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Robotic Manufacturing Cell: An Analysis of Variables Affecting Performance

Elvis Alicic
University of Northern Iowa

ROBOTIC MANUFACTURING CELL: AN ANALYSIS OF VARIABLES AFFECTING PERFORMANCE

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

Master of Science

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ABSTRACT

Analyzing the performance of manufacturing cells is a well established concept. The justification for conducting thorough analyses of manufacturing cells comes from the known advantages it can provide, including performance improvement and production planning improvement, both current and future. This study focuses on assessing the variables affecting performance of a robotic manufacturing cell through the measure of throughput. Initially, simulation modeling is utilized to model an existing robotic cell and compare the output to actual production output from the same cell. Additionally, general regression modeling is employed to analyze the following variables and their effect on throughput: machine downtime, off-plan time, setup time, weekly schedule requirements, scrap rate and preceding operation output. Results of the analysis show that off-plan time and setup time are the only significant predictors of performance throughput. Furthermore, general regression modeling based on real data, rather than simulation modeling, is more accurate in predicting throughput. Discussion and results are presented in this thesis, as well as the practical implications. Finally, an integrated methodology is proposed for analyzing the output performance of robotic manufacturing cells.

Keywords: manufacturing cells, performance analysis, robotic cells, simulation modeling, multiple regression, throughput analysis

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Date — Dr. Julie Zhang, Thesis Committee Member

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Date — Dr. Mark Ecker, Thesis Committee Member

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CHAPTER I

INTRODUCTION

Industrial automation is growing at a rapid rate. Many organizations are looking to utilize robotics and automated processes to improve quality, efficiency, safety, and productivity. Industrial robot sales have risen 30% in 2011, reaching over 150,000 units for the year and over one million total worldwide, according to the International Federation of Robotics (Bangert, 2009; Brown, 2008; Robot, Technology Sales Rise, 2012). Furthermore, the Robotic Industries Association (RIA) estimates over 203,000 industrial robots are being used in the United States (Robot Orders Surge, 2011). In today's world, automated processes using robotics are more established in assembly operations across many different industries. However, the demand for robots is becoming higher in areas such as handling, welding and clean room applications (Brown, 2008). In addition, robots today are not only found in automotive factories but also in industries such as: food and beverage, pharmaceuticals, metals, and medical devices to name a few (Brown, 2008).

Automated machining cells utilize robots to perform applications such as material handling, machine tending, palletizing, and inspection. The repeatability, reliability, and flexibility of the increasingly sophisticated robots have drawn many organizations to adopt robots into their processes (Bangert, 2009). Robots in machining operations tend to be highly dynamic and unique due to the differences from one cell to another. This dynamic environment and uniqueness allow for multiple alternatives and possibilities from a planning and layout standpoint. Automated machining cells consist of a combination of machines and robots arranged in circular or linear fashion. These machines are usually setup to machine single or multiple operations on a family of parts. Planning and implementation of automated cells is difficult and requires knowledge of process characteristics that are yet to exist in many situations. As Irizarry, Wilson, and Trevino (2001) argued, cell formation, design, and operation are the main issues associated with the implementation of new manufacturing cells. Unforeseen factors and constraints are anything but unusual in organizations that have experience in the design and implementation of automated cells. The significance and impact of these unforeseen factors have resulted in lost time, productivity, and capital for many organizations (Danford, 2012).

Simulation has become a widely utilized tool in the implementation of new manufacturing cells. Simulation offers benefits such as constraint and bottleneck analysis, performance analysis, better understanding of the process potential, better utilization of resources, and capability of seeing how changes in the process will affect productivity and operations (Componation, Gholston, Hyatt, & Simmons, 2003; Yazici, 2005). When used accurately and appropriately, simulation can greatly assist in the design and improvement of new manufacturing cells due to its ability to simulate highly dynamic and complex systems (Chen, Chen, & Lin, 2001).

Statement of the Problem

The problem presented for research in this study deals with capacity and process planning of an automated machining cell for maximum utilization of resources and an efficient analysis of constraints. Due to the dynamic nature of automated machining cells that utilize robots, determining the layout needs and constraints becomes very difficult. Many things tend to get overlooked when using static data to make decisions regarding the process and configuration of the cell. A more accurate way of determining capacity and constraint needs is needed to efficiently plan layout configurations of automated machining cells. Furthermore, performance of robotic cells has not been thoroughly evaluated and compared with data from actual implemented cells. This retrospective comparison will help assess the accuracy of the simulation model and give insight as to which factors are most critical for accurately modeling robotic machining cells.

Purpose of the Study

The purpose of the study is to utilize a simulation tool to build a model that dynamically simulates an automated machining cell. An analysis of data derived from the simulation will be directly compared to the actual data of the same automated machining cell to test the validity and accuracy of the simulation from a productivity/throughput perspective. Furthermore, an analysis will be conducted to help understand the most critical variables affecting the performance of robotic cells. If the simulation model is not predictive, further analysis of performance will be conducted in order to assess which variables are significant contributors of variation. The ability to use a tool to dynamically model and predict the behavior of an automated system can help improve efficiency, productivity and safety, in any machining operation. However, in many discrete-event simulations, the model is only as good as the input data. In addition, a model of a specific process or operation can be used to build other simulations involving entire departments or even factories, providing tremendous benefits from a supply chain and overall system perspective. Based on the results, a methodology for using simulation in the design and implementation of automated machining cells will be proposed.

Statement of Need

Accurate simulation of any process provides many benefits. Some of these benefits include an efficient analysis of system constraints and a better understanding of the process potential. In the world of automation, this becomes increasingly important and worthwhile as the details that play a major role in the success of the system tend to get overlooked. Effective simulation of intricate and complex systems can provide answers to all the necessary questions that are asked during capacity and process planning stages. This leads to quicker project delivery times, more flexibility, and a better utilization of resources (Yazici, 2005). In addition, Ziff argued, comprehensive simulation saves a lot of time and money during the planning phases of a job (Danford, 2012). There is great value in making sure that your process is going to be implemented correctly without any surprises. Simulation has become an effective method for improving the design and performance of manufacturing cells, due to its versatility in modeling complex and dynamic operations and systems (Chen et al., 2001). The use of simulation can help validate methods and plans before they are actually implemented on the floor (Ruiz, Giret, Botti & Feria, 2011). Majority of the research on simulation deals with production that is focused on optimization issues such as detecting bottlenecks or applying different control philosophies (Ujvari & Hilmola, 2006). A more convenient option of using simulation is during the investment phase, where new facilities or new cells are being designed and decisions need to be made (Ujvari & Hilmola, 2006).

Furthermore, Klingstam (2001) argued that during the early stages or the product life-cycle, there exists great potential for the use of simulation. Organizations that utilize cellular manufacturing (CM) principles to increase productivity by reducing throughput time and work-in-process (WIP) inventories, must have an accurate way of modeling and validating their project plans. Cellular manufacturing has provided the flexibility needed to meet today's changing customer demands while maintaining the productivity and economic advantages of a flow production system (Irizarry et al., 2001). Furthermore, Irizarry et al. (2001) argued that cell formation, design, and operation are the main issues that are associated with the implementation of new manufacturing cells. In order to accomplish successful cell design, parts need to be grouped in part families and machines need to be grouped in cells. Cell design for an automated system entails cell layout, configuration of material handling system, such as AGV's or robots and the unit load size. The operation of an automated cell is concerned with a great deal of things such as: quality control, machine failures, equipment breakdowns, preventative maintenance, machine setup times, operator assignments and movement rules, product scheduling and lot sizing, and sizing and storage of inventory or work-in-process material (Irizarry et al., 2001). According to Irizarry et al. (2001) much of the research on cellular manufacturing has focused on cell formation, layout, and material handling systems especially automated guided vehicles (AGV's). However, in a survey conducted by Wemmerlov and Hyer (1989) on existing users of cellular manufacturing in US Industries, they found that most problems are related to operation and not design. Many details are incorporated into the operation of an automated cell and some of these just cannot be conceived very easily before they are implemented. Thus, the use of an accurate and effective simulation tool can provide great benefits, not just from a design perspective, but also from an operations perspective. There exists a need to evaluate the performance of robotic cells and develop a methodology for using simulation as a tool in the design and implementation of automated machining cells.

Statement of Hypothesis

It was hypothesized that the simulation model would not provide an accurate summary of the cell's throughput in comparison to the actual data. Furthermore, it was hypothesized that the simulation model would effectively pinpoint any constraints in the process. It was also hypothesized that off-plan time, schedule requirements, and setup time would be critical factors affecting throughput.

Research Questions

1. Is there a significant difference between actual data and simulated data from a productivity standpoint?
2. Were there any unforeseen constraints not recognized by the simulation?
3. If the simulation model is not predictive, what are the contributing variables of performance variation measured by throughput?
4. Can simulation be used effectively in assessing performance of robotic manufacturing cells?

Assumptions

Assumptions are very important to the success of simulation practices. Every step of the process must be carefully examined to prevent unwanted assumptions to be executed in the model. The following assumptions are made in the pursuit of this study:

1. All the work assigned to the operators in the model is assumed to be executed without delay unless otherwise specified in the simulation (i.e. breaks and meetings).
2. The time study data and other input data in the model such as repair times are accurate.
3. The extent to which all of the input data in the model is accurate is the same extent to which the output results will be accurate.
4. The simulation software used is accurate and reliable.
5. Data is normally distributed.
6. No multicollinearity present between independent variables.

Limitations

This study will be conducted in view of the following limitations:

1. The model in the study is built specifically for a particular automated machining cell.
2. Results of the study are limited to the specific manufacturing cell. Other cells could yield different results.
3. The study focuses on five different part numbers in a cell with five machines and four operations.

Delimitations

This study will be conducted in view of the following delimitations:

1. The simulation software is specific to machining operations.
2. The software was developed and used internally in a specific organization.
3. Ability to get accurate input data is a struggle and the best estimates possible are used for certain simulation variables.
4. Development of custom modules for the simulation modeling software.

Definition of Terms

The following terms are defined to clarify their use in the context of the study:

1. Cycle Time – "The average time between completions of successive units or the elapsed time between starting and completing a job" (Jacobs, Chase & Aquilano, 2009, p. 161).
2. Downtime – "Time during which production is stopped especially during setup for an operation or when making repairs" (Merriam-Webster, 2012)
3. Automated Manufacturing Cell – A combination of multiple machines and/or robots setup independently to run multiple operations on a common part family (Gultekin, Akturk & Karasan, 2008).
4. Simulation Modeling – "Models are simplified abstractions of reality representing or describing its most important/driving elements and their interactions. Simulations can be regarded as model runs for certain real or designated, initial conditions" (Mitasova & Mitas, 1998).

5. Off-Plan Time – Organizational metric that is defined as the time spent outside of planned production. For this study, the time spent outside of running the robotic cell excluding machine failures and setups (i.e. meetings, rework, projects, layoffs) (Organizational definition).
6. Actual Cycle Time Standard (ACTS) – Number of hours required to produce 100 pieces (Organizational definition). The actual cycle time is synonymous with throughput time. It can be described as "time that the unit spends actually being worked on together with the time spent waiting in a queue" (Jacobs et al., 2009, p. 169).
7. Throughput – "The output rate that the process is expected to produce over a period of time" (Jacobs et al., 2009, p. 169).

CHAPTER II

LITERATURE REVIEW

Analysis of Manufacturing Cells

Literature on the analysis of manufacturing cells is extensive and focused on specific manufacturing cells and concepts that have evolved over time. The following sections present a brief summary of literature on flexible manufacturing systems and cellular manufacturing. Furthermore, literature on robotic cells is reviewed focusing on performance, layout considerations, and simulation-based analysis.

Flexible Manufacturing Systems (FMS)

Flexible Manufacturing Systems is a concept that evolved in the 1970's and can be defined as a group of automated machines, usually numerically controlled by a computer, that operate as an integrated system with appropriate material handling and storage systems (Talavage & Hannam, 1988). The key word that defines this concept is flexible. Today's market is filled with alternative options that create increased demand for customized products in many varieties with high quality and timely delivery (Wadhwa, Ducq, Ali & Prakash, 2009). Flexible manufacturing systems (FMS) provide manufacturing companies the flexibility needed to produce a variety of products in a timely fashion while maintaining quality, keeping up with customer demands, and adapting to new technologies (Rao & Parnichkun, 2009). A flexible manufacturing system can also be viewed as a combination of a job shop manufacturing system and a batch manufacturing system. It encompasses the flexibility of a job shop system with the efficiency of a batch system. Goswami, Tiwari and Mukhopadhyay (2008) state that the objective of a flexible manufacturing system is to achieve efficiency exhibited by transfer lines while maintaining the flexibility of low volume job shops.

A vast majority of the studies on flexible manufacturing systems (FMS) have focused on two aspects, flexibility and integration. Routing flexibility, machine loading and scheduling have been studied extensively. Routing flexibility is a critical component of FMS and helps distinguish FMS from other manufacturing systems (Joseph & Sridharan, 2011). Today, a flexible manufacturing system is considered to be one of the most strategic and effective systems in the competitive manufacturing environment (Ali & Wadhwa, 2010). The other key component of a flexible manufacturing system deals with integration. The decision system and the information system are considered to be highly interdependent and critical for integration success (Chan, Bhagwat & Wadhwa, 2008). The management of input data and control decisions is critical for integration success, as the control of a flexible manufacturing system is highly dependent on the availability of information received (Chan et al., 2008).

The studies on flexibility are extensive and define different types of flexibility. Joseph and Sridharan (2011) present a summary of literature on flexible manufacturing systems. Their review, along with additional literature is described in the following.

Browne, Dubois, Rathmill, Sethi, and Stecke (1984) identify eight different types of flexibility: machine flexibility, process flexibility, product flexibility, routing flexibility, volume flexibility, expansion flexibility, operation flexibility and production flexibility. Additional areas of flexibility were defined such as material handling flexibility, program flexibility, market flexibility (Sethi & Sethi, 1990) and automation flexibility, labor flexibility, new design flexibility and delivery flexibility (Vokurka & O'Leary-Kelly, 2000).

Operational decisions of a FMS can be categorized as either planning decisions, made before release or scheduling decisions, made after release (Joseph & Sridharan, 2011). The machine loading problem in a FMS has received attention from academia and practitioners as a planning decision problem. This problem deals with allocation of parts and assignment of operations for those parts in a numerically controlled environment in order to obtain certain objectives such as maximization of machine utilization, minimization of tooling costs and maximizing the total weight of assigned operations (Ozpeynirci & Azizoglu, 2009). Various flexibility and constraint issues are demonstrated by the machine loading problem due to part selection and operation assignments (Kumar, Prakash, Shankar & Baveja, 2006). Multiple researchers have addressed the machine loading problem. Studies have provided several solutions for solving this problem including, using fuzzy logic of the allocation decisions for operation-machine memberships by evaluating the constraints and goals of machine loading (Vidyarthi & Tiwari, 2001). Ozpeynirci and Azizoglu (2009) assessed the capacity allocation through development of a branch and bound algorithm for maximizing total weight of assigned operations. Similarly, Swarankar and Tiwari (2004) developed a hybrid algorithm based on tabu search and simulated annealing by focusing on two objectives, minimizing system unbalance and maximizing throughput. A two-stage approach using fuzzy-based logic and operation machine allocation to solving the machine loading and scheduling problems is proposed by Bilkay, Anlagan and Kilic

(2004). The first stage focuses on developing an algorithm for assigning part priorities and the second-stage focuses on re-generating schedules in case of machine breakdowns. Kumar et al. (2006) developed a constraint-based genetic algorithm that handles a variety of variables and constraints consistent with the loading problem. Biswas and Mehapatra (2008) utilized a meta-heuristic approach to solving the machine loading problem in a FMS by focusing on particle swarm optimization to reduce the effort required for computing and solution quality. Through the use of an integrated planning model, Gamila and Motavalli (2003) investigated the problems of part and tool loading and part routing and scheduling. Furthermore, Das, Baki and Li (2009) examined issues associated with machine loading, part type grouping, and tool allocation through integer programming models in efforts to develop a sequencing technique for optimization of run time, non-productive tool changes, and orientation changes. Moreover, an integrated constraint programming model established by Zeballos, Quiroga and Henning (2010) addressed the issues of machine loading, part allocation, part routing and scheduling accounting for a variety of constraints and objectives found in industrial environments.

The scheduling decisions, made after the fact, have received extensive attention as well from both academia and practitioners. One of the major components of a flexible manufacturing system is routing flexibility, or the ability demonstrated by a system to serve alternative routings. Ali and Wadhwa (2010) examined the impact of routing flexibility on performance in a flexible manufacturing system through the application of discrete-event simulation and Taguchi's method. Their findings show increasing routing flexibility cannot be treated as a key role in a system improvement, influence of control strategies on the performance exists, and the impact on the system performance due to the system load condition is the largest. In a similar study focusing on routing flexibility under various system load conditions, Wadhwa et al. (2009) found that there is a continuous reduction in performance, with increase in routing flexibility when both machine load and processing times are unbalanced. Researchers have proposed and utilized different measures of routing flexibility such as: average number of available routes for each part type (Chung & Chen, 1989), inverse of the number of available routes (Bernardo & Mohamed, 1992), sum of the average differences between each route and all other routes (Das & Nagendra, 1993). Further research on the effectiveness of routing flexibility has shown that flexible processing can reduce mean flow time while increasing machine utilization and throughput (Lin & Solberg, 1991). Benjaafar and Ramakrishnan (1996) distinguished and classified flexibility as either product or process related and utilized entropy (measure of system uncertainty and disorder) as a measure of routing and operation flexibility.

Garavelli (2001) used simulation to conduct a study of routing flexibility on the performance of FMS, showing that a system with limited flexibility as opposed to complete flexibility performs better from a lead time and work-in-process perspective. Chang (2007) incorporated multiple attributes of routing efficiency, versatility and variety in order to measure routing flexibility. Joseph and Sridharan (2011) focused on the same three attributes of routing efficiency, versatility and variety to evaluate routing flexibility using discrete-event simulation modeling for dynamic arrival of parts for processing. Their results showed that routing flexibility has a significant impact on system performance. In every case and level of flexibility studied, the mean flow time of the system showed a decreasing trend as the level of flexibility increased.

Fuzzy logic has been used in many studies of FMS where problems exist with a certain degree of uncertainty or vagueness. Certain variables can be expressed as fuzzy variables and used in a scheduling decision hierarchy, for example. Fuzzy logic deals with reasoning that is approximate or probabilistic in nature (Joseph & Sridharan, 2011).

Scheduling of flexible manufacturing systems is another area that has received attention in research. Basnet and Mize (1994) identified six main categories studies on FMS scheduling can be grouped into. They are as follows: mathematical programming, multi-criteria decision-making, heuristic-oriented, simulation-based, artificial intelligent-based and control theory-based. Yu, Shih and Sekiguchi (1999) utilized multiple objectives for developing a scheduling decision for FMSs based on fuzzy inference. Buyurgan and Mendoza (2006) developed a performance-based dynamic scheduling model based on the control theory of discrete event systems that outperformed many of the well known priority rules for most of the common performance measures. Pitts and Ventura (2009) utilized mixed-integer linear programming and a Tabu search algorithm that minimizes the manufacturing make-span to address scheduling problems in a flexible manufacturing cell. Their findings show significant savings in computational time for medium to large sized multi-machine problems.

Studies have also been done to evaluate alternative flexible manufacturing systems. During the planning phase of FMS integration, it can be greatly beneficial to assess alternative options through formal methods and rankings such as the ones proposed by Rao (2008) and Rao and Parnichkun (2009).

Cellular Manufacturing (CM)

Cellular manufacturing is a concept that has gained interest with the introduction of flexible manufacturing systems and lean manufacturing principles. Talluri, Huq and Pinney (1997) argued that it is an initial step an organization must take prior to implementing higher technology systems like flexible manufacturing systems (FMS) or computer integrated manufacturing (CIM). Cellular manufacturing is an enhancement philosophy and a specific application of group technology (GT) that involves processing similar parts or part families in a manufacturing cell with multiple machines (Wemmerlöv & Hyer, 1987). Furthermore, the concept of cellular manufacturing evolved based on the need for many organizations to adjust to changing demands, namely shorter product life-cycles and time-to-market and an increasing demand for a higher variety of products at mid-volumes. Linear design of manufacturing works well for high product volumes but does not respond well to product variety due to the frequency of setups required. Functional layouts, on the other hand, work well for high product variety but do not provide enough efficiency needed for the desired throughput. Cellular manufacturing design combines the best of both worlds in order to address production requirements (Wemmerlöv & Hyer, 1989).

Cellular manufacturing (CM) provides many benefits including reduced setup times, material handling, work-in-process inventory, market response time and better efficiency and quality in production (Ahkioon, Bulgak & Bektas, 2009). Furthermore, Talluri et al. (1997) argued that organizations who have successfully implemented CM have seen tremendous benefits in reducing work-in-process inventory, achieving better quality and production throughput, and facilitating better material handling.

According to Wemmerlöv and Hyer (1987) applicability, justification, system design, and implementation are major categories of research related to CM. Yin and Yasuda (2006) defined these categories further. Applicability is feasibility and relates to plant layout configurations. Justification deals with the comparison of performance between cellular and functional layouts. System design encompasses cell formation and layout and production planning. Lastly, implementation relates mainly to environmental, organizational and human implications.

Cell design and formation has received considerable attention in research focusing on effectiveness, competitiveness, and improvement potential. Cell design, in the CM context, is grouped into three main stages, which include, the cell formation problem, the layout of the cells in the plant, and the layout of the machines in each cell (Dimopoulos & Zalzala, 1998). Prior to cell design in a cellular manufacturing environment, parts must be grouped into families and assigned to specific machines. In a study conducted by Ballakur and Steudel, (1987) a taxonomy was developed for grouping part families and machines into cells. Several other researchers used this taxonomy to conduct cell design studies including Shafer and Meredith (1990). Their study was simulation-based and focused on various cell design methods and their effect on multiple performance measures. Manzini, Bindi and Pareschi (2010) also conducted a study on grouping machines and part families that focused on determining a threshold value of similarity based on similarity coefficients. Furthermore, Hachicha, Masmoudi and Haddar (2008) proposed a multivariate approach based on correlation analysis in order to form part families and machine groups. The results of the comparative study of variables showed that the proposed approach is very effective and practical based on several performance criteria.

Das and Abdul-Kader (2011) proposed a dynamic multi-objective model of integer programming for designing a cellular manufacturing system (CMS) that considers machine reliability and part demand changes over time allowing alternative part processing routes that maximize machine system reliability and minimize system costs. Ahkioon et al. (2009) investigated the design problem of CMS through introducing routing flexibility and alternate contingency routing in addition to alternate main routings. In addition, the study considers the trade-offs between increased flexibility and additional cost as a result of the contingency routings showing no significant increase in system cost with the additional routing flexibilities. In addition, Yazici (2005) conducted a simulation-based study in efforts to determine the influence of volume, mix, routing and labor flexibilities with respect to continuously changing demand in CM and job shops. The results of the study indicated, that added routing flexibility, leads to significantly (above 70 percent) shorter lead times with both low and high volume flexibility. Additionally, higher utilization and lower lead time is acquired with assignment of fewer but more multi-skilled workers. Adenso-Diaz and Lozano (2008) introduced the concept of dedicated cells per operation type instead of part type. Their results show that performance of dedicated cells may be similar to a process layout and better than other cellular approaches. In a study conducted by Djassemi (2005), the discrepancies between flexibility and uneven machine utilization in CM are examined through simulation modeling of a variable demand system and a flexible workforce environment. The results of the study indicated that use of flexible cross-trained operators can minimize load imbalance present in dedicated machines in CM and improve flexibility with respect to unstable demand.

Research concerning the operations of cells in CM has focused on similar issues seen in flexible manufacturing systems (FMS) such as, effective scheduling, routing, and sequencing algorithms (Talluri et al., 1997). Issues dealing with labor in cellular manufacturing systems have also received a great deal of attention in academia. Huber and Hyer (1985) conducted a study to compare worker's perceptions of job characteristics, job satisfaction, and attitudes toward cellular manufacturing both in cellular and functional designs. There was no negative impact exhibited by CM on these behavioral variables, according to the results of the study. Wall and Kemp, (1987) and Susman and Chase (1986) suggested provisions for upgrading and improving the workforce to acquire multiple skills in order to be better prepared to operate a manufacturing cell.

In an effort to consider the implementation challenges of cellular manufacturing systems, Talluri et al. (1997) proposed a methodology for evaluating cell performance and improvement by developing a modified version of the traditional window analysis to analyze multiple cell inputs and outputs and demonstrating its effectiveness.

Layout Considerations in Robotic Cells

In the limited literature on robotic cell layouts, three main layouts configurations exist: robot-centered cells, where the robot is the center of the cell and moves rotationally, in-line robotic cells, where the robot moves in a linear fashion, and mobile-robot cells, where, generally speaking, the robot moves both linearly and rotationally (Logendran & Sriskandarajah, 1996). Cell formation and design of robotic cell layouts are generally designed to be balanced in terms of machine utilization, flexibility, operator workload, and system efficiency. Layout design and formation has significant implications on cell performance, productivity, and flexibility. The following section summarizes the literature on robotic cell performance.

Robotic Cell Performance Evaluation

Majority of the research concerning robotic cells deals with scheduling of robotic movements to guide cell layout, improve process efficiency and flexibility. Robot-centered cells are generally known to take up less floor space as opposed to in-line robot cells. They have also proven to be more efficient, effective and flexible (Gultekin et al., 2008; Rajapakshe, Dawande & Sriskandarajah, 2011). In certain robotic applications where robots are control factors or constraints in the process, like the semiconductor industry, productivity and robotic programming methods become very important. Geismar and Pinedo (2010) and Shafiei-Monafared, Salehi-Gilani and Jenab (2009) thoroughly analyzed the processing times and productivity in robotic cells. Gultekin et al. (2008) investigated the scheduling problem in a robotic cell with identical parts and a given number of machines. Their findings in the process flexibility of robot move cycles indicated an optimal number of machines in order to reduce cycle time and in turn increase throughput.

Simulation-Based Analysis of Robotic Cells

Simulation modeling of manufacturing cells has gained popularity in research in the recent years for its ability to dynamically model complex systems. Simulation has been used as a tool in studying the performance and routing flexibility of flexible manufacturing systems (Garavelli, 2001; Chan, 2003; Joseph & Sridharan, 2011). Additionally, it has been used in studying flexibility in cellular manufacturing systems (Djassemi, 2005).

Furthermore, simulation has been used in analyzing manufacturing cells both automated and non-automated. It is an effective tool for improving cell performance through selection and testing of desired objectives (Watson & Sadowski, 1994). In a study conducted by Noh and Herring, (1988) a simulation model was developed in order to evaluate the performance on a individual robotic cell, compare it to a mathematical queuing model, and provide an example of a deadlock situation in the system. Park (1995) presented a simulation analysis of robotic service movements in a robot-centered cell. The goal of the study was to determine priority for robotic moves in order to maximize cell productivity. The results of the simulation showed that there are significant differences in make-span and mean flow time with different robot movement priorities. In addition, of the six priority rules that were studied, the shortest remaining process time first (SRPF) rule proved to be most effective in terms of mean flow time and make-span.

The primary goal of simulation from an engineer's perspective is to obtain an optimal solution through the analysis of simulation outputs such as: throughput, utilization, number in queue, and number in system. Only then will they be able to improve the system by changing parameters such as number of machines, speed/type of robots (Chen et al., 2001). Furthermore, Chen et al. (2001) argued that in order to use simulation efficiently and effectively in the decision process, an integration of knowledge based systems, also known as expert systems, is necessary. O'Keefe (1986) developed a taxonomy for combining simulation with knowledge-based systems, resulting in four main model types: embedded model, intelligent-front-end model, parallel model, and cooperative model. Only in the cooperative model the user is able to interact with both simulation and the expert system. The first three models allow for interaction with only one of the two. Chen et al. (2001) developed a knowledge based system containing a set of facts and three levels of rules consistent with a manufacturing cell configuration. The results of their industrial study demonstrated effectiveness for improving the performance of manufacturing cells and identifying constraints. In order to develop a knowledge-based system, capturing the domain knowledge of manufacturing experts must be done. Even today, capturing this domain knowledge remains a challenge to knowledge-based system developers (Chen et al., 2001).

Furthermore, Irizarry et al. (2001) developed a simulation model of a manufacturing cell in order to evaluate the effects of world-class manufacturing practices on cell performance. The results of their study showed, through modular structure and a formulated annualized cost function, evaluation of alternative cell configurations and design is capable in order to assist the decision making process. Furthermore, the simulation models developed showed the following characteristics to be critical for the cells studied: "cell characteristics such as type of material handling equipment, cell size, machine types, and product flow, cell design and operation issues of interest to cell users and realistic economic measure of cell performance" (p. 828).

The purpose of this study is to evaluate the performance of a robotic manufacturing cell by directly comparing simulation modeling with actual cell performance data on the performance measure of throughput. In addition, this study aims to find which factors are most significant in affecting the accuracy of simulation in a robotic manufacturing cell. Lastly, based on the results, a methodology for using simulation modeling in robotic machining cells will be proposed.

CHAPTER III

METHODOLOGY

Robot-Centered Machining Cell

The manufacturing cell analyzed in this study consists of one robot centered between four Computer Numerical Control (CNC) machines and a washer, equaling a total of five machines (see Figure 1). The cell is designed to run a specific part family of roughly 12 different parts. The parts are introduced into the cell through a pallet system holding a maximum of 36 parts. Likewise, the parts are released from the cell through a pallet system holding a maximum of 36 parts.

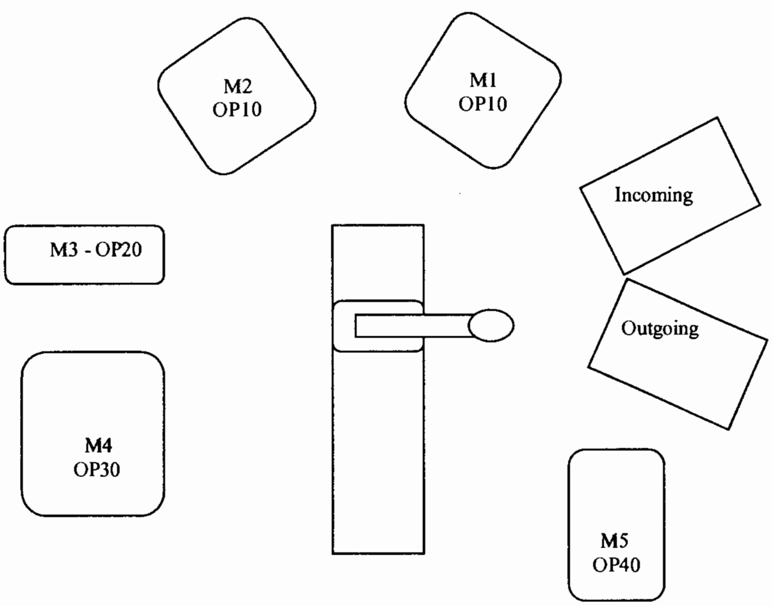

Figure 1. Cell Layout

Part Processing

The part is processed through four different operations in sequential order as follows: operation 10 (OP10), operation 20 (OP20), operation 30 (OP30) and operation 40 (OP40). In order to balance the cycle times in the cell, machine 1 (M1) and machine 2 (M2) are identical machines performing the same operation, OP10. In other words, the workload for OP10 is split between two machines.

The cell is capable of running only one part number at a time. One operator is in charge or running the cell and is responsible for setting up machines, changing machine and robotic tooling, trucking in and out material via the pallet system, performing inspection on all required features per designated frequency, and maintaining a clean and safe cell. This is the last group of operations before the parts are sent to heat treat. For the parts studied, the processing times are presented in Table 2. The highlighted machine is the constraint machine for that specific part.

Table 1.

Part Processing Times Per Machine (minutes)

PART #	M1	M2	M3	M4	M5
A	7.415	7.415	2.65	1.52	1.96
B	7.6	7.6	2.65	1.52	1.96
C	7.82	7.82	2.53	4.493	1.96
D	8.57	8.57	2.65	4.51	1.96
E	7.9	7.9	2.65	4.564	1.96

Robot Characteristics and Sequencing

The robot used in this cell is a FANUC R2000iB 165F. This is a standard floor mounted industrial robot suitable for material handling applications up to 165kg in total weight. This robot has six individual axes and it is mounted on an external track, giving it seven axes in total. Each axis is powered by a servo motor and the robot is connected to a controller. The end-of-arm tooling is a dual gripper design, capable of handling up to two parts at one time. The grippers are designed to handle all the parts in the specific part family.

The robot programming capabilities are quite extensive and can change priority in real-time. The sequence must be followed according to the order of operations. For M1 and M2, the robot will service whichever machine is ready, requesting a part and whichever machine the operator selects the robot to service. If both machines are requesting and selected, priority is given to M1. Robot will complete a full cycle before M1 is finished, allowing the robot to service M2. The main concern from a programming standpoint is to make sure the robot is not the bottleneck in the system. Majority of this responsibility relates back to the design of the cell. Table 2 shows the robot sequencing in detail for startup of an empty cell. Once a steady state is achieved, the sequence remains constant, looping continuously from steps 27-48. The sequence shows that there are actually seven parts in the system before one part is placed on the outgoing pallet. The capability of the robot programming allows for this complexity, in order to maximize the use of machines and create a much more efficient cell. The use of dual grippers (GP1 & GP2) allows for additional flexibility and efficiency.

Table 2.

Detailed List of Robot Sequence – Startup of Empty Cell

STEP	ROBOT TASK	STEP	ROBOT TASK
1	Unload Part 1 From Inc Pallet GP1	25	Load Part 2 in M3 GP1
2	Load Part 1 in M1 GP1	26	Load Part 1 in M4 GP2
3	Unload Part 2 From Inc Pallet GP1	27	Unload Part 7 From Inc Pallet GP1
4	Load Part 2 in M2 GP1	28	Unload Part 5 From M1 GP2
5	Unload Part 3 From Inc Pallet GP1	29	Load Part 7 in M1 GP1
6	Unload Part 1 From M1 GP2	30	Unload Part 3 From Drip Stand1 GP1
7	Load Part 3 in M1 GP1	31	Load Part 5 on Drip Stand 1 GP2
8	Load Part 1 on Drip Stand1 GP2	32	Unload Part 2 From M3 GP1
9	Unload Part 4 From Inc Pallet GP1	33	Load Part 3 in M3 GP2
10	Unload Part 2 From M2 GP2	34	Unload Part 1 From M4 GP2
11	Load Part 4 in M2 GP1	35	Load Part 2 in M4 GP1
12	Load Part 2 on Drip Stand2 GP2	36	Load Part 1 in M5
13	Unload Part 5 From Inc Pallet GP1	37	Unload Part 8 From Inc Pallet GP1
14	Unload Part 3 From M1 GP2	38	Unload Part 6 From M2 GP2
15	Load Part 5 in M1 GP1	39	Load Part 8 in M2 GP1
16	Unload Part 1 From Drip Stand1 GP1	40	Unload Part 4 From Drip Stand2 GP1
17	Load Part 3 on Drip Stand1 GP2	41	Load Part 6 on Drip Stand2 GP2
18	Load Part 1 in M3 GP1	42	Unload Part 3 From M3 GP2
19	Unload Part 6 From Inc Pallet GP1	43	Load Part 4 in M3 GP1
20	Unload Part 4 From M2 GP2	44	Unload Part 2 From M4 GP1
21	Load Part 6 in M2 GP1	45	Load Part 3 in M4 GP2
22	Unload Part 2 From Drip Stand2 GP1	46	Load Part 2 in M5 GP1
23	Load Part 4 on Drip Stand2 GP2	47	Unload Part 1 From M5 GP1
24	Unload Part 1 From M3 GP2	48	Load Part 1 on Out Pallet GP1
			STEADY STATE ACHIEVED

Simulation Model Building

The first phase of this study consisted of building a simulation model in order to assess the predictability of the model by comparing it to actual production data. The simulation runs are executed for longer periods (greater than 20 weeks) of time across five different part numbers. It was hypothesized that the model would detect any unforeseen constraints. It was also hypothesized that the model would not be very predictive of actual performance of the cell, measured by throughput.

SLX Platform

The simulation model is built using an internally developed interface specific to machining operations in the organization. The programming language used to run the simulation is called Simulation Language Extensible (SLX), a product of the Wolverine Software Corporation. SLX is a general purpose simulation language similar to the C programming language and is known for its capability and extensibility. The interface built to model machining operations in this study is an example of its extensibility. The way SLX conducts the simulation is through tracking of discrete-events, based on the input data, and outputting statistical summaries.

Simulation Input Data

If the model has no programming errors and does not predict actual cell performance well, then, more likely than not, input data is either incorrect or lacking for critical variables. It is very difficult to accurately simulate processes without accurate input data. In many cases, this data does not exist without the existence of knowledge systems that have collected data over longer periods of time. The input data for the simulation model included the following:

1. Machining Cycle Times Per Part
2. Robot Movement Speeds

3. Conveyor Movement Speeds
4. Machine Failures and Downtime
5. Operator Walking Times
6. Machine Setup Times
7. Scheduled Break Times

This data was collected through official time studies and some of the data such as machine failures and setup times were estimated averages. The simulation model is capable of producing an effective prediction of throughput under optimal conditions; however, this is rarely the case. To further investigate the variables affecting throughput, collection and analysis of additional data is needed. The procedure for collecting additional data is outlined in the following section.

Data Collection Procedure

In order to determine critical factors affecting the performance of cell, a cause and effect diagram (see Figure 2) was developed. The following six independent variables were determined to be critical for performance variation measured by throughput:

1. Machine Downtime
2. Off-plan time – (Time spent doing things other than running the cell, i.e. Meetings)
3. Quality/Scrap Rate
4. Total Setup time/Number of Setups
5. Weekly Schedule Requirements
6. Preceding Operation Output

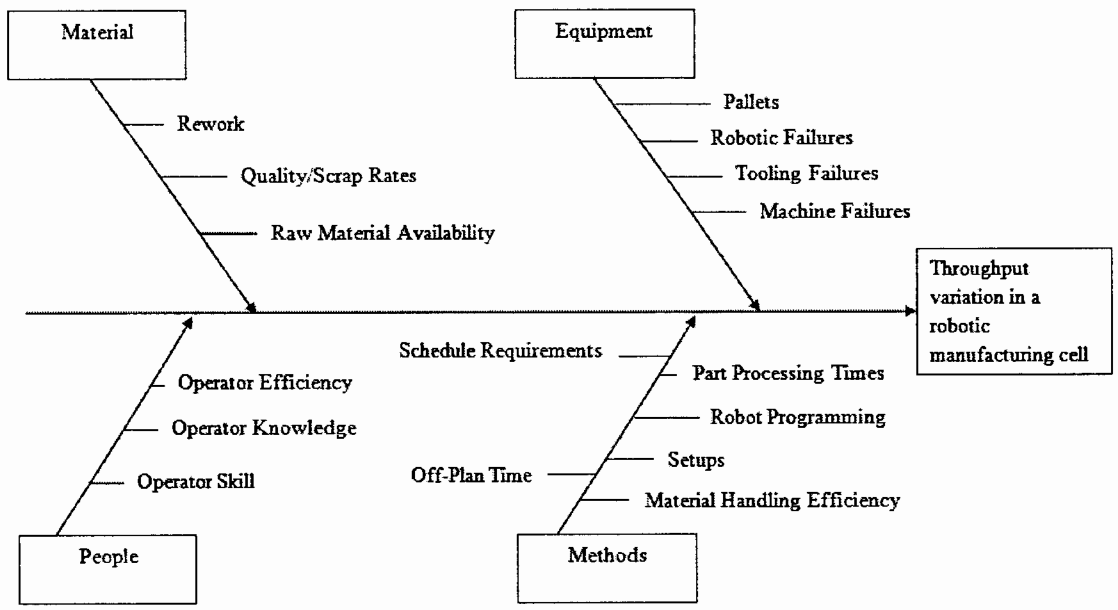

Figure 2. Cause-and-Effect Diagram

The collection of data for these variables came from enterprise system software and the department supervisor. Queries from the data system and certain departmental reports were utilized in acquiring the data for a period of roughly two months, giving a dependent variable sample size of 39. In order to determine the relationship between each of the independent variables and cell throughput, a regression analysis was employed. Based on the results, a methodology for using simulation in robotic machining cells will be proposed.

CHAPTER IV

ANALYSIS OF DATA

Results and Discussion

Initially, a simulation model was developed and compared with actual production data for the basis of assessing the accuracy of the simulation based on a common measure of performance known as throughput. The comparison showed that the simulation model did not effectively predict system performance in terms of throughput. For example, the average throughput predicted for Part A in the simulation model (see Figure 3) of 50 weeks shows the average number of parts unloaded per day to be 163.4. Furthermore, a summary of throughput (see Table 3) shows that both estimated expectations, based on the actual cycle time standard (ACTS), and simulated experiments are not accurately predicting actual throughput.

Table 3.

Summary of Throughput I

PART #	ACTS	AVG DAILY THROUGHPUT EXPECTED	AVG DAILY THROUGHPUT SIMULATED	AVG DAILY THROUGHPUT ACHIEVED
A	15.6	220	163.4	77.0
B	16.0	220	156.5	94.3
C	10.5	180	140.8	75.4
D	11.2	180	124.1	58.6
E	10.1	180	134.6	68.9

In order to determine which variables most affect performance, a multiple regression analysis was performed in a statistical software package known as Statistica. Naturally, the analysis was setup with actual throughput achieved being the dependent variable and six independent variables being: machine downtime, off-plan time, scrap rate, setup time, weekly schedule requirements and preceding operation throughput.

General

Simulation Weeks	50
Total Demand (Parts)	500000

Loads

Total Number of Parts Loaded	57221

Part Type	Parts Loaded
A	57221

Average Number of Parts per Day	163.49

Unloads

Total Number of Parts Unloaded	57204
Discarded Parts	0

Part Type	Parts Unloaded
A	57204

Average Number of Parts per Day	163.44

Figure 3. Simulation Model Results for Part A

In order to ensure assumptions of normality are valid, a normal probability plot (see Figure 4) was constructed showing the data distribution. The plot shows no alarming concerns. Additionally, a predicted versus residuals plot (see Figure 5) was generated to check for constant variance. The graph shows the distribution of points to be generally spread equally and randomly around 0. There seems to be a few outliers present that might suggest unequal variances as the predicted values increase. This would more than likely be eliminated with a bigger sample size and the removal of outliers. Therefore our assumption of constant variance is valid. To confirm this assumption, a predicted versus residuals plot is generated without the top three outliers (see Figure 6).

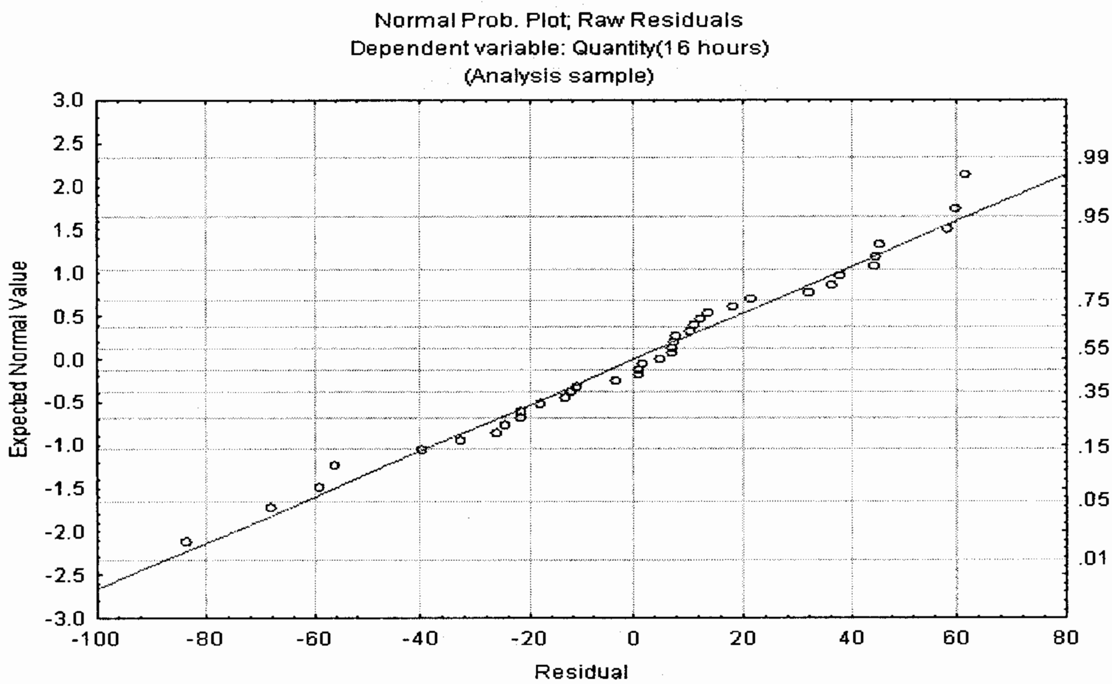

Figure 4. Normal Probability Plot

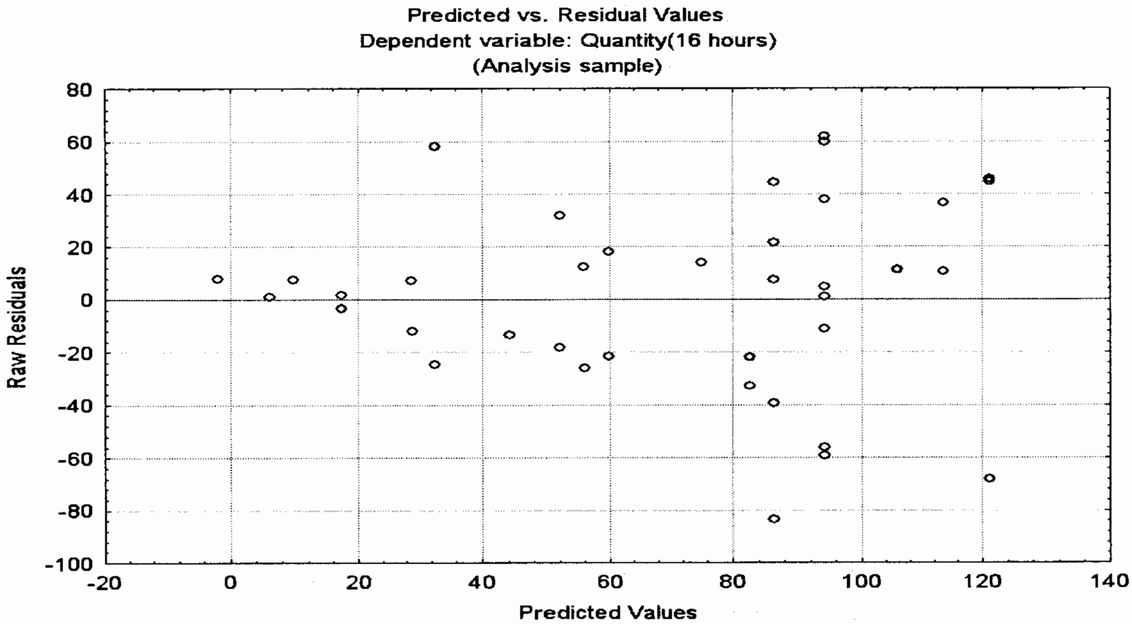

Figure 5. Predicted vs. Residuals Plot

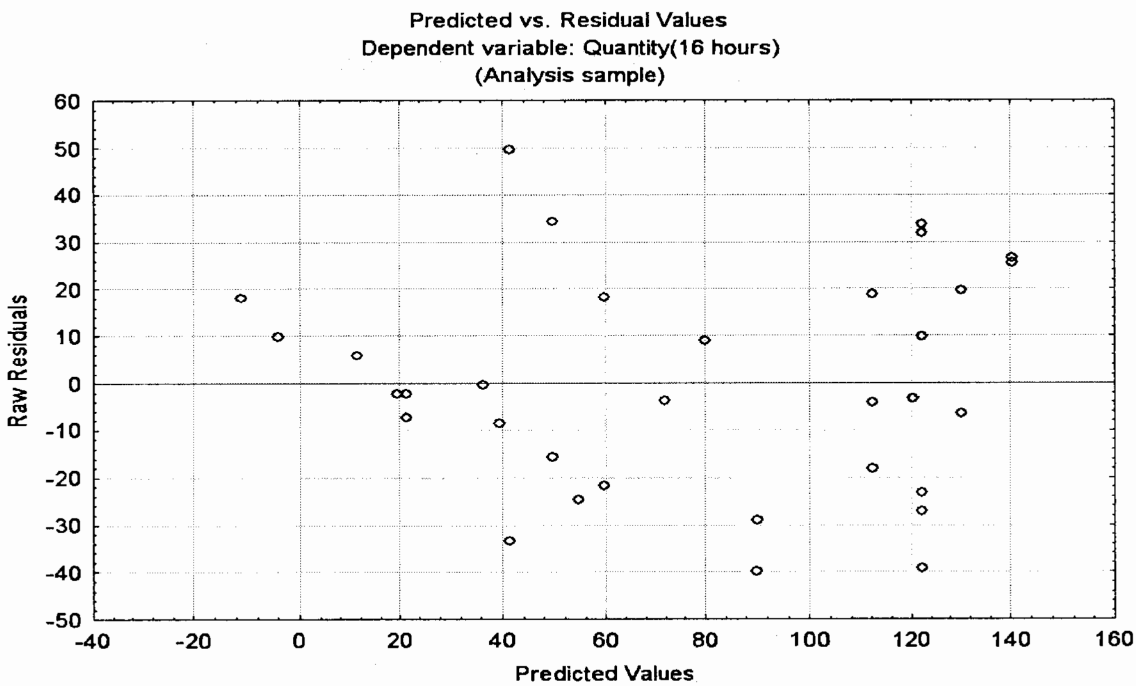

Figure 6. Predicted vs. Residuals Plot (w/o outliers)

Furthermore, redundancy checks were performed to ensure no multicollinearity existed. The results of the checks (see Table 4) show that there is no high correlation between any of the predictor variables.

Table 4.

Redundancy Check Results

	Toleran.	R-square	Partial	Semipart
Off-Plan Time (Hours)	1.000000	0.000000	-0.644765	-0.644765
Weekly Schedule Requirements (Hours)	0.994801	0.005199	0.072828	0.055668
Scrap ($) Last two years	0.954457	0.045543	-0.002359	-0.001803
Machine Downtime (Hours)	0.977594	0.022406	-0.147483	-0.112733
Preceding Operation Output	0.784733	0.215267	0.029655	0.022667
Setup Time (Hours)	0.937950	0.062050	-0.343019	-0.262197

Instances where the R-squared value is high indicate the presence of multicollinearity. The tolerance column is interpreted as one minus the R-squared value. Therefore, a high tolerance indicates little or no multicollinearity. The predictor variable that is most highly correlated with other predictor variables is preceding operation output, with a tolerance of 0.78. This is expected because this is another measure of output. The preceding operation is a manual manufacturing cell that feeds the robotic manufacturing cell in this study. The output produced in this cell could be a critical factor of throughput of the robotic manufacturing cell, thus justifying its inclusion in the study.

Multiple model building techniques were utilized in the regression analysis. Initially, a model with all the effects combined was built. This model showed (see Table 5) that the only two significant variables included setup time and off-plan time. Next, the backwards stepwise regression approach was completed at a p-value of 0.15. The summary of the stepwise regression (see Table 6) also indicated that setup time and off-plan time are the only two variables that significantly affect the throughput of the robotic manufacturing cell. An additional forward stepwise approach was conducted, (see Table 7) which also resulted in setup time and off-plan time being the only two significant factors. When the model was tested at a p-value of 0.05, setup time was determined to be insignificant and off-plan time was the only significant variable. Due to the sample size and nature of the study, the p-value of 0.15 was chosen.

Table 5.

Multiple Regression Model – All Effects Results

	SS	DF	MS	F	p
Intercept	49762.81	1	49762.81	32.60159	0.000003
Scrap ($) Last two years	4.34	1	4.34	0.00284	0.957811
Off-Plan Time (Hours)	31417.45	1	31417.45	20.58281	0.000076
Setup Time (Hours)	5340.92	1	5340.92	3.49905	0.070574
Machine Downtime (Hours)	94.53	1	94.53	0.06193	0.805062
Weekly Schedule Requirements (Hours)	0.09	1	0.09	0.00006	0.993827
Preceding Operation Output	367.86	1	367.86	0.24100	0.626835
Error	48844.55	32	1526.39		

Table 6.

Multiple Regression Model – Backward Stepwise Results

	Steps	DF	F to	P to Remove	F to	P to Enter	Effect
Scrap ($)	1	1	0.0028	0.9578			In
Off-Plan Time		1	20.5828	0.0001			In
Setup Time		1	3.4991	0.0706			In
Machine Downtime		1	0.0619	0.8051			In
Schedule Reqrmnts		1	0.0001	0.9938			Removed
Preceding OP Output		1	0.2410	0.6268			In
Scrap ($)	2	1	0.0032	0.9553			Removed
Off-Plan Time		1	21.7460	0.0000			In
Setup Time		1	3.8388	0.0586			In
Machine Downtime		1	0.0657	0.7993			In
Preceding OP Output		1	0.2634	0.6112			In
Schedule Reqrmnts		1			0.0001	0.9938	Out
Preceding OP Output	3	1	0.2799	0.6002			In
Off-Plan Time		1	24.9175	0.0000			In
Setup Time		1	4.0699	0.0516			In
Machine Downtime		1	0.0662	0.7985			Removed
Scrap ($)		1			0.0032	0.9553	Out
Schedule Reqrmnts		1			0.0003	0.9857	Out
Preceding OP Output	4	1	0.3071	0.5830			Removed
Off-Plan Time		1	27.6465	0.0000			In
Setup Time		1	4.9802	0.0321			In
Machine Downtime		1			0.0662	0.7985	Out
Scrap ($)		1			0.0018	0.9663	Out
Schedule Reqrmnts		1			0.0014	0.9699	Out
Setup Time	5	1	4.8007	0.0350			In
Off-Plan Time		1	33.2228	0.0000			In
Preceding OP Output		1			0.3071	0.5830	Out
Machine Downtime		1			0.0870	0.7698	Out
Scrap ($)		1			0.0000	0.9953	Out
Schedule Reqrmnts		1			0.0080	0.9293	Out

Table 7.

Multiple Regression Model – Forward Stepwise Results

	Steps	DF	F to Remove	P to Remove	F to Enter	P to Enter	Effect
Scrap	1	1			0.7328	0.3975	Out
Off-Plan Time		1			26.3260	0.0000	Entered
Setup Time		1			0.3251	0.5720	Out
Machine Downtime		1			1.6727	0.2039	Out
Schedule Reqrmnts		1			0.0030	0.9565	Out
Preceding OP Output		1			3.1250	0.0853	Out
Off-Plan Time	2	1	26.3260	0.0000			In
Scrap ($)		1			0.0002	0.9888	Out
Setup Time		1			4.8007	0.0350	Entered
Machine Downtime		1			0.8005	0.3769	Out
Schedule Reqrmnts		1			0.1920	0.6639	Out
Preceding OP Output		1			0.0317	0.8597	Out
Off-Plan Time	3	1	33.2228	0.0000			In
Setup Time		1	4.8007	0.0350			In
Scrap ($)		1			0.0000	0.9953	Out
Machine Downtime		1			0.0870	0.7698	Out
Schedule Reqrmnts		1			0.0080	0.9293	Out
Preceding OP Output		1			0.3071	0.5830	Out

In summary, the final model included off-plan time and setup time as the independent variables. The multiple regression model with these two predictors produced R-squared = .485, $F(2, 36) = 16.915$, $p < .00001$. The percentage of variability that is explained by off-plan time and setup time is 48% (see Table 8). In other words, about half of the total variation can be attributed to these two variables, making them very good predictors of throughput quantity.

Table 8.

Final Model Results

Regression Statistics	
Multiple R	0.696458604
R Square	0.485054588
Adjusted R Square	0.455629135
Standard Error	37.50863699
Observations	38

Furthermore, applying the results of the regression, the model can be used to predict future throughput based on off-plan time and setup time. The regression equation is fitted to the line: Throughput (y) = 121.5 - 7.74*(Off-Plan) - 6.66*(Setup). The equation suggests that both off-plan time and setup time have a negative effect on throughput. The throughput is expected to decrease by 7.74 units with every unit increase in off-plan time, assuming all other variables are constant. Likewise, throughput is expected to decrease by 6.66 units with every unit increase in setup time, assuming all other variables are held constant (see Table 9).

Table 9.

Regression Coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 85.0%	Upper 85.0%
Intercept	121.5252	12.0949	10.0477	0.0000	103.7235	139.3269
Off-Plan Time	-7.7380	1.3618	-5.6823	0.0000	-9.7423	-5.7337
Setup Time	-6.6603	3.1448	-2.1179	0.0350	-11.2890	-2.0317

Data gathered from summaries is utilized to predict future performance of the cell. For setup time, the minimum and maximum setup time, 0 and 4.5 respectively, is used while keeping off-plan time constant at 0. The actual average throughput (see Table 10) of this manufacturing cell over a two month period was 71. Table 11 shows the results of the predictions and the prediction limits computed at plus or minus 95 percent. The predicted value when setup time is 0 and all other variables constant, is 121.2. The predicted value at when setup time is 4.5 hours is 90.8.

Furthermore, off-plan time is predicted by entering the average off-plan time (4.55 hours) over a two month period, while keeping setup time constant at 0. The prediction results show throughput to be 86.2. The combination of maximum setup time and average off-plan time predicts throughput to be 55.8 on a daily basis. These results show that the use of multiple regression modeling is much more accurate in predicting throughput performance in a robotic manufacturing cell when compared to simulation modeling. Table 12 summarizes the performance between different modeling techniques.

Table 10.

Descriptive Statistics

	Valid N	Mean	Min	Max	Std.Dev.
Quantity(16 hours)	39	70.974	3.00	167.00	50.2030
Scrap ($) Last two years	39	518.026	55.00	868.00	299.1834
Off-Plan Time (Hours)	39	4.551	0.00	15.00	4.6535
Setup Time (Hours)	39	2.256	0.00	4.00	2.0094
Machine Downtime (Hours)	39	0.391	0.00	7.81	1.3945
Weekly Schedule Requirements (Hours)	39	8.631	0.00	19.44	4.5363
Preceding Operation Output	39	55.205	2.00	127.00	34.7807

Table 11.

Prediction Results

	b-Weight	Value	b-Weight
Off-Plan Time (Hours)	-7.68339	0.00	0.0000
Setup Time (Hours)	-6.76388	0.00	0.0000
Intercept			121.2057
Predicted			121.2057
-95.0%PL			42.3171
+95.0%PL			200.0943
	b-Weight	Value	b-Weight
Off-Plan Time (Hours)	-7.68339	0.00	0.0000
Setup Time (Hours)	-6.76388	4.50	-30.4375
Intercept			121.2057
Predicted			90.7682
-95.0%PL			12.9965
+95.0%PL			168.5400
	b-Weight	Value	b-Weight
Off-Plan Time (Hours)	-7.68339	4.55	-34.9594
Setup Time (Hours)	-6.76388	0.00	0.0000
Intercept			121.2057
Predicted			86.2463
-95.0%PL			8.8807
+95.0%PL			163.6119
	b-Weight	Value	b-Weight
Off-Plan Time (Hours)	-7.68339	4.55	-34.9594
Setup Time (Hours)	-6.76388	4.50	-30.4375
Intercept			121.2057
Predicted			55.8088
-95.0%PL			-21.5419
+95.0%PL			133.1595

Table 12.

Summary of Throughput II

PART #	AVG DAILY THROUGHPUT EXPECTED	AVG DAILY THROUGHPUT SIMULATED	AVG REG MODEL PREDICTION	AVG DAILY THROUGHPUT ACHIEVED
A	220	163.4	88.5	77
B	220	156.5	88.5	94.3
C	180	140.8	88.5	75.4
D	180	124.1	88.5	58.6
E	180	134.6	88.5	68.9

CHAPTER V

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

This study focused on assessing the performance of a robotic manufacturing cell through simulation modeling and general regression model building in an effort to determine the most significant variables that affect the performance of the cell as measured by throughput. Capacity and production planning can greatly be improved with accurate assessments of performance of robotic manufacturing cells. The ability to predict the performance of a cell is highly beneficial in project planning for new cells and integration of flexible manufacturing systems. An inaccurate prediction used in decision making for implementation of new cells can cause organizations to lose a lot of time, resources and money.

Chapter II reviews the literature on robotic manufacturing cells. The review describes concepts such as flexible manufacturing systems (FMS) and cellular manufacturing (CM). In addition, literature on robotic manufacturing systems and performance of manufacturing cells is reviewed, focusing on simulation based studies. While extensive research exists for flexible manufacturing systems, cellular manufacturing, and performance of manufacturing cells, the performance of robotic cells as measured by output is lacking. The current research deals mostly with performance of robotic sequencing in manufacturing cells utilizing a variety of algorithms and search techniques for maximum efficiency.

Chapter III explains the background of the study in more detail and outlines the procedures to be employed in the study. The robotic manufacturing cell studied is explained in detail. Furthermore, it discusses the use of simulation as a model of prediction as well as utilizing general regression models to determine significant variables. Additionally, Chapter III discusses the data collection procedures for critical variables in accordance with the study.

Chapter IV summarizes the data analysis performed including the simulation model building and the regression model building. The results from the study are displayed and interpreted.

Conclusion and Findings

The research presented in this study investigated the performance of a robotic manufacturing cell in multiple phases. The initial phase consisted of building a simulation model based on historical and time study data. The simulation model results were compared to actual production output data. The comparison showed that the simulation model was not predictive of actual output by consistently predicting higher output amounts. Next, an investigation was performed to determine which factors are most significant in affecting the throughput of a robotic manufacturing cell. Upon determining the critical factors, (machine downtime, off-plan time, setup time, weekly schedule requirements, scrap rate and preceding operation output) data was collected and acquired for a period of roughly two months on a robotic manufacturing cell. In order to determine the significance of each of the variables on throughput, multiple regression analysis was employed. The results of the regression model, both backward stepwise approach and forward stepwise approach, indicated that off-plan time and setup time are significant variables affecting throughput, as hypothesized. It was also hypothesized that weekly schedule requirements are a significant factor of throughput. However, the results of the study showed otherwise.

The practical implications of this study suggests that a lot of time is being spent doing setups and off-plan activities such as meetings, projects, layoffs, and working in other areas.

Recommendations

Simulation based modeling is a well established method of analysis used in many different environments. Chapter II highlights some of the key studies that have utilized simulation modeling successfully to analyze manufacturing systems and effectively pinpoint constraints overlooked in project planning. However, the success of simulation modeling is highly dependent on the quality of input data. Majority of the time, this data does not exist without a knowledge or expert system. In order to accurately simulate a process, all the critical variables have to be accounted for. Simulation modeling is frequently restricted by the lack of input data that either cannot be obtained or cannot be simulated. Therefore, simulation models usually present best-case scenarios and predictions.

In a highly dynamic automated manufacturing cell, simulation modeling can be greatly beneficial for effectively and efficiently pinpointing bottlenecks and constraints in the process. However, for purposes of measuring output performance, statistical modeling based on real data can provide much more accurate results. Therefore, an integrated methodology of simulation modeling and statistical modeling can provide more accurate predictions for planning future cells by focusing on significant factors of output.

Future Research

Future work includes studying the same group of variables, as well as some additional variables, over longer periods of time. Duplication of this study in other organizations and environments is encouraged. In addition, the use of an expert or knowledge-based system can be used to acquire accurate input data that can be used to create a more predictive simulation model. Once an accurate simulation model is built, additional statistical analysis can be performed to analyze variables that are most critical in simulating accurately.

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