literature

2.1. Company Background

The SRG Global plant located in Morehead, KY is an injection molding plastics manufacturing facility that specializes in the production and electroplating of plastic grilles, moldings, and other trim for the automotive industry. Originally called Guardian Automotive, the company became SRG Global in 2008 after the acquisition of Siegel-Robert Automotive. With this acquisition, SRG Global became one of the largest producers of electroplated plastic products in the world (SRG Global, 2012).

The Morehead plant is one of 17 SRG Global facilities worldwide, with ten facilities in the US alone. The Morehead plant produces products for a number of automakers including Ford, GM, Toyota, Nissan, and more. One of the largest volume products produced in the facility is the grille for the newest generation of Ford F-150 pickup truck. Nearly 600,000 F-150s were sold in 2011, making it the most popular vehicle model in the world.

2.2. Assembly Cell & Product Background

The assembly cell to be studied in this project is the singular cell that assembles every one of the F-150 grilles that are produced at the Morehead plant. This grille program is known internally within the plant as the P415 and the assembly cell is known as the P415 Assembly Cell. The cell uses a combination of autonomous robots and human assemblers to complete each of the eight different variants of F-150 grilles currently in production. This type of cell is known as a robot-human hybrid cell (Rahimi & Hancock, 1986). Also utilized is an automated conveyor system which uses specialized nests into which each grille components snaps. These nests are on a continuous loop which runs and stops into each operation station within the cell so as each grille can be assembled. At each of these stations, a different operation is performed. At the end of the cell process, a completed grille can then be removed, inspected, and packed into totes for shipment from the plant to the customer.

The layout of the cell resembles a loop where each long run is stacked one atop the other. This stacked layout helps maximize the use of space within the assembly area. The layout of the cell can be seen in the figure 1. The nests carrying the various parts are raised and lowered via an elevator system at each end of the loop. Both, raw grille beginning assemblies and finished grilles are transferred from the same station, which is known as Operation 70 or Op70 seen at the far right end of the cell in figure 1. This is where the process both begins and ends. From Op70, a raw grille surround is placed into a nest with a plastic isolator insert and sent through, initiated into the system with a press of a ready button by the Op70 operator. From here, it will travel down an elevator, run below the assembly operation and queue in line at the opposite elevator waiting to begin the assembly process. Once up the second elevator, the part first comes to Operation 10 or Op10 seen in figure 2(a), which is where a human operator places the specific inner into the grille surround and stages 5 clips which will later be fully inserted into place by one of the robotic operations.

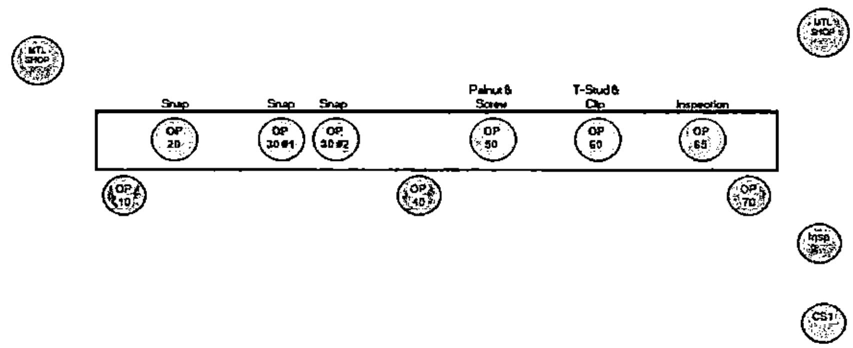


Figure 1: Schematic of P415 Human-Robot Hybrid Assembly Cell

Each of the different grille variants receives different types of inner components for aesthetics, all of which remain staged at the Op10 station.

Once complete at Op10 the carrier will travel to Operation 20 in figure 2(b) where the inner and surround are partially snapped into place at snap locations between the two components. This operation is completed by a robot applying exact pressure into specific locations to ensure a fast and accurate mating of the surround and inner.

Once Operation 20 is completed, the carrier will then travel to Operation 30. At Op30, seen in figure 2(c), two more robots finish the snapping operation initiated by the Op20 robot. This snapping operation is done by robots in order to ensure a more even and proper mating of the inner grille and surround than what can be accomplished by a human operator.

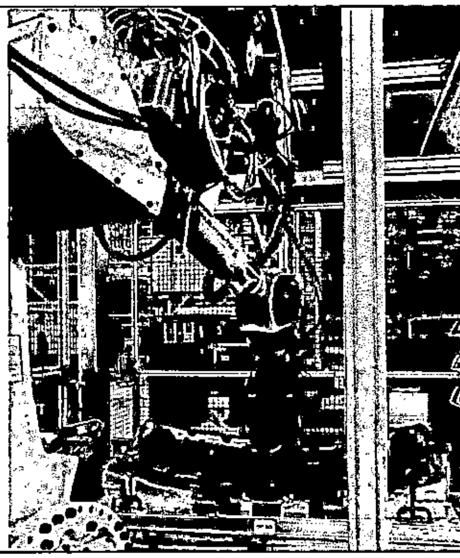
At Operation 40 in figure 2(d), a human operator adds a metal bracket, rubber bumper components, inserts two clips, and stages palnuts for later robotic insertion.

Operation 40 is a human operation due to the varied nature of the components that are placed into the grille.

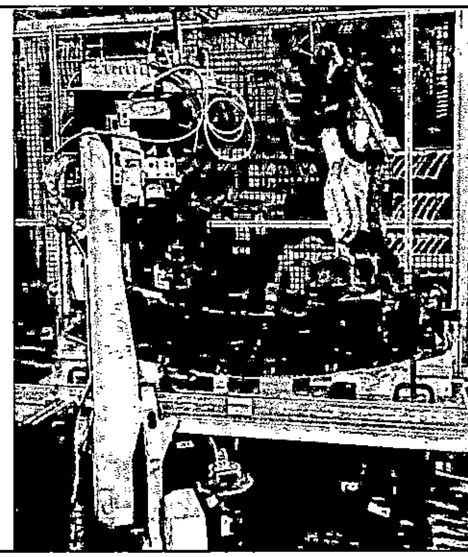
(a) Operation 10 | (b) Operation 20 | (c) Operation 30 | (d) Operation 40

Figure 2: P415 Assembly Cell Operation Photos

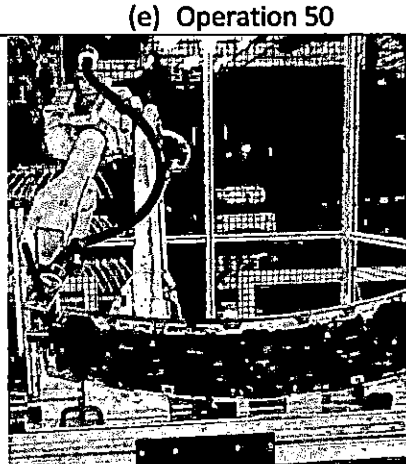
The bracket, being approximate 40" in length, would be unwieldy for a robot to handle. The palnuts and clips are by comparison much smaller and oddly shaped making robotic feeding and insertion problematic.



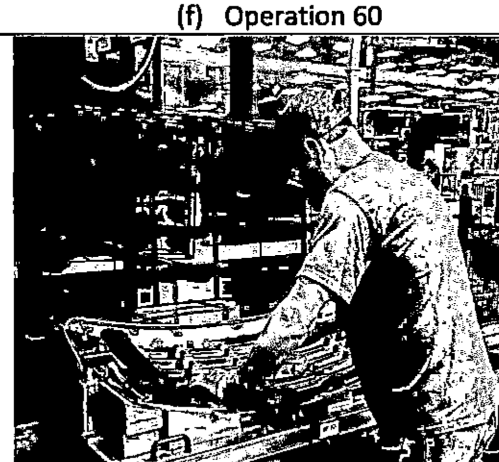
(e) Operation 50



(f) Operation 60



(g) Operation 65



(h) Operation 70

Figure 3: P415 Assembly Cell Operation Photos Continued

Operation 50, seen in figure 3(e), is where 4 more screws are added into the grille and the palnuts placed at Op40 are driven by a robotic assembler. This robot utilizes a dual operation end-of-arm tooling. At Operation 60, two robots will then place clips and studs into the grille. Figure 3(f) shows Operation 60 in action placing the clips and studs. The clips being placed by the aft robot are those same clips that the operator at Operation 10 staged earlier onto a stand integrated into part pallet. The robot in the foreground picks up a set of six studs that are staged from a hopper at the base of the robot and clicks the plastic-base studs into recesses within the lower portion of the grille.

And the final robotic operation, Operation 65 in figure 3(g), is an inspection which utilizes a metal-sensing device on the end-of-arm tooling to sense for the presence of the vital components and pieces of each grille that have been placed by the prior operations before passing on the product back to Op70. After this, the carrier with finished grille in tow arrives back at the original Op70 station where it began. Here a human operator visually checks and marks each grille for the presence of all components and then unloads the finished grille onto a turntable capable of holding two grilles. From here, a quality inspection specialist checks each grille for defects. Once passed, the grille is then placed into a returnable tote which is then readied for shipment and shipped when needed to one of Ford's truck assembly plants.

Material handling is done in a couple of different ways within this assembly cell. The raw parts that are molded in-plant are trucked to the assembly cell via forklift within carts and containers used for collection of WIP product. At the Op70 load/unload area of the assembly cell, there is a staging area where these containers are brought in.

Conversely, there is also a staging area for the returnable totes where the finished grilles are placed. The isolators, which are also molded at the plant, are staged opposite the conveyor of the Op70 operator for easy access. The small components like the clips, screws, and studs are loaded into hoppers and fed into the heads of each of the robots that insert them. With this system, these components are always at hand and in a position where the robot can use them without human supervision or guidance.

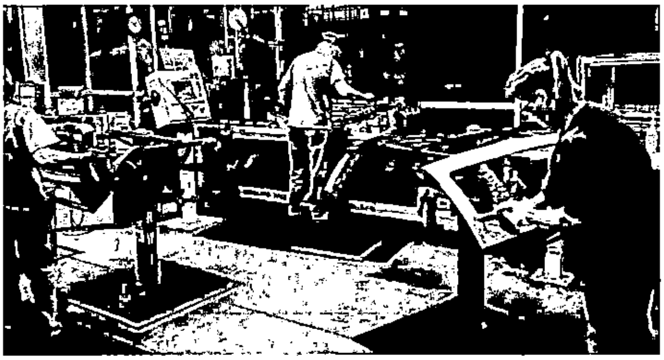


Figure 4: Operation 70, Surround Inspect, & Final Inspect Full-View Photo

Figure 3(h) as well as figure 4 gives a look at the Operation 70 operator's station, the surround inspect station, and the final inspect and pack. The focal points of this area are the two turntables used by the operators at the final pack and surround inspect stations. These turntables are where the Operation 70 operator both unloads the finished grilles and gets surrounds allowing the operator to simply turn to access their needed areas which limits unneeded movement.

2.3. Simulation Background

As mentioned briefly before, simulation has been around as a concept for many years and its beginning of widespread use was jumpstarted by the advent of computing technology. This technological jump allowed for the large amounts of data crunching that would go into even a simple simulation, allowing professionals in all fields to begin to utilize the benefits of simulation. Computer simulation aids in the mitigation of one of the more inherent worries in most scientific endeavors: how does one reduce the amount of risk involved with a certain scenario or choice? By allowing for a way to closely mimic and repeatedly trial a scenario many times over, much more insight can be gained than from simply investigating the principles that make up the scenario separately outside of a simulation. With a simulation, the behavior of interaction between two entities can be seen and studied in such a way that cannot be done by simply trying to blindly infer. However, a simulation is only as good as the simulation model and the data that is put into it. This leads to considering the different types of simulation that is used today. These simulations run the gamut, allowing for the application of simulation in various fields such as entertainment, biology, engineering, meteorology, etc.

According to McHaney (2009), the four primarily used types of simulations are:

- Continuous Simulation
- Monte Carlo Simulation
- Discrete Event Simulation

- Agent-Based (or Intelligent Objects-Based) Simulation Modeling

Continuous simulation depends upon crafting a set of mathematical equations that come to represent a system. This system is set to continuously vary in order to mimic the inherent rate of change within a normal system state. An example model that would use continuous simulation would be a marketing modeling that indicates supply and demand as two separate but interlinked sets within a 'market'. The continuous simulation model would have a set of differential-based equations that would indicate exactly how the rate of supply and demand may ebb and flow based upon set market parameters. These simulations are commonly developed using spreadsheets, mathematical software, or computer programming languages.

Monte Carlo simulation depicts simulations based upon "a scheme employing random numbers, which is used for solving certain stochastic or deterministic problems where the passage of time plays no role" (A.M. Law, 2000). Where as in discrete event simulation time is a factor, Monte Carlo simulations conduct simulations with no reference to time but simply to the generation of random numbers that gives Monte Carlo simulations good ability to simulate scenarios where events aren't completely predictable but do occur under some system of probability that can be accurately measured. The random number functions within most computer programming languages become the basis for most Monte Carlo simulations. Discrete Event Simulation simulates models based upon event-driven actions which trigger randomly depending upon chances as time passes. This model is one that is useful for a manufacturing-based simulation model. This model can best be described with the thought of an assembly line. The 'event' that begins the process in motion is the arrival of a raw part into the assembly line. Once the part is introduced into the system, the system initiates and processes the part until finished. If there are no parts, the system will go dormant once again waiting for the next part. The outcome of the simulation hinges upon the set of variables that dictate the amount and frequency of parts that arrive at the line over a period of time. GPSS or General Purpose Simulation Software is a discrete event simulation software released by IBM in 1961 and whose basis hinges on a program with a series of control and executable statements (Karian & Dudewicz, 1999). These control commands indicate the amount and frequency of event occurrences and the executable statements indicate the different events that can occur.

Agents-based simulation, also known as intelligent objects-based simulation, bases model simulation upon the simultaneous interaction of many small and intelligently-driven objects within a system that combine to create a holistic and complex overall model. Each of these individual objects are programmed with their own motives, instructions, and interests and the primary assumption of such a system is that the simple local behaviors of small objects generate complex top-level behavior. This type of modeling is very useful in a manufacturing setting. With an assembly cell, such as the P415 Assembly Cell, each of the different operations can be thought of as intelligent objects interacting with each other, transporting grilles in differing states of completion between each other based upon the behavior assigned to each object. With this type of simulation, data collected on each individual object can be assigned and the objects interconnected properly, and the model can be expected to behave similar to the real life cell. The simulation software that is used in this study, Simio, uses this type of simulation methodology.

2.4. Simio Background

Simio is a recently developed simulation software that utilizes the aforementioned object-based simulation style. Simio uses these objects to indicate and define the physical components of whatever system is being simulated (Simio, 2010). As such, there are many different types of objects usable in Simio. There are four object types available in Simio: fixed object, agents, entities, links and nodes, and transporters (Pegden, Intelligent Objects: The Future of Simulation, 2010). For instance, objects can be set to stand for forklifts, conveyors, or workstations within a manufacturing simulation. The facet that differentiates the different objects is the logic that is input into them by the user. Each object can be programmed to operate logically and intelligently within the simulation system it operates within, hence intelligent-objects. Once objects are set and programmed a simulation can be run with what is present or the present model can be saved as an object itself. This allows a smaller and simpler process to be made into its own object and used as a sub-assembly within a larger model. This gives much freedom and flexibility when dealing with larger simulations. For the purposes of the SRG project, this software poses some succinct benefits over competing software suites. The objects-based structure of the software lends itself well to the manufacturing environment where different stations, material handling, and operators make up what can essentially be called independent but interconnected intelligent objects whose work together as a system yields a product. For this study, each of the operations in the P415 assembly cell will become their own object with conveyors connecting them to form a system. The material handling and forklifts will be their own objects as well, set to deliver a certain amount of desired product in a pull-type system. Each of these objects will be programmed with their own intelligence and logic which will set what functions they will perform when a part reaches them and also the timing that their operation will take. This will all culminate in a simulated overall assembly cell that should closely mimic the real-life system in terms of production rate and cycle times.

2.5. Similar Studies

Simulations have been used by a variety of industries, especially in recent years with the advent of cheap and powerful computers to carry out the calculations necessary. Some of the fields in which applications of simulation are common are listed below:

- Military
- Medicine
- Transportation
- Biology

- Entertainment
- Advertising
- Manufacturing

Gan, Chan, and Turner (2006) used interoperating simulations to reenact an automatic material handling system interacting with various manufacturing processes in a 300 mm silicon wafer fabrication plant. A sticking point was found when working with simulations for the material handling system and attempting to interact them with the manufacturing process simulation. The currently available simulation software was not able to model both processes and allow them to interact with any degree of accuracy in terms of rendered results.

A similar study using pioneering computer simulation technology was done in order to predict the behavior of hospital emergency rooms (Saunders, Makens, & Leblanc, 1989). This study found it possible to emulate emergency room activity rates and also use these simulations to infer the impact of changes done to the emergency room without actually having to implement the changes. This outcome is markedly similar to the aim of the current study at hand.

Simulation has also been used extensively in the study of population and species viability analysis. RC Lacy (1993) used a simulation model called VORTEX to provide a population viability analysis that could incorporate population survival threats into models of the normal species extinction process. This model used a probabilistic approach, granting certain probabilities to different species in terms of morality rate, extinction rate, procreation, and chance of catastrophic event. This models allowed input for many of a variety of different species from long lifespan creatures such as mammals and birds down to short lifespan creatures such insects.

Simulations have been in military use for years. Outcomes of battles, skirmishes, and even entire large-scale wars have been simulated by warring nations in order to detect a pattern, strategy, or weakness before carrying out battles. Domninger (1986) uses an early computer simulation to test a well-known military/social game known as Axelrod's Tournament. This game was built to accentuate the proclivity of the Prisoner's Dilemma. This theory contends reasoning as to why two individuals, or countries in military terms, may not choose to cooperate even if it is in their best interests to do so. The simulation of this scenario yields results that share insight into the outcomes of situations where cooperation may be key to maximizing benefit and reducing loss. While in a game this is frivolous but when applied to military strategy the results could prove quite useful.

Chapter 3: Methodology

The first important step in our methodology will be production data collection and data validation. All of the production data used within the study will be gathered from time studies conducted on the P415 assembly cell as well as data that is logged onto on-site computers near the robot stations. This log data provides average cycle times for each of the machine operations throughout the assembly cell. In addition to cycle time data, downtime and product scrap data will be collected in order to be able to analyze some of the inefficiencies within the assembly cell. This data will prove useful in gaining an insight on some root causes of process inefficiency and provide potential areas of concern where solutions can be formed from. The collected data will be appropriately tabulated as well as analyzed from a statistical and process control standpoint.

The flowchart shown in Figure 5 outlines the important steps in the methodology described above. Mirroring what has already been mentioned, the study will begin with the collection of data from the P415 Assembly Cell. This data collection step will help in two ways. Not only will the data collection provide the basis and backbone of what the current process simulation model will be based upon, but it will also allow gaining familiarity with the process that will allow for better synthesis of solutions later in the study. Once the data collection process is complete, statistical analysis of the data and probability triangulation can begin.

P415 Assembly Cell Simulation Study Methodlogy Flowchart

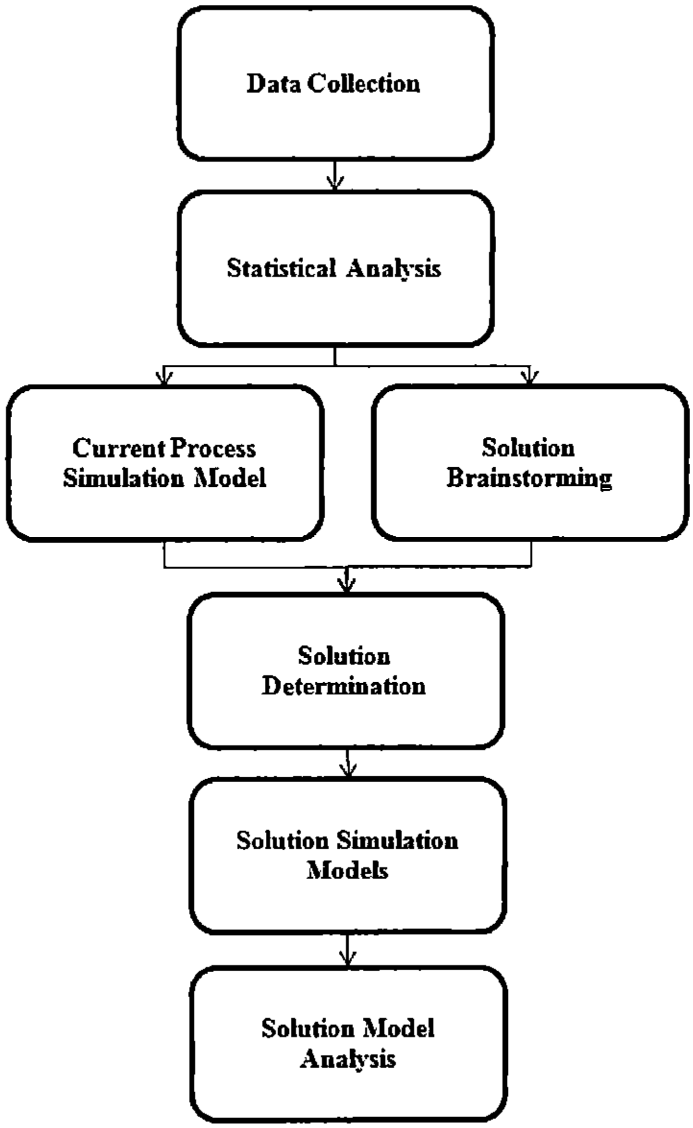


Figure 5: P415 Human-Robot Hybrid Assembly Cell Simulation Study Flowchart

The statistical analysis of the data will include the determination of normal descriptive statistics such as the mean, median, mode, and standard deviation for the time study and other data. This allows easier integration of the data into the simulation model. During the statistical analysis stage, the data will be used to also obtain a triangular distribution for each of the cycle times for each operation of the assembly cell process. Triangular distributions are a form of probability distribution that is used to pinpoint three points in a data range: minimum, most likely, and maximum (Forbes, Evans, Hastings, & Peacock, 2011). This type of distribution is used in situations where data is scarce and is used most often in business statistical situations such as simulations. From the minimum, most likely, and maximum values of a data set a simulation can attempt to mimic the behavior of the variance within a process.

Simio makes the use of the triangular distribution quite easy within the software. Once the minimum, maximum, and most likely values are found one must simply plug them into the object and the processes that run through the object will mimic the distribution based upon these values.

After data analysis and obtaining parameters of the triangular probability distribution for each individual operation, the simulation model for the current assembly cell process can be developed. In Simio, each of the operations within the assembly process will be represented by a server object which will signify the particular operation performed by either robot or human. Parts within the system, in this case the in-process grilles, will be signified by entities. These entities will be programmed with logic to flow through the system properly from operation to operation until completion. The material handling will be signified by source and sink objects. These source and sink objects will introduce and then remove entities from the system respectively. The conveyor linking the operations within the assembly loop will be signified by links through which the entities will flow along at a predetermined transfer rate. From this simulation, a recreation of the current cycle times will be achieved and the numbers generated from a long term simulation run should show similar production numbers to the current process. This model will be the test bed from which any potential changes will come from and be tested against.

While the current process model is being constructed, brainstorming of possible solutions will be undertaken. This brainstorming will be sustained with observations of the current process in action and meetings with SRG engineers to get a better idea of both the inefficiencies of the process and the constraints the process is under. Understanding the constraints of the process are key in coming up with logical and feasible ideas. Constraints in the form of technology, physical space, budget, and production must be known in order to determine the criteria with which to judge prospective solutions. From this solution brainstorming a group of prospective solutions that could boost efficiency within the process will be selected.

After brainstorming potential solutions, the group of prospective solutions will be narrowed down to a small selection that could be deemed effective enough to move forward with. With these solutions settled upon, a new simulation model of the process will be made incorporating each of the potential solutions. These solution models will then be tested in the same fashion as the current process model and that data could provide some indication of the potential effectiveness of the potential solutions.

Finally, the results and findings of the study will be discussed and a finite conclusion will be rendered. After this, future work will be explored in the form of continuation of this simulation study throughout other parts of the plant.

Chapter 4: Data Collection & Analysis

The P415 Human-Robot Hybrid Assembly Cell consists of ten separate operations that work in concert to produce the grilles. Table 1 categorizes these operations in two categories: human based operations and robot based operations. The data collection consists of observations and time studies on each of the operations that make up the entirety of the assembly cell. This data will be the key to driving the simulation model that will be used to recreate the current process and render data that mirrors the current production rate of the assembly cell.

Table 1: P415 Assembly Cell Operation List

Human Operations	Robot Operations
Operation 10	Operation 20
Operation 40	Operation 30
Operation 70	Operation 50
Surround Inspection	Operation 60
Final Pack/Inspection	Operation 65

The time studies for each operation consisted of the recording of approximately 70 cycles. A cycle for each operation is defined as the period starting from when the part enters into the operation area through the time that the robot or operator has completed their actions to the part and the part is ready to move forward in the process. No wait times were recorded in an effort to get an accurate idea of the process at its natural state without other outside circumstances interfering. The statistical parameters obtained from time study on each operation will be inputted into the intelligent object which represents that operation within the model in order to make it behave similarly to the actual operation. The results of the time studies on all operations are summarized in Table 2 showing the average cycle time, standard deviation, mode, minimum, maximum, and range for the time study data collected for each operation.

Table 2: P415 Assembly Cell Time Studies Summary

P415 Assembly Cell Time Study Summary (in seconds)						
	Average	**St. Dev.**	**Mode**	**Minimum**	**Maximum**	**Range**
Operation 10	18.9	5.4	19.5	8.5	28.8	20.3
Operation 20	19.1	5.2	24.1	12.3	28.9	16.6
Operation 30	14.1	6	9.7	8.1	29.2	21
Operation 40	22.1	2.9	21.1	17.4	29.3	11.9
Operation 50	23.8	1.2	23.8	21.1	28	6.9
Operation 60	25.1	0.6	25.1	24.2	26.6	2.4
Operation 65	20.5	0.4	20.7	19.6	21.4	1.8
Operation 70 Load	7.6	0.78	7.4	6.7	9.2	2.5
Operation 70 Unload	12.4	1.71	11.8	10.5	16.3	5.8
Surround Inspect	28.7	16.97	18.8	9.2	105.6	96.4
Final Inspect	22.5	12.86	20.9	9.8	88.5	78.7

As can be seen from Table 2, it takes an average cycle time of 18.9 seconds for a human operator to install an inner and components to the already present surround in the pallet at Operation 10. Minimum cycle time was 8.5 seconds and maximum was 28.8 seconds. The higher values for range and standard deviation are due mainly to the fact that Operation 10 is one of the three operations where different grille variants call for different work to be done. This causes a wide variation in the times that are required to complete Operation 10.

Operation 20 represents the first of two snapping operation. The average time taken to complete this operation is 19.1 seconds and a minimum of 12.3 seconds and maximum of 28.9 seconds. With a standard deviation of 5.2 and a range of 16.6, Operation 20 shares a similar attribute with Operation 10 in that it performs differently with different grille variants. The different grilles need a different series of snapping forces in very specific areas. These specific areas are dictated by the type of inner grille that is placed into the surround. Operation 30 is also similar in this regard.

With an average of 14.1 seconds, the two robots at Operation 30 finish the entire snapping operations. Standard deviation and range are both high as well due to the higher variations in different snapping operations for the different grille variants.

Operation 40 starts the standard operations where the cycles each time are similar regardless of grille variant. As such, the standard deviation and range are much lower, at 2.9 and 11.9 respectively.

Operation 50 has an average cycle time of 23.8 seconds and standard deviation of 1.2. Minimum cycle time for the operation was 21.1 seconds and maximum was 28.0 seconds. Operation 50, being a robotic operation, was very repeatable and had little variance from a cycle to cycle basis.

Operation 60 has an average cycle time of 25.1 seconds, a standard deviation of 0.6, and a range of 2.4. This operation is quite repeatable with low standard deviation and range. Minimum cycle time was 24.2 seconds and maximum was 26.6 seconds.

Operation 65 shows that the average cycle time was 20.5 seconds with a minimum of 19.6 seconds and a maximum of 21.4 seconds. The standard deviation was 0.4 and the range is 1.8 making operation 65 the least variant and most repeatable element in the cell.

The time study for Operation 70 was divided into two distinct operations, mainly due to limitations within the simulation software to route both finished and unfinished entities through at once. Therefore, the times for Operation 70 are divided into load and unload elements. In Appendix A1 these summaries are shown.

These aspects of the Operation 70 element appear fairly repeatable but quite dependent upon the performance of the material handlers handling both raw surrounds for loading and the finished grilles for pack. Average time for the loading of Operation 70 is 7.6 seconds with a standard deviation of 0.78 and range of 2.5. For the unload element, average processing time was 12.4 seconds with a standard deviation of 1.71 and range of 5.8.

The Surround Inspect element showed a high level of variance in cycle times collected. With a standard deviation of 16.97 and a range of 96.4, the dispersion of the data is quite large. The probable cause for this would seem to be the varied time it takes the material handler to inspect and ready each surround. The material handler has multiple responsibilities that frequently cause them to abandon surround inspection and hold up material flow in the process. This situation will be covered later in the solution brainstorming section. The final inspect summary in Table 2 rendered similar results to the surround inspect and for similar reasons. This element has an average of 22.5 seconds, a standard deviation of 12.86, and a range of 78.7. The range and standard deviation are again high. There were several instances where the material handler had other responsibilities that took them away from the main task of inspecting and packing the finished grilles.

In addition to time study data, other data was collected as well. Cell downtime data was collected from daily production logs. This data will be attempted to be built into the current process simulation model to reflect the current situation with the cell in terms of downtime minutes each day. The data was collected for every shift each day for two months. In addition to the amount of downtime had each day, reasons for the downtime were given as well. This will afford an insight into what individual issues are causing downtime and will give a starting point from which to look for potential improvements during the solution brainstorming phase.

Figure 6 depicts a run chart summarizing the number of daily downtime minutes for the P415 assembly cell from December 2011 to February 2012. The fully tabulated downtime data that was collected can be found in Appendix A at the end of the report. From the downtime data, the average amount of downtime per shift was 57 minutes. Assuming an available time of 432 minutes per shift, downtime equates to taking up 13.2% of each shift. A look at the Pareto chart of the downtime causes for the P415 assembly cell in figure 7 shows a clear picture.

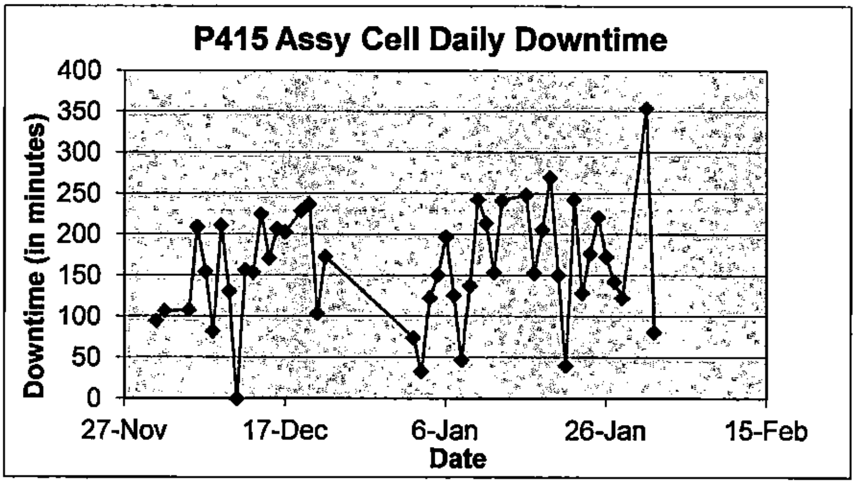


Figure 6: P415 Assembly Cell Daily Downtime Chart 12/1-2/1

Issues with the robots as well as stud and clip feeding on operation 60 accounted for 50.5% (or 255 out of 505) of the downtime frequency in the timeframe studied. This is a disproportionate amount of cause stemming from one source.

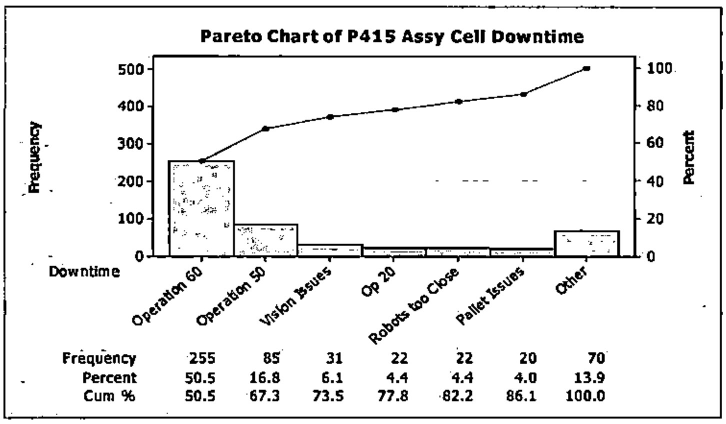
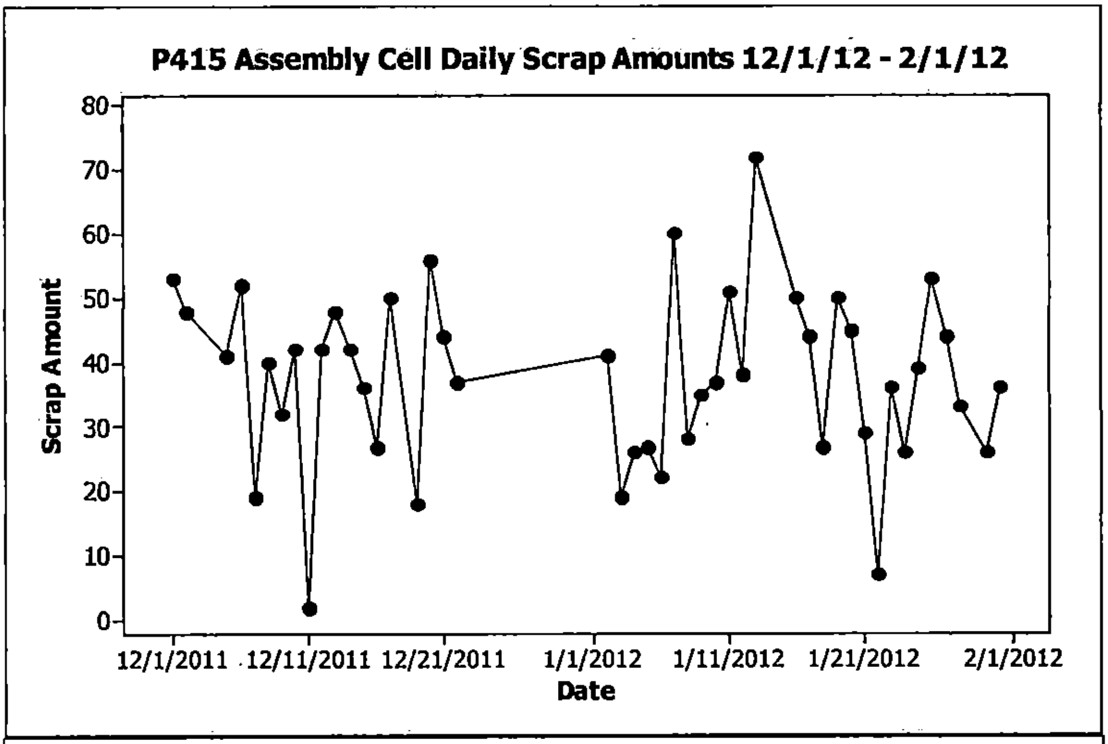


Figure 7: P415 Assembly Cell Downtime Pareto Chart



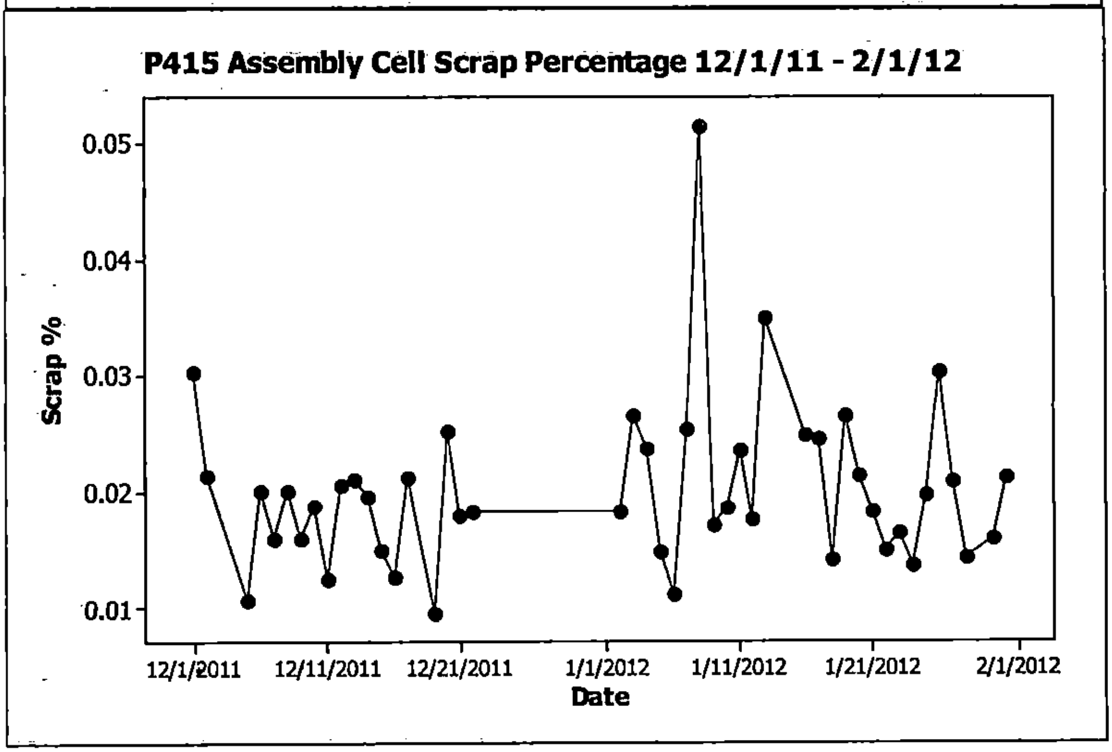


Figure 8: P415 Assembly Cell Daily Scrap Totals/Percentage 12/1/11 – 2/1/12

Figure 8 shows two charts summarizing the daily scrap amounts and scrap as a percentage of total parts assembled for the P415 assembly cell over a two month period. With the exception of an outlier of 5.15% on 1/8/12, the dates recorded yielded a scrap percentage of between 0.95-3.5 percent. This leads to an average of 38 scrapped parts out of 1884 total ran per day over the span of dates recorded.

As the solution brainstorming process progresses there may be additional information that proves useful in unearthing other facets of the process than may be improved in the simulation models. Processing time, downtime, and scrap data obtained from the P415 Assembly Cell will be mainly used to build the simulation model of the current process.

Also collected and calculated was the overall daily parts produced per hour by the assembly cell over the course of the same two month run from December 2011 through January 2012. The parts per hour produced (PPH), is a common way to measure the overall throughput of a manufacturing cell or process. This would provide a good basis on which to conduct the validation of the current process simulation model. Comparison of the actual collected PPH data and the simulated model PPH data will show that the simulation model is indeed a valid simulation of the real world P415 assembly cell process. What follows in figure 9 is a run chart of the total daily PPH for all shifts over the two month period stated earlier. The average PPH from the two month segment of data added up to 108 qty. in an average up time per shift of 6.38 hours.

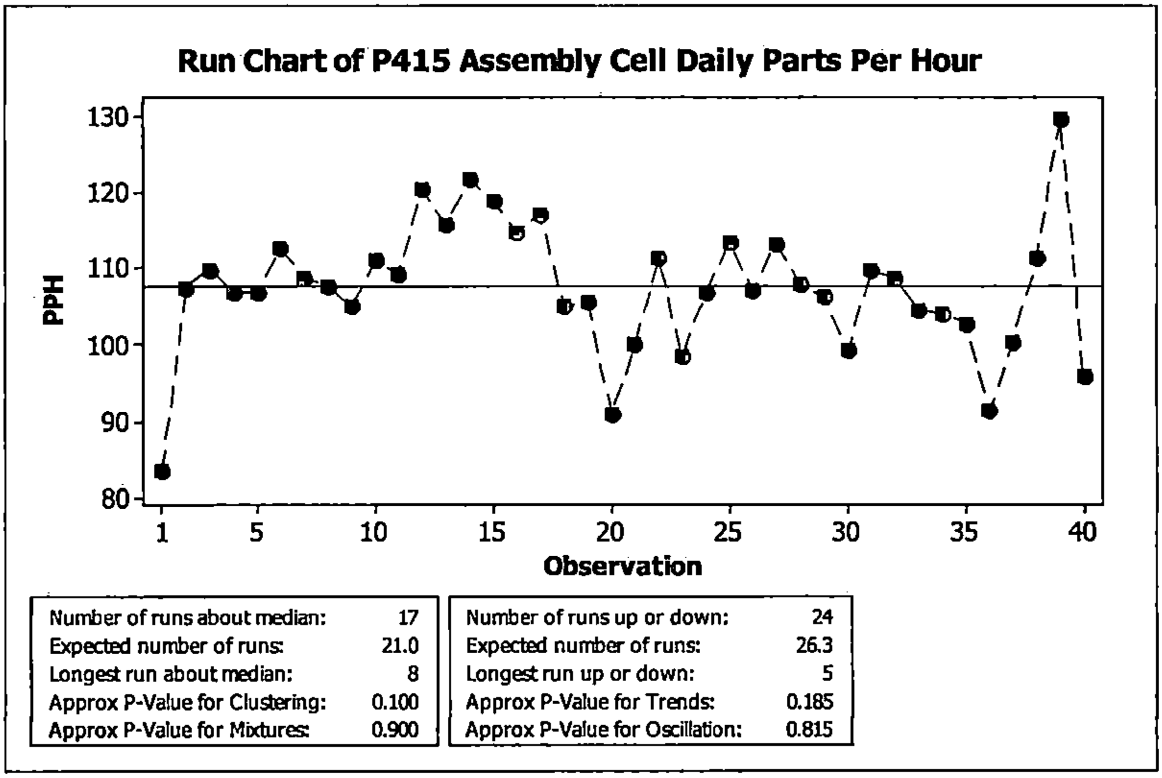


Figure 9: P415 Assembly Cell Parts Per Hour Run Chart Dec 2011-Jan 2012

Chapter 5: Current Process Simulation Model Construction

5.1. Introduction

This chapter discusses the construction of current process simulation model in Simio using the production data discussed in Chapter 4. The steps which were followed in building the model are listed below:

- Collect & process data for each element in the assembly cell
- Assign intelligent objects for each element in the cell
- Input & set logic for each object based upon real-world element behavior
- Connect all elements with links for material transfer
- Run test simulations against historical production data for validation
- Add three dimensional objects to enhance aesthetics of the model

Validation of the simulation model will be done by testing the output data of the model against production rates and cycle times from the cell obtained from production documentation. Successful validation will depend upon the adherence of the model's output to these historical production rates. This validated simulation model will provide the baseline for the implementation of the proposed improvements that are to be devised and discussed later.

5.2. Time Study Data Processing

The data collection process for the assembly cell has been discussed at length thus far in the study. The raw data collected from time studies on each element in the process is the driving information for the simulation model, especially those value-added elements such as operations 10-70. This data provides the processing time for each element. The raw data must be processed and a probability distribution should be obtained for individual elements in order to properly simulate the variance of processing times that will mimic the real-world operation of the assembly cell.

The triangular distribution was chosen for simulating processing time of individual elements in the simulation model. With a triangular distribution, the main parameters needed are the minimum value, maximum value, and an indication of central tendency of the data. In case of this particular situation, the best indication of central tendency would be the mode of the data. The mode proves more indicative of the central tendency than the average would due to the mode being unaffected by outliers. Also, in a repetitive continuous process like the individual operations in the assembly cell, the most likely processing time for each element is more likely to be the modal portion of the time study data than average. So in review, the parameters needed from the time study data are minimum processing time, maximum processing time, and modal processing time for each element.

Once those parameters were obtained, the triangular distribution would be used within the simulation to realistically disperse the processing times during the running of individual processes in the simulation model. Triangular distributions are continuous probability distributions in which there is a lower limit a, upper limit b, and mode c. In this simulation study, the lower limit would be the minimum value of the time study data, the upper limit would be the maximum value, and the mode would provide the indication of central tendency.

To illustrate the use of triangular distribution within the simulation, let's take a detailed look at its application in operation 10 of the assembly cell process. The lower limit of the data would be 8.5 seconds, the upper limit would be 28.8 seconds, and the mode would be 19.5 seconds for operation 10 as gathered from the time study data in the Time Study Summary in Table 2. From these values, the probability density function and the cumulative distribution function for the triangular distribution can be obtained. (Weisstein, 2012).

The probability density function's formula mathematically illustrates the relative likelihood that a particular random variable, which is signified with x, will take on a given value. The function is always a nonnegative number and its integral over the entire space under what is ultimately a curve is equal to one. The equation as it pertains to operation 10 is as follows:

$$f(\mathrm{x}) = \begin{cases} \dfrac{2(\mathrm{x}-a)}{(b-a)(c-a)} \; for\, a \le x \le c \\ \dfrac{2(b-x)}{(b-a)(b-c)} \; for\, c < x \le b \end{cases}$$

$$f(\mathrm{x}) = \begin{cases} \dfrac{2(\mathrm{x}-8.5)}{(28.8-8.5)(19.5-8.5)} & for\ a \leq x \leq c \\ \dfrac{2(28.8-\mathrm{x})}{(28.8-8.5)(28.8-19.5)} & for\ c < x \leq b \end{cases}$$

This equation sets the probability for any random processing time between the upper and lower limits for operation 10. Once set in Simio, the probability of running a particular processing time will be determined on a cycle-by-cycle basis by this equation. In addition to mathematically illustrating the probability density function for a triangular distribution, it can also be graphically illustrated.

The probability density function for the processing time of operation 10 is shown in Figure 10. This provides a look at how the distribution falls for the processing times for the operation with the most likely time being the top point of the plotted triangle and the minimum and maximum the lower two points of the triangle. This shows the probability of the processing time falling within a certain range. From the function there is a 90% probability that all processing times for operation 10 will fall between 11.84 & 25.73 seconds.

The cumulative distribution function for the processing time of operation 10 is shown below. It mathematically describes the probability that a random variable with a given probability distribution will be found at an instance that is less than or equal to x (Reimann, Filzmoser, Garrett, & Dutter, 2008).

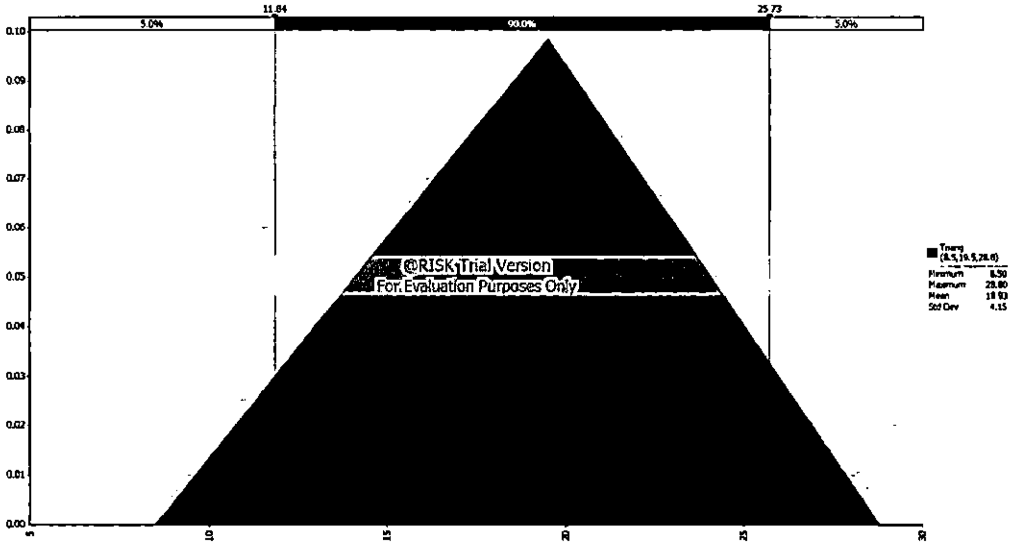


Figure 10: Operation 10 Triangular Distribution Probability Density Function

Think of this function as a 'probability up to this point' calculation. The equation for the cumulative distribution function is as follows:

$$F(\mathrm{x}) = \begin{cases} \dfrac{(\mathrm{x}-a)^2}{(b-a)(c-a)} \; for\, a \leq x \leq c \\ 1 - \dfrac{(b-x)^2}{(b-a)(b-c)} \; for\, c < x \leq b \end{cases}$$

$$F(\mathrm{x}) = \begin{cases} \dfrac{(\mathrm{x}-8.5)^2}{(28.8-8.5)(19.5-8.5)} \; for\, a \leq x \leq c \\ 1 - \dfrac{(28.8-x)^2}{(28.8-8.5)(28.8-19.5)} \; for\, c < x \leq b \end{cases}$$

Like the probability density function for the triangular distribution, the cumulative distribution function illustrates the probability of a random processing time between the upper and lower limits. The only difference is that the cumulative distribution function represents total probability up to whatever value that the random variable is.

The cumulative distribution function for the processing time of operation 10 is illustrated in figure 11.

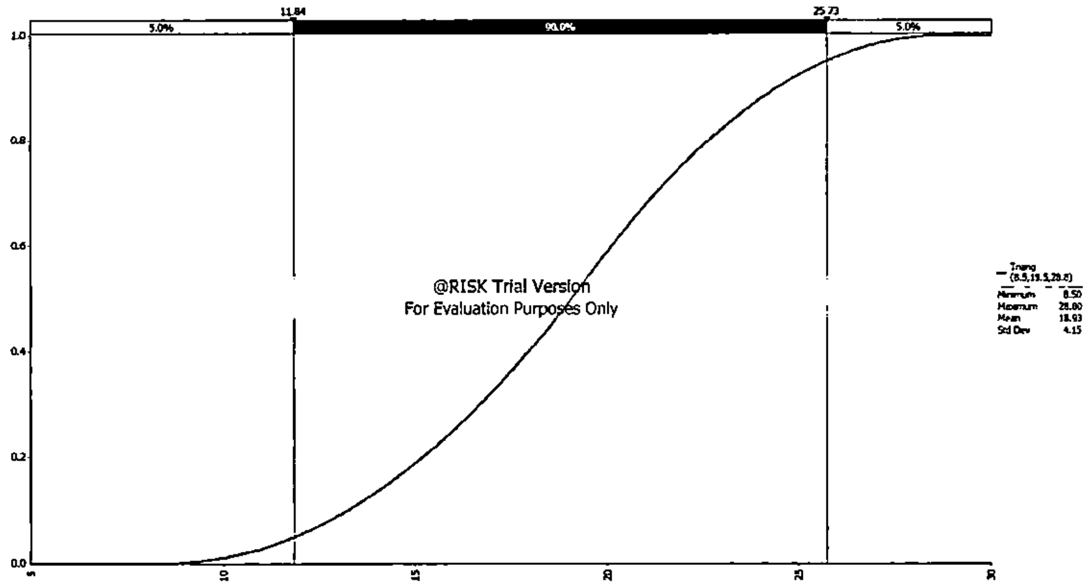


Figure 11: Operation 10 Triangular Distribution Cumulative Distribution Function

5.3. Intelligent-Object Assignment

Assignment of Intelligent-Objects for each of the elements in the assembly cell is next. First, the actual elements that merit assignment of an object in the Simio simulation must be determined. For the purposes of this simulation, the important elements are those that factor into the completion of a grille. So obviously, all of the operations 10-70 will be included. Also, all elements where main grille components are brought to and fed into the system must be added as well. And finally, the modes of conveyance of the material through the assembly cell must be addressed as objects in the simulation.

Once the elements that are to be modeled are identified, the types of intelligent-objects that each are to be comprised of will be determined. The Simio object library contains a number of usable objects that cover needs in many simulation scenarios. These objects in Simio are shown in Figure 12.

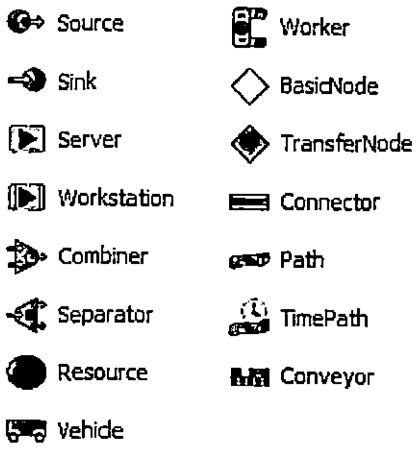


Figure 12: Simio Object Types

From these objects, the model of the P415 Assembly Cell can be built. However, the appropriate type of object must be matched to the correct element of the process in order to properly simulate the cell. One must analyze the use of the objects as well as the function of the elements in the system to be able to do this. For the operations 10-70, an object that simulates a value-added work cycle individually would be sought. This narrows down the choices to the server or workstation objects. Both of these objects simulate a resource or process that becomes capacitated when a part enters them for work and frees up when the processing time is over. The main difference between them is that the server object is more of an assembly line element where only part processing time is taken into account in the intelligent logic of the object. With the workstation object, not only is processing time taken into account but also setup and teardown time. This object would be better suited for elements such as a CNC machine or molding press that requires a predetermined amount of setup and teardown time. Since the elements in the P415 Assembly Cell are repeating processes that do not have any setup or breakdown between parts, the server object is the choice for the operations in the P415 cell.

For the material flow into and out of the cell, objects must be assigned. The main focus of material flow in this simulation is the flow of two main factors. The incoming surrounds that are to be set into the assembly nests to start the process and the outgoing finished grilles that are coming off the operation 70 element each cycle. While there are other components that go into the grilles such as studs, screws, and brackets, these components are either stocked at the cell enough before each shift to cause negligible amounts of downtime or are stocked and fed via feeder systems. As such any inclusion of these into the simulation would be superfluous and not have measurable impact on the validity of the model. As such, the two main aspects of material flow to focus upon in terms of simulation are the material carts for surrounds and the returnable totes that the finished grilles are packed into. For these elements, simulation objects must be selected that will introduce parts into the system and then remove them upon completion. These objects in Simio are the source and sink objects. The source object is an intelligent object which is used to generate entities within the system and is the start of the simulation model. This object will be used as the beginning of the simulation and will comprise the surround pack element in the current model. The returnable pack element will be the sink object. This object is where entities that have completed the entire process are removed

The conveyance of the grilles throughout the system must now be assigned objects. The available objects for material conveyance within Simio are the Path object, TimePath object, and Conveyor object. The only difference between these is how the conveyance of the entities is measured within the system. The Path object connects two element nodes and works on travel distance and speed to determine travel time. TimePath is similar to the Path object except instead of distance and speed determining travel time, the time is user-determined. And the Conveyor object is similar to the Path object save for allowing for a choice of allowing travelling entities to accumulate on the path. Given that the process is a closed loop that cannot afford parts passing along the path and accumulating at whatever bottlenecks there are, it is apparent that the proper object for material conveyance is the conveyor object.

Table 3 shows the breakdown of how each of the intelligent-objects will be assigned to each element in the assembly cell. The breakdown has all of the operations 10 through 70 as servers which hold each part for a certain length of time to simulate the processing time for each operation. As mentioned in the previous chapter, this processing time is determined by a triangular distribution. The introduction of parts into the simulation starts at the source object which will simulate the surround pack that is shopped for the workers at operation 70. The sink object is where finished parts are extracted from the system. This simulates the returnable pack where finished grilles are placed for shipping.

Table 3: Intelligent-Object Types in Current Cell Simulation

Object Type	Elements Involved
Server	Op 10-70, Surround Inspect, Final Inspect
Sink	Returnable Pack
Source	Surround Pack
Conveyor	Material conveyance between operations

5.4. Intelligent-Object Logic Programming

After determination of the types of intelligent objects that represent individual elements of the assembly cell, these objects must be given logic in order to behave in such as way as to accurately simulate the physical behavior of the assembly cell. To do this, each object must be programmed within Simio from a bank of options for the properties of each object. For explanation, an in-depth illustration for one of each of the four types of objects that will go into the simulation is shown below.

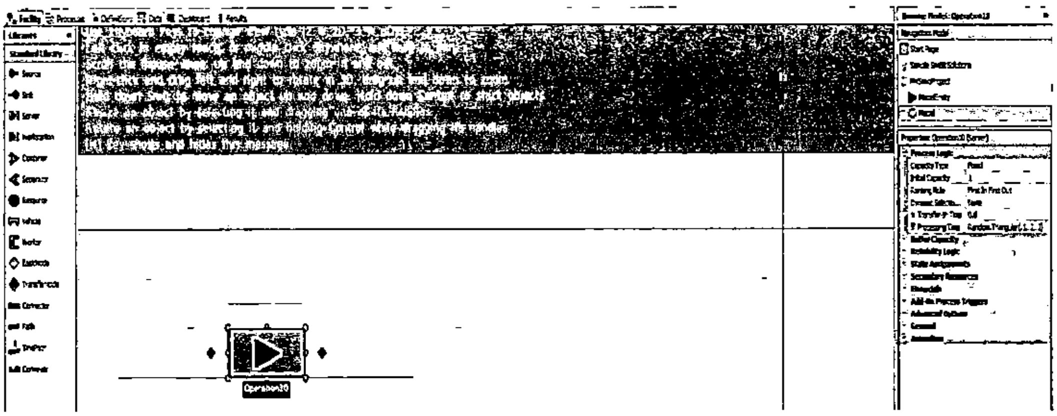


Figure 13: Insertion of Operation 10 Server into Model

To start, the server object is dragged from the Object bar on the left onto the modeling area as shown in Figure 13. Once in position, the name of the object can then be changed to 'Operation10'. The green lines seen on the left, right, and top of the grey server object represent buffers. On the left is the input buffer where if the server object will have an area to hold a queue of parts to be worked, they will be held here. The same goes for the right side except for the station output instead of input. The top line represents the in-process queue of the station at the time.

Once the object is placed, the logic can then be input. The input is done on the properties window of the objects and input mostly in the form of equations for parameters. These parameters control the full function of the object and make it behave in a way that the real life counterpart will. The main parameters that must be addressed with the objects in this simulation concern object entity capacity, processing time, buffer capacity, and downtime logic and can be seen in figure 14.

Since the operations in the process only can contain and work on a part at a time, the initial capacity is set to one. This only allows one entity in the operation to be processed at one time. Processing time is simulated next and it utilizes the triangular distribution discussed earlier. This is done by inputting the equation *Random.Triangular(min,mode,max)*. For the min, mode, and max 8.5, 19.5, and 28.8 are entered respectively. This is the min, mode, and max as observed from the time study information for operation 10. This sets the triangular probability distribution for the processing times in operation 10 and will govern the dispersion of processing times through any simulation run. All processing times for the simulation models done in this study will be denoted in seconds.

The buffer capacity is also set as a parameter for the object. Since there is no waiting buffer for either the input or output of any object in the assembly cell, the value for buffers for this object and all other operations within the cell will be set to zero. Reliability and downtime is the last parameter to be set for the object. Failure Type is set first. This parameter denotes the count type by which to determine when downtime will occur. The count type chosen for this model is *Calendar Time Based.* This type does counts between downtime failures based upon elapsed time.

So the operation will experience downtime based upon measure of machine runtime within the simulation. The type of distribution used to determine the exact times for a downtime failure in the simulation is an exponential distribution.

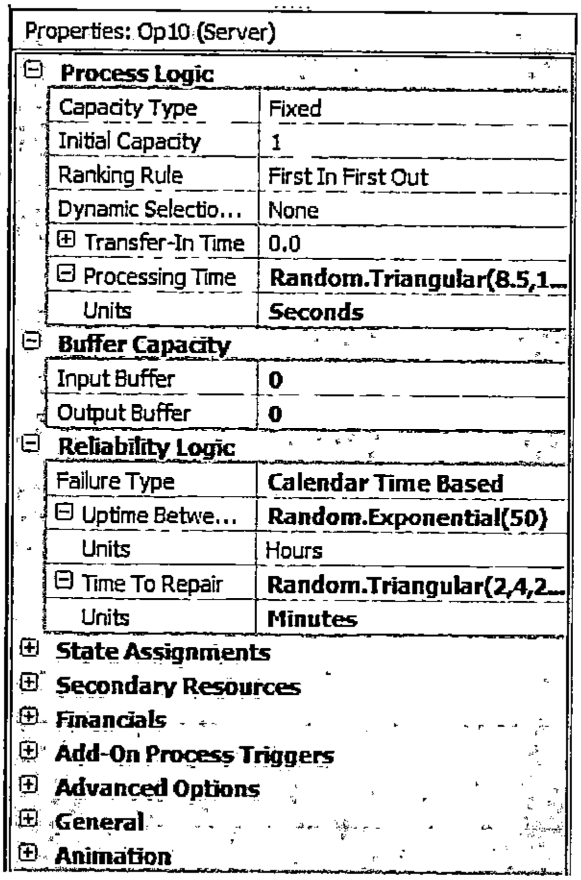


Figure 14: Operation 10 Simio Object Properties

This distribution allows the downtime to occur dispersed about a single mean. The equation for this in Simio is *Random.Exponential(mean)*. The mean value provided is the mean number of hours it took for a downtime occurrence happen at the operation. As such, we are saying that the downtime in operation 10 will occur at some point around an average of every 50 hours of runtime. This is determined from analyzing long term downtime data and the Pareto chart in Figure 7. Since the mean is 50 hours, operation 10 is an element of the assembly cell where downtime occurrences are infrequent. Also determined is the length of repair time that occurs with each downtime occurrence. This data is also dispersed in the simulation using a probability distribution, in this case a triangular distribution is used to determine the processing time for the elements. From the downtime data for operation 10, the repair times in the distribution are set for a minimum of 2 minutes, a most likely of 4 minutes, and a maximum of 20 minutes.

Once all the necessary parameters of the object representing operation 10 are defined, then it truly simulates operation 10 within the P415 assembly cell. The same process is used to build all of the other working elements within the cell. This includes operations 10-70 and material inspections. Other operations such as material handling and introduction into the system are comprised of other objects.

These other objects are the sink and the source objects that represent the entry and exit of parts within the system. The source object is the surround pack where un-built grille surrounds are shopped for the inspectors and first introduced into the system. The programming for the source object can be seen in the screenshot of the object properties window in figure 15. The main parameters that are set for the source object depend upon part arrival.

Parts in this case refer to the surrounds onto which the rest of the grille is built. The interarrival time for each batch of parts for the surround pack source object is set as an exponential distribution about a mean of 17 minutes. This arrival time mean was determined by a study of the material shoppers who supply the surrounds to the surround inspector.

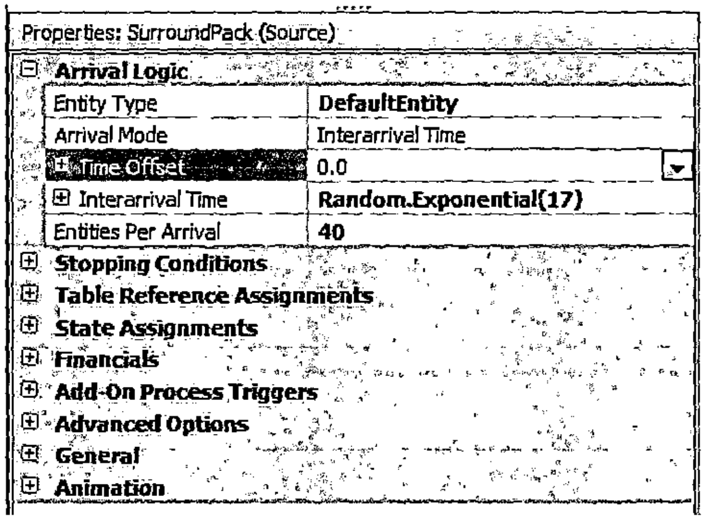


Figure 15: Surround Pack Simio Object Properties

The study rendered a mean time between surround pack arrivals at 17 minutes. An exponential distribution was used due to the fact that it needs only a mean value by which to distribute values. Since the times between surround pack arrivals is so large, it would have been impractical to collect a similar number of observations for this as the time studies on operations 10-70. As such, a handful of surround pack arrivals were measured and a mean was determined from them which is now used to determine the interarrival time in this object. The number of parts per arrival is determined by the capacity of the surround pack carts that are supplied to the cell. All packs have a capacity of 40 surrounds and as such there will be 40 parts arrive with each pack arrival. In this source object, these parts arrive and queue here while they await introduction into the system.

The sink object in the system is the returnable pack. The returnable pack is where the finished grilles are placed for shipment to the customer. This is the point where they officially leave the system. This object is the termination point for entities in the system and parts that make it here are officially considered finished and count as parts made in the system. Since the only objective for this object is to terminate parts in the system, it is able to do this with the default parameters of the object. There is no need to change parameters for this to be able for it to function properly within the simulation.

The final object to place into the system is the material conveyance throughout the system. These objects will be illustrated as links between the different elements within the system. These links will form the loop that defines the material flow throughout the system. The properties for these conveyor objects can be seen in figure 16. The main parameters that are altered for these objects are the capacity, speed, and size. The capacity is set with the traveler capacity field and the accumulating field. The traveler capacity sets how many parts can be on the particular stretch of coveyor at once. Since this system is closed loop which allows no passing and all travelers cannot move until the entire line is complete with their process, there will be no accumulating on any of the conveyors that connect the operations on the top part of the assembly cell. The one conveyor where accumulation will be allowed is the bottom section where fresh surrounds are fed to operation 10 to start. There can be accumulation in the lead up to operation 10.

Properties: Conveyor2 (Conveyor)

⊟ Travel Logic	
Traveler Capacity	1
Entry Ranking Rule	First In First Out
⊟ Initial Desired Speed	60
Units	Feet per Minute
Entity Alignment	Any Location
Drawn To Scale	False
⊟ Logical Length	5
Units	Feet
Accumulating	False
⊟ Routing Logic	
Selection Weight	1.0
⊞ Reliability Logic	
⊞ State Assignments	
⊞ Financials	
⊞ Add-On Process Triggers	
⊞ Advanced Options	
⊞ General	

Figure 16: Conveyor Simio Object Properties

After placement and logic programming of all objects that comprise the model, the end product for the current process simulation model looks as shown in figures 17-19. Symbols have been introduced for the objects to closely resemble what they are within the real world process in order to give a visual illustration on exactly what each object is by looking at the model. All models developed from this point within the study will resemble this base model, as the major layout of the cell will most likely not be changed. The results and validation of this current process model are the next objectives for the study.

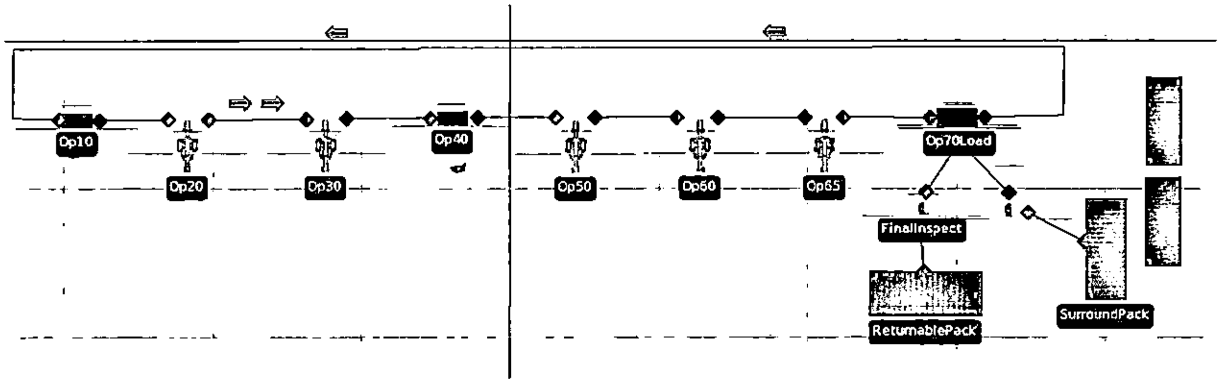


Figure 17: Current Process Simulation Model in Simio

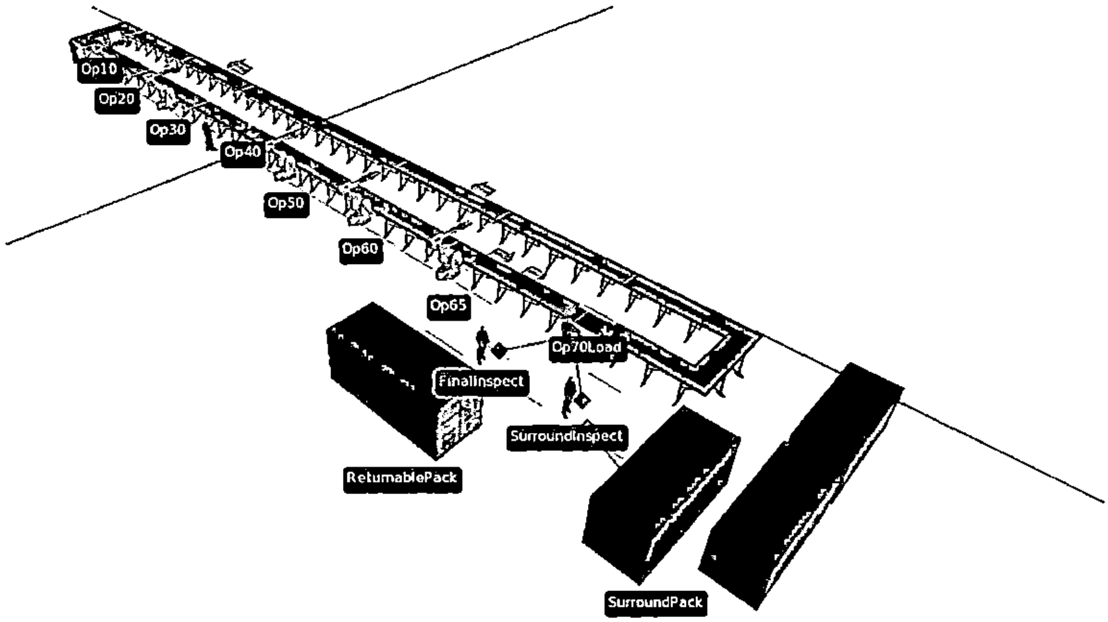


Figure 18: Current Process Model in 3D Viewing Mode

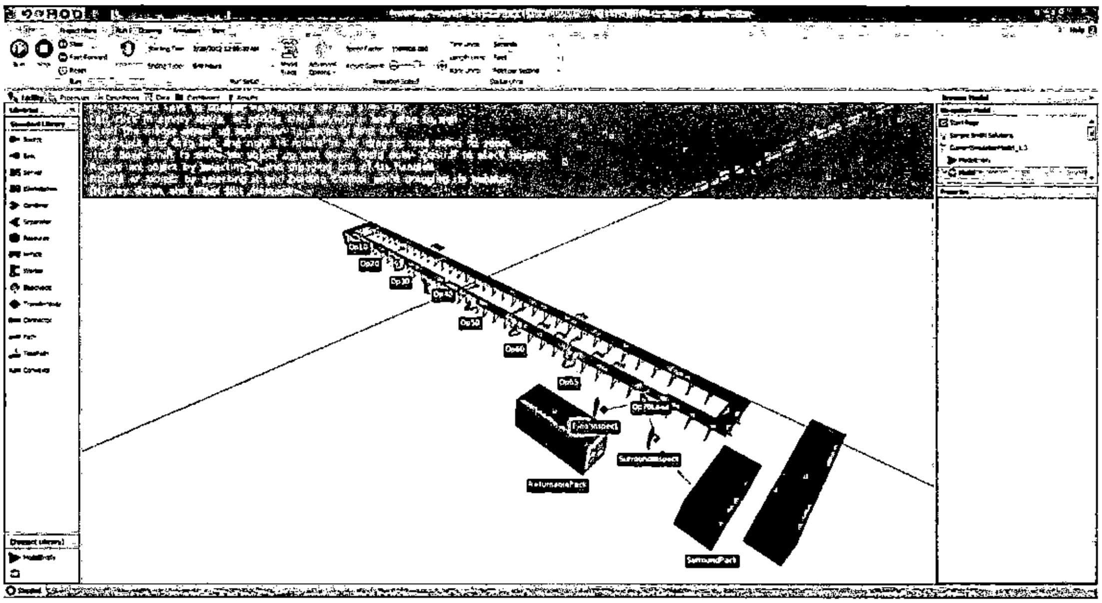


Figure 19: Current Process Model in Interactive Mode Window

5.5. Current Process Simulation Model Data & Validation

Once the current process model has been fully built and debugged from logical faults, data can be collected from it and in turn validated against the production data gathered during the data collection phase of the study. This will provide a check against which the validity of the model can be tested and provide a measure of confidence in the model in its function as a control in the testing of proposed efficiency solutions later. Data is collected from the model over a testing period of one simulated year of production. This simulated year follows the proposed production schedule of the cell which is 240 days per year at three 8 hour shifts per day. During each shift, allowances were provided for breaks and lunches for operators. Due to this, each shift covers an average 7.2 hours per shift. At 7.2 hours per shift, that equates to 21.4 hours per day and 5136 hours per year. So the simulated run for the model covers a total of 5136 hours to properly simulate a year of production time. This extended length of time will result in lowered variation in the data from the distributions that control processing and downtime. It will allow for a more uniform data set and should generate results that more closely mimic the real world production of the P415 assembly cell.

Table 4 documents the data generated by the initial simulation run of the current process model. The total number of parts produced in the yearlong simulation for the assembly cell rendered a total parts count of 550,792. This equates to a PPH number of 107.24. The recommended yearly part production to meet upcoming demand is 564,000. This total part count of the simulated model is close to the demand and also analogous to the actual numbers pulled from the production data of the cell.

Table 4: P415 Assembly Cell Current Process Simulation Results

Current Process Simulation Results	
Total Parts Produced	**PPH**
550792	107.24

Table 5 shows the comparison between the simulation data from the current process model results and the collected and calculated production values from the assembly cell data. As per the actual production data, the assembly cell produces an average of 108 parts per hour over a two month segment of collected data. The current process simulation model rendered a result of 107.24 parts per hour. This results in a difference of 0.76 PPH.

Table 5: P415 Assembly Cell Simulation Results Comparison & Validation

P415 Assembly Cell Simulation Results Comparison	
Source	**Part Per Hour**
Current Process Simulation	107.24
Collected Production Data	108

In an effort to further validate the model, a comparison between daily production part totals for the simulated current process and the gathered data on real world assembly cell has been performed. The current process model was run through a series of replications each totaling 21.4 hours which is the exact amount of time the cell is projected to run daily after operator lunches and breaks are taken into effect. From these, a randomly selected group of ten simulated days were selected using a random number generator to choose a number assigned to each replication. This rendered the ten values shown in the *Simulated* column in table 6. To provide a comparison, ten days of production were randomly selected using the same process as the simulated value. These days were selected from the data gathered during the data collection phase of the study. The results of this validation step are promising. The average daily parts produced for the simulated replications are 2268 while the average for the randomly selected days was 2259.

Figure 20 shows this data graphically in a line plot. From this plot, it can be seen that the two data sets share a similar range with every value collected being between approximately 2100 and 2400 parts produced daily.

Table 6: Current Process Model Validation- Randomly Selected Daily Production Totals vs. Randomly Simulated Daily Production Totals

Current Process Simulation Validation: Daily Production		
#	Simulated	Randomly Selected
1	2345	2348
2	2299	2102
3	2332	2410
4	2324	2314
5	2232	2159
6	2194	2314
7	2158	2247
8	2340	2136
9	2242	2363
10	2214	2196
Average	**2268**	**2259**

The variation and trending up and down of these values in the line plot should not be looked deeply into as these values were randomly generated and are not expected to follow any sort of trend or pattern. With that said, this exercise appears to further confirm that the simulation model closely mimic the characteristics of the P415 Assembly Cell.

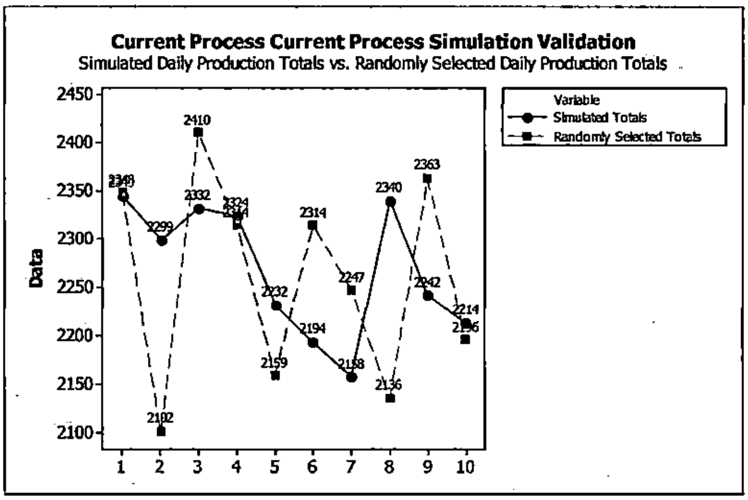


Figure 20: Current Process Model Validation- Line Plot with Simulated Daily Production Totals vs. Randomly Selected Daily Production Totals

Chapter 6: Solution Determination and Modeling

6.1. Solution Brainstorming

With the current process modeling complete for the P415 Assembly Cell, the potential solutions that are desired to be modeled can be sought. What are called solutions in this study are observed inefficiencies within the assembly process at the assembly cell that could be realistically and feasibly improved through some means. These solutions will be gathered through observation of the assembly cell in action, talks with the operators at the cell, brainstorming meetings with cell supervisors and engineering staff, and observations of the data already collected on downtime and other production data.

After a thorough analysis of the assembly cell through various means described above, three primary solutions are settled upon for simulation modeling. These solutions are simulated in a modified version of the current process model and the results are compared against the results of the current process model. These comparisons are the basis of the findings of the overall study.

Initial observations of the P415 assembly cell uncovered several areas of focus in terms of inefficiencies. The areas within the assembly cell where efficiency can ostensibly be assumed as being currently maximized are operations 10, 20, 30, 40, and 65. This leaves various issues observed at the areas of operations 50 and 60 as well as operation 70 and the inspection processes.

The observations on operations 50 and 60 mainly deal with downtime accrued. The downtimes on these operations are not only frequent but persistent and causing longer than normal repair times. Addressing these downtime causes could work to increasing productivity quickly at a relatively low cost in both financial and production impact terms.

For operation 70 and inspection processes, the observations and discussions have rendered a couple of areas of improvement. The operator at operation 70 has a large list of activities to complete since he is stationed at the operation which both begins and ends parts through the cell. The operator must check off all components for finished grilles coming off operation 65 using a marker, then he must remove the grille to the final inspection station, and grab a surround from the surround inspect station. Once the surround is in the newly empty nest, the operator must then place an isolator on the surround and then press a cycle start button to signal to the assembly station that the cycle is complete. Along with this, the operator here must sometimes address downtime issues on some of the robots at operation 50 and 60. This is addressed in the time study data done on the operation. Eliminating some portion of the operator's responsibilities could work toward freeing up a bottleneck in the process.

The inspection processes present inefficiencies in the form of workspace layout leading to operators falling behind in his tasks. At these inspection stations, there are stands that the operation 70 operator uses to either get inspected surrounds from the surround inspector or put the finished grilles on for final inspection. These stands hold two parts each which provide a buffer between the inspection elements and operation 70. The problem with these stands is that when inspectors get busy with scrapping parts or doing rework activities, the two part buffer is not always large enough to keep operation 70 busy. This leads to starved time for operation 70 which causes the entire cell to come to a halt as the operation 70 operator has to either wait on space to store a finished grille or an inspected surround to fill the empty assembly nest.

In addition to the buffer capacity, the surround inspection operation has some observable flaws in the standardized work that the operator does to accomplish his or her task. In the course of inspecting the grille surrounds, the operator rejects surrounds for certain levels of defects that fall outside the acceptable range set by the customer. This happens most frequently on chrome plated surrounds as the surface can easily be scratched during handling and also incur defects in the chrome finish itself that are manifestations of the plating process. When the inspector rejects a part, he must scrap the part in the appropriate marked container for scrapped surrounds. This container is located approximately 40 feet from the inspection station. This not only adds time to the inspection process for the surround parts but also adds unneeded work and movement to the inspector which toward the end of a full shift could result in less than full attention paid to surround inspection. Overall, these are the observed and discussed inefficiencies that could merit attention in the P415 Assembly Cell.

From these observations and notes taken from those working closely with the cell, a list of specific and concise solutions are generated and their impact on the cell's performance then modeled in subsequent simulation experiments.

6.2. Solution Determination

After considering all of the visual observations and input from brainstorming activities regarding the targetable inefficiencies in the P415 Assembly Cell, a list of three apparent and feasibly implemented solutions emerged. These solutions are:

- Reduction of systematic and long-term downtime issues at Operation 60.
- Minimize travel distance and work time at material inspection stations.
- Increase buffer capacity at Operation 70 and at material inspection stations.

From the Pareto chart shown in Figure 7, it can be seen that an inordinate amount of downtime stems from the activities performed by the robots at operation 60. These problems are mainly caused by the feeder and placement systems employed to provide a flow of the clips and studs that are placed into each grille by the robots. Focus on this process and addressing the root causes of these downtime occurrences could lead to a measurable reduction in downtime for the entire cell. From the data collected, 50.5% of downtime that was recorded at the cell could be attributed to this operation alone. Experiments will be performed on the base simulation model adjusting for a certain level of reduction in the downtime at operation 60. It will provide us insights into how the reduction in downtime at operation 60 will affect the overall throughput of the cell.

The distance traveled by the surrounds inspection operator was troubling as well and struck as a needless waste of time spent within the cell. Cutting down the walking distance from 40 feet to 5 feet for every scrapped part for instance would impact the processing for the surround inspection operation. A model for this scenario will be simulated to measure its proposed impact on the overall throughput of the cell.

The buffer capacity for surrounds and finished grilles at the operation 70 area, which is represented in the cell as the grille stands used for inspection and staging, is the final area of improvement that will be modeled. If the buffer capacity of the stands could feasibly be increased from two grilles per stand to four, the impact could lead to less wait time for the operation 70 operator and the final inspection operator. Many instances were observed where the operation 70 operator would get ahead of the final inspection process to the point of filling the stand completely. This situation causes a scenario where the operation 70 operator must stand holding the finished grille just removed from the nest and wait for an opening to free up on the stand in order to continue the process. It is a situation where the inspection process repeatedly takes longer than the entirety of two cycles of unloading and then reloading the operation 70 nest. The two corrections for this would be either to decrease inspection time which is unacceptable or to increase the buffer capacity to a level that more easily matches the longer inspection times with a comparable number of operation 70 cycles. The simulation model for this potential improvement will analyze if the increase in buffer will indeed increase overall productivity of the cell.

6.3. Solution Scenario 1: Operation 60 Downtime Improvement

In order to be able to accurately measure the effects of improving the downtime occurrences at operation 60, the exact parameters of the improvement must first be determined. Then, necessary adjustments can be made to the base simulation model to incorporate this change. These parameters will be determined for this particular solution based an assumed decrease in downtime occurrences. These occurrences are assumed to be reduced contingent upon if upgrades and maintenance were to be performed on the robot, stud feeding mechanism, and clip feeding mechanism. This decrease will be set at 50% based upon information gained from the tooling engineers about the potential decreases in breakdown with the maintenance and upgrade options that are available to them. As for the parameters as they pertain to the model itself, the main changes will be in the reliability logic that is in the operation 60 server object. This reliability logic change is shown in Figure 21.

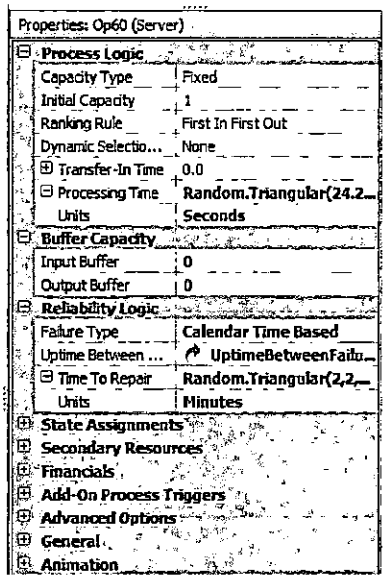


Figure 21: Reliability Logic for Operation 60 Object

The parameter that will be selected in order to properly simulate a reduction in the downtime occurrences at operation 60 will be the *Uptime Between Failures* programming. This will be changed by the predetermined amount of 50% by changing the length of uptime between failures from 3.9 hours to 7.7 hours. This was done by using the same downtime data that the original reliability logic was programmed with and random selections of one half of the occurrences were removed and then the new uptime between failures number was obtained from this. The impact of this change on the assembly cell can be measured in terms of the total number of parts produced throughout a set number of replications of each simulation scenario: both the current process and the new process with the proposed downtime reduction at operation 60.

This comparison will be done via an experiment ran within the Simio software that sets a control variable and a response variable and runs a number of replications. In figure 22, the experiment window can be seen in Simio. The different simulation scenarios are shown in the two different rows of the table, the replication status is shown afterward along with the status of the control variable and the response variable. There will be ten replications of each scenario in this experiment. Each replication will simulate two total months, or 1284 operational hours, of production time. This length of time was chosen due to the fact that it was the longest period of simulation time that the Simio Academic software could properly handle with the simultaneous computation of 20 separate replications. Simulations of any longer length led to the failing of simulation replications due to overuse of system memory. In the experiment, it was stipulated in the simulation settings that only replication results that fell within the interquartile range of the total data be counted in order to reduce the effect of an outlier on the results of the experiment.

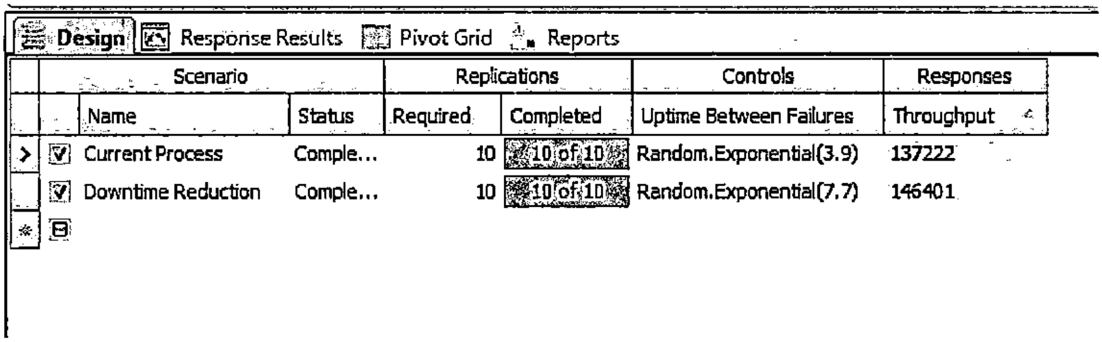


Figure 22: Operation 60 Downtime Reduction Simio Experiment Window

The results of the simulation experiment on the operation 60 downtime reduction scenario are shown in Figure 23. These results are in the form of the average of each of the accepted replications of each simulation scenario: that of the current process and the new scenario with reduced downtime at operation 60. The results show that with the feasible reduction in downtime occurrences at operation 60 of 50%, there would be an increase in production rate over a two month period from 137,222 parts produced to 146,401 parts produced. To put that into a more useable and versatile figure, that equates to a rise from 106.87 PPH to 114.02 PPH. That equates to an increase in production of 6.27%. Over the course of a year of production that increase would result in a rise from 548,884 parts produced to 585,607 parts produced or a total of 36,723 grilles produced each year.

The confidence interval for the scenario 1 experiment is shown in Figure 24. The graph depicts the totality of the experiment results graphically for both the current process and the downtime reduction scenarios. The box-and-whisker portion of the graph shows the full range of the replications that fell within the usable limits set for the experiment. The minimum for the current process was 134,838 parts produced and the maximum was 138,942 parts. The lower percentile value from 25 to 50% is 136,370. The upper percentile value from 50 to 75% is 137,953 parts. For the downtime reduction scenario replications, the graph shows a minimum value attained of 145,442 parts produced and a maximum of 147,614 parts produced. The lower quartile value is 145,647 and the upper quartile value is 146,897. The group of bars extending from each plot is a histogram that shows the range over which the replications in each scenario fell.

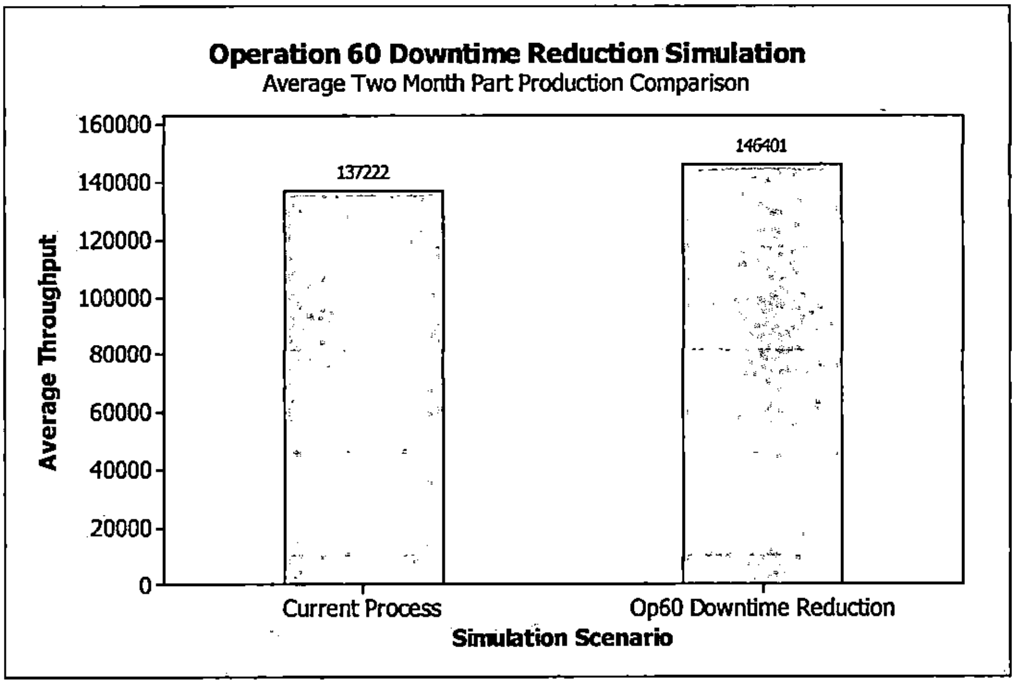


Figure 23: Operation 60 Downtime Reduction Simulation Results

A look at the plot for each scenario shows that not only did the reduction in downtime increase average part production over a series of replications but it also decreased variation. The range for the current process is 4,104 parts, while the range for the downtime reduction is 2,172 parts. This is also a promising sign as reduction in variation can prove to be as important as increase in efficiency.

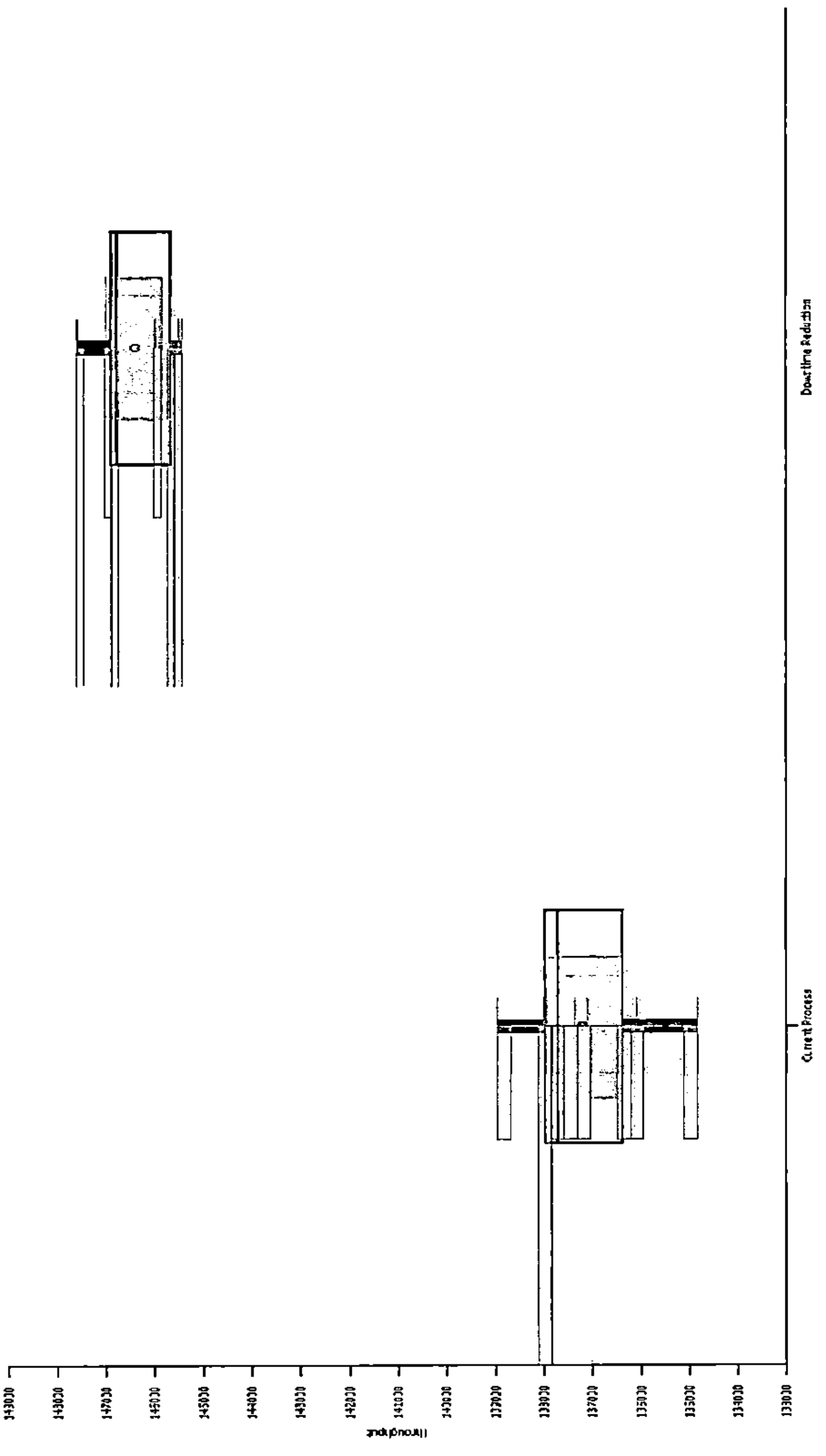


Figure 24: Solution Scenario 1 Confidence Interval Chart

6.4. Solution Scenario 2: Surround Inspection Scrap Distance Reduction

At the surround inspection station, it is desired to reduce the distance the inspection personnel must walk in order to scrap a surround. The current distance is approximately 40 feet and takes the operator away from the station for too long of a period. This period causes a lull in the part inspection process which leads to gaps in feeding of material to operation 70 and continually starves it of material. For the purposes of this simulation experiment, a scenario is created in which the container in which scrap is placed is moved from the current position of 30 feet away to a distance away of 8 feet. Based on observations, it has been noticed that it takes roughly 13 seconds to cover this current distance to the scrap container. By applying a proportionate ratio to this, we can state that the reduction in distance from 30 feet to 8 feet would result in a reduction in time of 9.5 seconds. The overall impact of this reduction in time on the assembly cell will be tested in the simulation experiment for this particular solution.

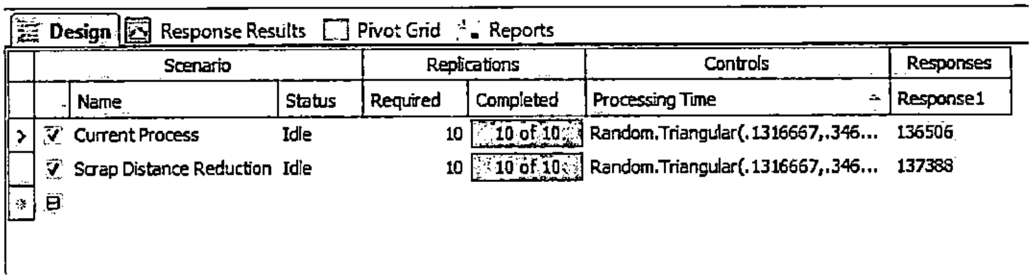
Properties: SurroundInspect (Server)

Process Logic	
Capacity Type	Fixed
Initial Capacity	1
Ranking Rule	First In First Out
Dynamic Selectio...	None
⊞ Transfer-In Time	0.0
Processing Time	**ProcessingTime**
Buffer Capacity	
Input Buffer	**1**
Output Buffer	**1**

Figure 25: Process Logic For Surround Inspect Object

For the simulation experiment, the focus will be on the processing time at the surround inspect server object. As the maximum time for this element and most all observed long cycles were due to the scrapping of parts, this reduction in time in scrapping parts will be subtracted from the maximum time stated within the triangular distribution that dictates the processing times for the surround inspect element. This change can be seen in Figure 25.

The experiment window for this experiment is displayed in Figure 26. The processing time variable, which is the control for this experiment, had to be changed due to the program reverting to the default unit of time measurement, hours. As such, the processing time in seconds were converted to the processing time in hours. This rendered usable data. Just as in the previous experiment, there were 10 two month simulation replications of each scenario and the response variable is the average number of parts from each of these scenarios that was produced through all replications. Just as previous, only replications whose results fell within the interquartile range were counted toward the average to reduce the effects of outliers on the variance.



Scenario		Replications		Controls	Responses
Name	Status	Required	Completed	Processing Time	Response1
Current Process	Idle	10	10 of 10	Random.Triangular(.1316667,.346...	136506
Scrap Distance Reduction	Idle	10	10 of 10	Random.Triangular(.1316667,.346...	137388

Figure 26: Surround Inspect Scrap Distance Reduction Simio Experiment Window

Figure 27 shows the results of the surround inspect scrap distance reduction experiment. Over a two month simulated production period, the reduced distance scenario resulted in an average production of 136,506 parts and the current process resulted in 137,388 parts produced. The current process actually outperformed the proposed change scenario slightly. The current process renders 0.64% more parts than the proposed change scenario. This difference is negligible and it can be assumed that the proposed change of moving the scrap bin closer to the surround inspect operation would have little to no effect on the production rate of the assembly cell.

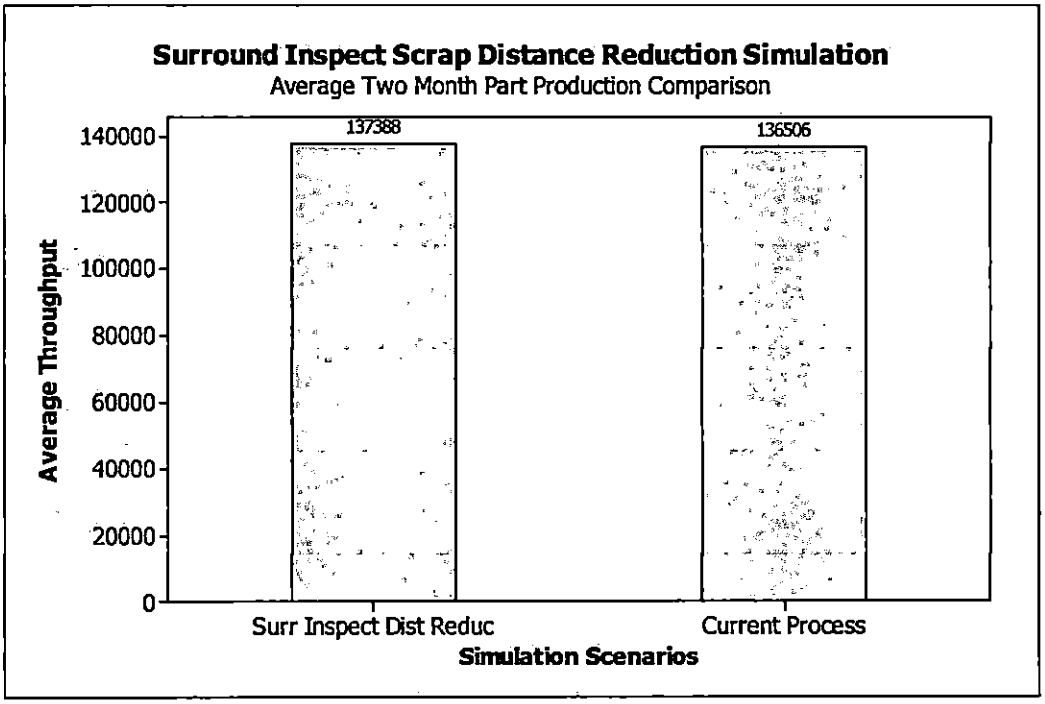


Figure 27: Surround Inspect Scrap Distance Reduction Simulation Results in Average Two Month Part Production

Figure 28 depicts the confidence interval graph output for scenario 2. The current process has a minimum of 134,904 parts and a maximum of 138,764 parts. The lower percentile value for the current process is 135,610 and the upper percentile value is 137,032 parts. For the scrap distance reduction scenario, the minimum is 134,838 and the maximum is 139.030 parts. The lower percentile value is 137,094 parts and the upper percentile value is 137,993 parts. Also shown is a histogram showing the range in which the replication values fell for each of the scenarios. .

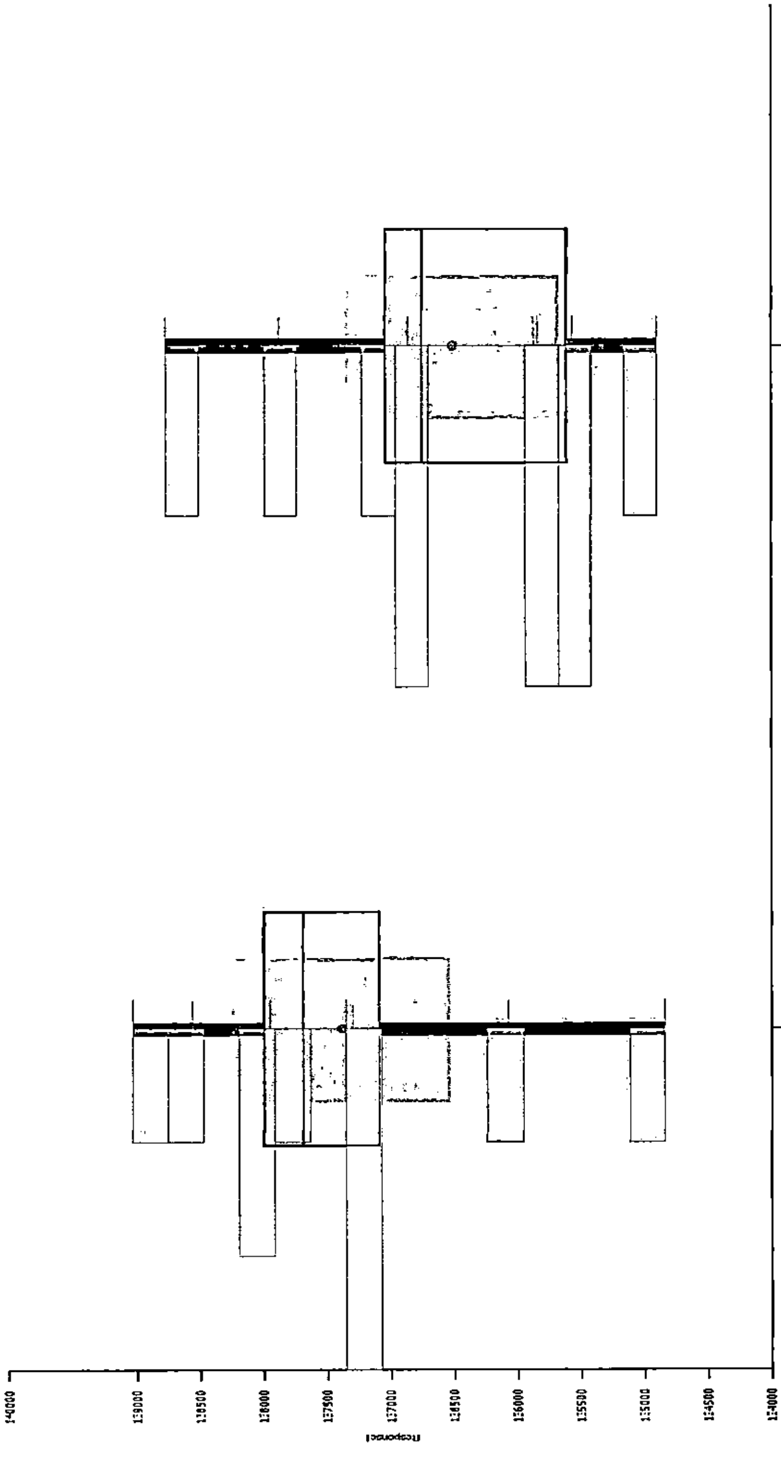


Figure 28: Solution Scenario 2 Confidence Interval

6.5. Solution Scenario 3: Inspection Buffer Capacity Increase Simulation

The buffer capacity at the material inspection areas of the surround and final inspect stations are the focus of the third and final solution experiment in this study. The current setup affords a two part buffer capacity at both the surround inspect and final inspect stations. As discussed earlier, this number may be too few to provide an appropriate buffer amount to keep operation 70 fed properly in the event that the inspection operators are disrupted from their normal cycle times.

The proposed solution for this would be to expand the current buffer stands that are used at the inspection stations from two part capacities to four. Within the Simio simulation, the change would focus on the input and output buffers for each of the inspection objects.

Currently the objects have two buffers each, an input and an output, set at one part each for a total of two total. The new scenario would increase both buffers to two parts each, increasing the total buffer capacity for each station to four parts. Figures 29 & 30 illustrate this as the control variable in the objects. These variables will be left at the normal one part input and output buffer for both objects on the current process scenario and for the increased buffer capacity scenario both the input and output buffers for each object will be increased to two.

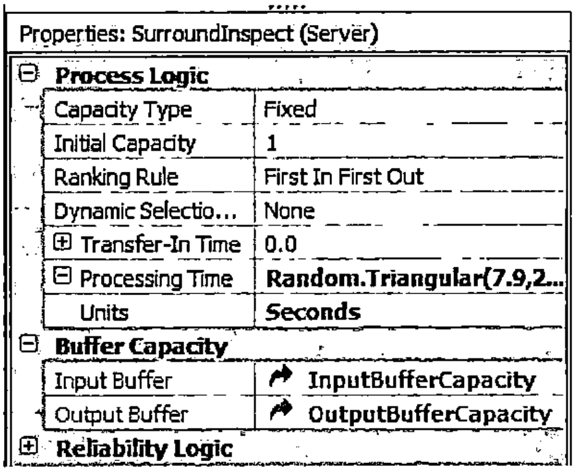


Figure 29: Process Logic For Surround Inspect Object

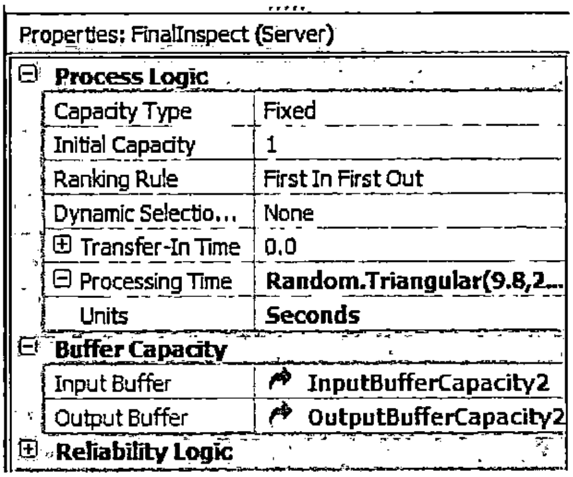


Figure 30: Process Logic For Final Inspect Object

Figure 31 shows the experiment window for scenario 3. The current process control variable depicts the current one part input and output buffers while the buffer capacity increase scenario shows the increase to two parts per buffer. In the following graph, the response variable for the experiment is graphed.

Design | Response Results | Pivot Grid | Reports

Scenario		Replications		Controls				Responses
Name	Status	Required	Completed	Input	Output	Input	Output	Throughput
Current Process	Idle	10	10 of 10	1	1	1	1	137222
Buffer Capacity Increase	Idle	10	10 of 10	2	2	2	2	137300

Figure 31: Experiment Window for Scenario 3

The response variable is shown in figure 32. These results show the average two month part production for each of the two simulation scenarios for scenario 3. As can be seen, with only a difference of 78 parts between the current process and the buffer capacity increase, there is little difference in the throughput increase with the increase in inspection buffer. This difference equates to 0.057% which would not return enough of a throughput increase to merit the implementation of the buffer capacity increase. To put this into PPH figures, the current process works out to 106.87 PPH and the buffer increase equates to 106.93 PPH. This is only a difference of 0.06 PPH. This is far too little to entertain as a viable option to increase production.

The confidence interval for scenario 3 is shown in Figure 33. From the plot, it can be seen that the two scenarios are very similar in location and shape. The only difference is the range of the data. The buffer capacity increase replications are more centered on the mean than the current process. The minimum for the current process replications for this experiment is 134,838 parts and the maximum is 138,942 parts. The lower percentile value is 132,370 parts and the upper percentile value is 137,953 parts.

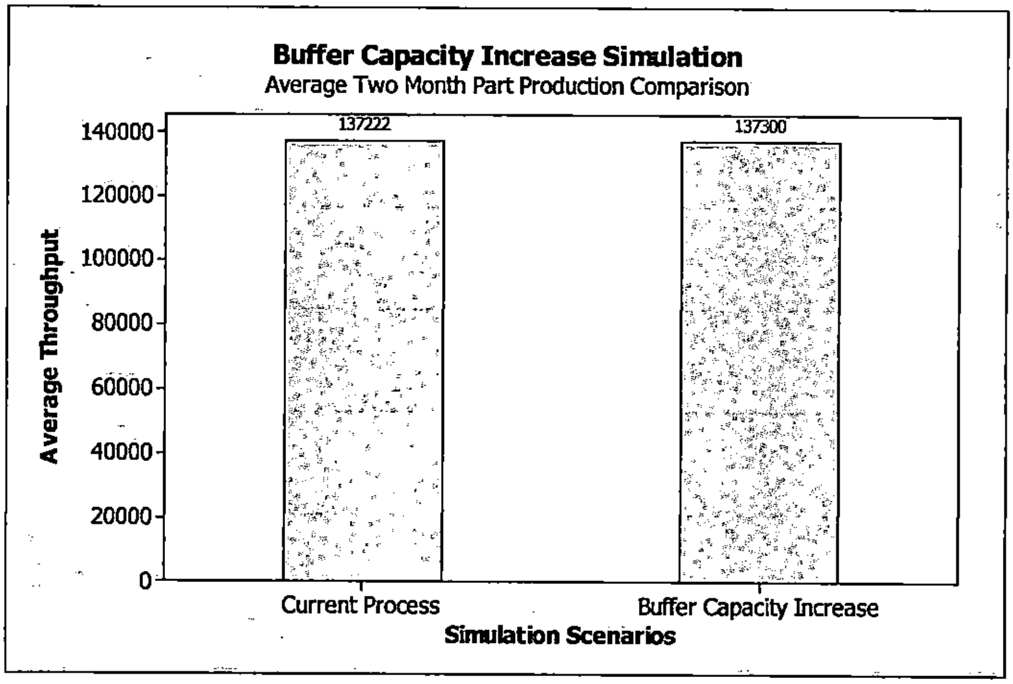


Figure 32: Buffer Capacity Increase Simulation Results in Average Two Month Part Production

For the buffer capacity increase scenario, the minimum is 135,569 parts and the maximum is 138,510 parts. The lower percentile value is 136,446 parts and the upper quartile value is 137,929 parts.

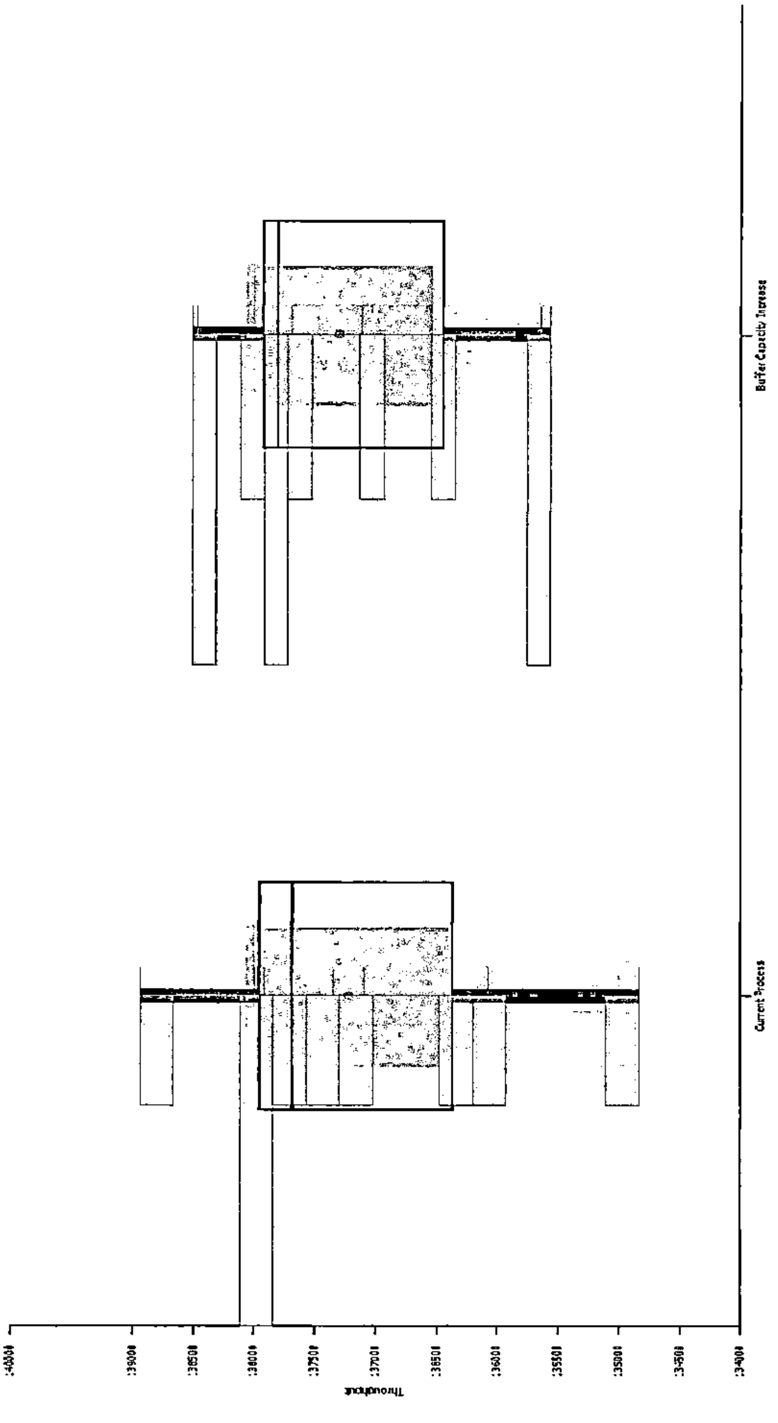


Figure 33: Scenario 3 Confidence Interval

Chapter 7: Future Work & Conclusion

7.2. Conclusion

This case study and the results obtained from it demonstrate the application of intelligent objects-based simulation in a manufacturing setting. The building of a valid simulation model of a currently running manufacturing assembly cell illustrates the concepts discussed initially in this thesis. The intelligent objects-based modeling can aid tremendously in simulating and analyzing with a manufacturing process without stopping the production. The experiments that proceeded next illustrated the ability to use the base simulation model as a test bed for experimenting with the manufacturing process. These tests allow us to discover the potential impact of a change without actual physical implementation of the change. Ultimately, this allows the management the ability to gather evidence and generate usable data to support the hypothesis before spending resources on any new projects.

The overall impact of the experiments performed on the P415 Assembly Cell was significant. One of the three solution scenarios was effective at increasing overall part production for the assembly cell. Scenario 1, which is the downtime reduction scenario at operation 60, rendered an increase in throughput of 36,723 parts. This increase is substantial and allows for the alleviation of a current bottleneck in the overall assembly cell. However, the other two solution scenarios were not as effective. Scenario 2, which was a reduction in the distance required to scrap a surround during the inspection step, did not increase the throughput of the process much at all. The increase was only 0.64%. Scenario 3 was a similar case. The increase of the buffer capacity at the inspection stations in the assembly cell only resulted in an increase in production of 0.057%.

Overall, this study rendered a robust and viable model of a currently working manufacturing process and illustrated the ability to experiment with and collect data on changes within this process that makes for an overall excellent tool in the analysis of the efficiency of a process. This study accentuates Simio's ability to simulate manufacturing environments.

Simio can provide an excellent tool in the arsenal for those looking for an avenue to analyze and generate a reliable estimation for any of a number of industrial processes. From a single assembly cell to material flow throughout an entire facility, intelligent objects-based simulation can prove valuable. Being able to simulate a process, study it, and even tweak and tune it without any disturbance can give valuable insight that can provide access to information that can save an organization much resources if utilized properly.

With the use of Simio being easily implementable and user-friendly while also being more powerful than past simulation software methodologies, simulation could go from specialized work done simply by outside specialists to a tool that any industrial engineer can incorporate into their analysis of processes under their watch.

7.1. Future Work

The current study can be extended in a number of different directions. Another similar study could be performed focusing simply on the material flow throughout the cell. The tracking and scheduling of the different grille variants through the cell and the combination of the different components that go into each grille could be simulated in order to properly trace the route material takes throughout the entire plant to get to the assembly cell. The surrounds and inners for the grilles could be simulated with origins at the injection molding machines and track through the plant from molding to chrome plating or paint and in storage while waiting for use in the cell. This extensive simulation could provide insight into the true nature of the material flow through the entire process of the P415 grille assembly.

In addition to just focusing on the P415 assembly cell, the simulation could be used on all aspects of the plant. Molding, plating, paint, or any other aspect of the manufacturing process at the SRG Global facility could be simulated and even linked. Ultimately, an entirely networked and interacting simulation model of the whole facility could be created, with outputs such as scrap, downtime, and overall part production being simulated far in advance. This could be beneficial in studying the effects of subtle changes such as new part introductions, labor changes, and process changes on the overall operation of the plant.

Appendix

A. Time Study Data

P415 Assembly Cell Time Study Data: Operation 10		
TIME	ROUNDED TIME	COMMENTS
25.98	26.0	
24.54	24.5	
23	23.0	
24.83	24.8	
16.47	16.5	
20.93	20.9	
19.46	19.5	
24.67	24.7	
21.31	21.3	
19.23	19.2	
22.34	22.3	
19.57	19.6	
18.12	18.1	
28.81	28.8	
20.55	20.5	
25.98	26.0	
22.7	22.7	
22.25	22.2	
22.37	22.4	
28.78	28.8	
19.39	19.4	
19.31	19.3	
9.62	9.6	
26.15	26.1	
19.18	19.2	
25.46	25.5	
14.68	14.7	
22.54	22.5	
11.73	11.7	
12.32	12.3	
18.75	18.7	
19.44	19.4	
18.73	18.7	
17.61	17.6	
13.68	13.7	

P415 Assembly Cell Time Study Data: Operation 20		
TIME	ROUNDED TIME	COMMENTS
15.99	16.0	
18.64	18.6	
13.86	13.9	
24.93	24.9	
14.75	14.8	
17.01	17.0	
25.31	25.3	
15.28	15.3	
13.35	13.4	
24.92	24.9	
25.75	25.8	
23.50	23.5	
24.00	24.0	
24.09	24.1	
26.92	26.9	
13.66	13.7	
13.03	13.0	
13.84	13.8	
23.78	23.8	
12.99	13.0	
16.60	16.6	
12.76	12.8	
17.44	17.4	
22.05	22.1	
24.71	24.7	
14.70	14.7	
28.89	28.9	
22.99	23.0	
15.25	15.3	
21.2	21.2	
17.68	17.7	
25.53	25.5	
25.11	25.1	
22.16	22.2	
15.4	15.4	

P415 Assembly Cell Time Study Data: Operation 30		
TIME	ROUNDED TIME	COMMENTS
9.78	9.8	
9.55	9.6	
9.22	9.2	
17.96	18.0	
16.89	16.9	
8.87	8.9	
8.90	8.9	
9.83	9.8	
9.56	9.6	
17.58	17.6	
29.13	29.1	
17.87	17.9	
17.98	18.0	
17.32	17.3	
17.55	17.6	
8.67	8.7	
9.89	9.9	
9.47	9.5	
9.10	9.1	
9.61	9.6	
9.73	9.7	
16.29	16.3	
8.12	8.1	
9.22	9.2	
16.96	17.0	
17.21	17.2	
17.45	17.5	
28.85	28.9	
29.03	29.0	
18.42	18.4	
9.7	9.7	
18.29	18.3	
28.67	28.7	
10.07	10.1	
10.12	10.1	

P415 Assembly Cell Time Study Data: Operation 40		
TIME	ROUNDED TIME	COMMENTS
21.38	21.4	
20.83	20.8	
25.31	25.3	
21.54	21.5	
21.13	21.1	
19.26	19.3	
21.77	21.8	
22.86	22.9	
20.06	20.1	
19.14	19.1	
18.69	18.7	
20.71	20.7	
21.08	21.1	
22.99	23	
18.42	18.4	
20.76	20.8	
19.70	19.7	
22.05	22.1	
23.08	23.1	
23.89	23.9	
26.60	26.6	
23.40	23.4	
22.34	22.3	
20.77	20.8	
21.65	21.7	
21.05	21.1	
18.82	18.8	
17.87	17.9	
24.01	24	
21.65	21.7	
20.22	20.2	
22.43	22.4	
22.09	22.1	
22.03	22	
23.33	23.3	

P415 Assembly Cell Time Study Data: Operation 50		
TIME	ROUNDED TIME	COMMENTS
25.47	25.5	
24.01	24.0	
24.83	24.8	
24.27	24.3	
28.87	28.9	
24.65	24.6	
24.29	24.3	
23.13	23.1	
24.22	24.2	
23.61	23.6	
23.45	23.4	
22.44	22.4	
22.82	22.8	
22.25	22.2	
22.19	22.2	
24.16	24.2	
23.73	23.7	
22.28	22.3	
23.13	23.1	
26.85	26.8	
25.96	26.0	
23.16	23.2	
23.04	23.0	
22.92	22.9	
22.84	22.8	
23.23	23.2	
22.54	22.5	
23.66	23.7	
22.91	22.9	
25.63	25.6	
23.82	23.8	
22.90	22.9	
23.49	23.5	
22.42	22.4	
23.16	23.2	

P415 Assembly Cell Time Study Data: Operation 60		
TIME	ROUNDED TIME	COMMENTS
25.96	26.0	
25.27	25.3	
25.33	25.3	
26.42	26.4	
25.20	25.2	
25.14	25.1	
26.39	26.4	
25.11	25.1	
26.07	26.1	
24.67	24.7	
24.68	24.7	
24.53	24.5	
24.82	24.8	
24.31	24.3	
25.03	25.0	
25.41	25.4	
24.25	24.2	
24.85	24.8	
25.14	25.1	
24.27	24.3	
25.25	25.2	
25.15	25.1	
25.25	25.2	
24.52	24.5	
24.61	24.6	
25.03	25.0	
24.67	24.7	
25.38	25.4	
25.11	25.1	
25.35	25.3	
24.74	24.7	
25.41	25.4	
25.03	25.0	
25.16	25.2	
24.81	24.8	

P415 Assembly Cell Time Study Data: Operation 65		
TIME	ROUNDED TIME	COMMENTS
19.59	19.6	
20.30	20.3	
20.40	20.4	
20.26	20.3	
20.14	20.1	
20.33	20.3	
20.48	20.5	
20.19	20.2	
20.04	20.0	
20.01	20.0	
20.40	20.4	
20.41	20.4	
20.12	20.1	
20.34	20.3	
20.16	20.2	
20.59	20.6	
20.82	20.8	
20.36	20.4	
20.71	20.7	
20.69	20.7	
20.21	20.2	
20.94	20.9	
21.11	21.1	
20.59	20.6	
20.10	20.1	
20.06	20.1	
20.00	20.0	
20.94	20.9	
20.36	20.4	
20.92	20.9	
20.92	20.9	
20.37	20.4	
20.60	20.6	
21.00	21.0	
21.35	21.3	

P415 Assembly Cell Time Study Data: Operation 70		
TIME	ROUNDED TIME	COMMENTS
34.50	34.5	
21.62	21.6	
18.73	18.7	
21.55	21.5	
32.09	32.1	
22.43	22.4	
19.81	19.8	
41.06	41.1	
20.01	20.0	
39.45	39.4	
61.25	61.2	
41.03	41.0	
17.56	17.6	
21.56	21.6	
26.41	26.4	
18.16	18.2	
22.80	22.8	
22.63	2.6	
19.31	19.3	
17.36	17.4	
18.89	18.9	
21.58	21.6	
18.35	18.3	
17.63	17.6	
19.39	19.4	
22.94	22.9	
19.48	19.5	
20.14	20.1	
31.68	31.7	
23.88	23.9	
19.1	19.1	
17.47	17.5	
22.31	22.3	
21.76	21.8	
21.98	22.0	

P415 Assembly Cell Time Study Data: Surround Inspect		
TIME	ROUNDED TIME	COMMENTS
9.23	9.2	
55.76	55.8	
43.17	43.2	
28.69	28.7	
17.52	17.5	
28.34	28.3	
18.60	18.6	
105.56	105.6	
13.15	13.1	
24.26	24.3	
21.16	21.2	
20.99	21.0	
22.09	22.1	
25.10	25.1	
28.26	28.3	
19.81	19.8	
39.66	39.7	
15.89	15.9	
19.26	19.3	
24.45	24.4	
18.46	18.5	
33.39	33.4	
29.04	29.0	
37.40	37.4	
25.22	25.2	
23.90	23.9	
26.23	26.2	
24.71	24.7	
22.23	22.2	
19.76	19.8	
30.89	30.9	
14.67	14.7	
22.72	22.7	
34.29	34.3	
46.56	46.6	

P415 Assembly Cell Time Study Data: Final Pack Inspect		
TIME	ROUNDED TIME	COMMENTS
27.78	27.8	
20.07	20.1	
25.46	25.5	
18.07	18.1	
42.14	42.1	
18.81	18.8	
13.62	13.6	
19.59	19.6	
17.26	17.3	
21.13	21.1	
13.86	13.9	
19.70	19.7	
15.46	15.5	
88.51	88.5	
21.78	21.8	
19.23	19.2	
17.20	17.2	
20.92	20.9	
30.78	30.8	
13.71	13.7	
37.63	37.6	
18.67	18.7	
20.25	20.2	
12.60	12.6	
14.23	14.2	
22.79	22.8	
13.95	14.0	
13.49	13.5	
15.2	15.2	
20.42	20.4	
18.17	18.2	
20.28	20.3	
21.75	21.7	
16.64	16.6	
18.27	18.3	

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