THE IMPACT OF DISRUPTIVE TECHNOLOGY ON THE MANUFACTURING PROCESS, AND PRODUCTIVITY IN AN ADVANCED-MANUFACTURING ENVIRONMENT

Salawu Ganiyat

218087898

In fulfillment of the Doctoral degree in Mechanical Engineering at the School of Engineering, University of KwaZulu-Natal, Howard College, Durban.

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As the candidate's Supervisor, I agree with the submission of this dissertation.

Supervisor: Prof. Glen Bright

------------------------ February, 2022.

Co-Supervisor: Dr. Chiemela Onunka

February, 2022.

DECLARATION 1 - PLAGIARISM

I, Salawu Ganiyat, declare that

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DECLARATION 2 - PUBLICATIONS

DETAILS OF CONTRIBUTION TO PUBLICATIONS:

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I LOVE YOU ALL!

Dedication

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Abstract

Disruptive technology plays a critical role in the performance of mechatronic systems in an advanced manufacturing environment. Robots were used to perform pick and place task in a virtual manufacturing environment. Newton-Raphson model, renewal theorem and queuing theory were used to model the disruptive technology and develop decision-making algorithms in an advanced process. The motion of the conveyor belt system starved modeled and simulated to determine suitable design parameters that were compatible with the tasks of the pick and place robot.

MATLAB and Engineering Equation Solver (EES) were used to determine static solutions and simulated solutions to the pick and place problem in the advanced manufacturing process. The results from the simulations were used to develop suitable task-dependent operational conditions in the advanced manufacturing environment. The simulation results were used to determine the optimal conveyor speeds required for the robotic tasks. Comparing the throughput rate of the developed system with the simulated system indicated that optimal productivity was achieved when the decision-making algorithms were implemented at the early stages of the manufacturing process.

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List of Acronyms

AMT	Advanced Manufacturing Technology
EES	Engineering Equation Solver
DES	Discrete Event Simulation
SD	System Dynamics
ABS	Agent-Based Simulation
DOF	Degrees of Freedom
OTS	Operator Training Simulators
MSO	Modeling, Simulation, and Optimization
CAD	Computer-Aided Design
SLM	Selective Laser Melting
HRC	Human-Robot Collaboration
DSM	The Dependency Structure Matrix
FIFO	First in, First out
D-H	Denavit-Hardenburg

MR ^{2}G	Mechatronics and Robotics Research Group

CHAPTER ONE

1.0 Introduction

1.1 Research Rationale

Recent innovations in the fourth industrial revolution enhance traditional automation processes using advanced manufacturing technologies [1]. The fourth industrial technology goal was to improve the efficiency of the manufacturing process, improve product quality, boost productivity, and enhance safety and security in an advanced manufacturing environment [1]. The technology was set to lay out strategic operational and technological methods of improving an advanced manufacturing environment. Industry 4.0 involved the integration of smart, disruptive technologies into the manufacturing environment by focusing on automation, real-time data, artificial intelligence, machine learning, etc. The new technology used its automation approach to boost productivity and output, increase efficiency, and created an intelligent manufacturing environment. Industry 4.0 has emerged with various disruptive technologies that can transform various manufacturing sectors from labor-intensive to a modernized automation process [1] [2].

The importance of disruptive technology in enhancing a manufacturing process has become more apparent due to its technological impact on an advanced manufacturing environment. Recently, there have been various attempts to improve the service of an industrial robot to perform some of the complicated and time-consuming tasks in the manufacturing environment [3]. Implementing industrial robots as a disruptive tool in performing tasks has enabled technological growth in the manufacturing sector [4].

Disruptive technology is an innovative technology that strengthened the value of existing technology by providing a more effective m manufacturing means that enhances productivity. Disruptive technology can be described as an innovation that can enhance an existing technology [5]. Advanced manufacturing technology has positively impacted the economic growth of the globalized world by bringing in a new set of innovations, ideas, and skills into the existing technology to improve the production output of the manufacturing firm. The disruptive innovative process creates a new market that benefits the consumers by coming up with cheaper products and allows consumers to access goods and services of their choice. Products manufactured through disruptive technologies are cost-effective. Examples of such technology include personal laptops and computers, email, smartphones, cloud computing, autonomous and near-autonomous vehicles, automated machines, etc.

Advanced manufacturing technologies have been considered an essential part of the continuous effort towards reducing the development time and cost of a product and reducing the development time and cost of a product and reducing the development time and cost of a product and the expansion in customization options. Simulation-based technology is a crucial process targeted by manufacturers to solve problems related to the manufacturing process. The disruptive technologies allow for proper experimentation of the production process before implementation in the actual manufacturing configurations. The use of an automated system like an industrial robot in the manufacturing process has also disrupted the use of human labor. Industrial robots are used to control the production process by using information technology to program their operation. The process reduces or eliminates human labor in many stages of production. Implementing robots as a disruptive tool improves the quality of work achieved and supports effective control of the production cost. Implementing disruptive technologies saves a considerable amount of manufacturing time, saves costs, and improves the throughput rate. The use of classical mathematical models to describe and represent various stages of the manufacturing process enables identifying and correction of errors that might affect the overall output. The production process and output can be optimized to improve the efficiency of the manufacturing process. Disruptive technologies are constantly evolving, and they are positively leading towards more efficient manufacturing systems.

The research presented in the thesis studied disruptive technology's impact on manufacturing, and productivity in an advanced manufacturing environment. The study adopted industrial robots to carry out selected time-consuming tasks in an advanced manufacturing environment. The waiting time during the manufacturing stage was studied using queuing theory and numerical approach. The industrial robots were implemented in the packaging section to perform the pick and place task in a virtual manufacturing environment to study its effect on throughput. The operating and design parameters of the conveyor system were modeled and studied to determine the best design parameters that yielded optimal throughput during the pick and place task. A suitable mathematical model that can be implemented during the planning stage of a manufacturing process for an optimal throughput rate was developed. The operation of an industrial robot was also studied to determine the best operating angle that yielded an optimal throughput during the manufacturing task.

1.2 Background to the research

Manufacturing industries require a flexible manufacturing system that can be cost-effective and produce high-quality products at a reduced cost. Manufacturing industries are often faced with various challenges in improving manufacturing processes such as the product design stage, planning stage, production stage, scheduling, and final output [6] [7]. The development and implementation of industry 4.0 innovations into the advanced-manufacturing environment introduced disruptive technologies that helped manufacturers improve their performance and productivity level in the advanced-manufacturing environment [8]. The industrial revolution enabled the potential transformation of manufacturing industries towards using disruptive innovation and adoption of advanced manufacturing technologies (AMT) into the various manufacturing process [9] [10]. Advanced manufacturing technology (AMT) as a disruptive technology, strengthens and introduces new ways of improving existing technologies [11] [12]. Disruptive technology impacts economic growth by creating better product infrastructure using different labor skills and creating new markets and new business practices [13] [14]. AMT triggers changes in the manufacturing environment by introducing a high-level manufacturing automation level and facilitating human-to-machine communication [15] [16].

The introduction of automated systems such as robots in the manufacturing process has led to positive disruptions in technology and process development [16] [17] [18]. The availability of industrial robots in advanced manufacturing environments enhances the control of the production process through the use of information technology and the internet of things [19] [20]. The use of automation technology in collaboration with human labor reduces or eliminates human labor in certain production stages [21] [22]. Disruptive technologies assist manufacturers to maintain a highly competitive advantage in the labor market adequately. The introduction of new innovative processes in the manufacturing system reduces processing time, increases product output, improves quality, effectively controls production cost, and enhances productivity in an advanced manufacturing environment [23] [24] [25]. Disruptive innovations in an advanced manufacturing environment require further research to determine the impact of disruptive technology on the manufacturing process and productivity in an advanced manufacturing environment. The pick and place task have been a common manufacturing process that requires adequate solutions for improved productivity. The focus of the research was to develop adequate disruptive measures to improve the production process for optimal productivity.

1.3 Aim of the Research

The research aims to research the impact of disruptive technology on the manufacturing process and productivity in an advanced manufacturing environment.

1.4 Objectives of the Research

The specific research objectives are:

i. To research the impact of using robots as a disruptive technology on the process of manufacturing and productivity in an advanced manufacturing environment.

ii. To model the impact of disruptive technology on the manufacturing process mathematically.

iii. To model the throughput rate of an automated manufacturing process.

iv. To model and determine the optimal design parameters for a conveyor system in an automated manufacturing process.

1.5 Significance of the Research

Manufacturing forms the basis for economic growth in the world and requires adequate improvement in the operational process for improved productivity. The research is of significant importance to manufacturing process designers, manufacturers, and process enhancement developers. There are numerous applications of robots in the manufacturing environment—the use of robots as a disruptive technology of interest to the manufacturing community. The research was envisioned to determine how the manufacturing process can be improved for optimal efficiency using disruptive technology. Therefore, it was important to determine the impact of disruptive technology on the manufacturing process and productivity in an advanced manufacturing environment. The research is of significance in an advanced manufacturing environment in order to ensure that complex manufacturing systems are optimal in their productivity.

1.6 Research Contribution to the Field of Knowledge

The research outcome provided some valuable results that can be introduced during a decision-making stage before embarking on any manufacturing process. The implementation of disruptive tools during manufacturing would assist manufacturers in achieving a quality output with improved throughput. The high precision rate and efficiency of industrial robots make them suitable in most applications in an advanced manufacturing environment. Industrial robots were implemented to perform some complex manufacturing tasks. The use of classical mathematical models to describe a manufacturing scenario can be helpful among manufacturers when decision-making is required in the early stage of a manufacturing process. The classical models were analyzed using numerical tools (Newton-Raphson Iteration formula, queuing theory, Engineering equation Solver) and the MATLAB simulation software to arrive at suitable results. The research also arrived at a suitable expression that can be introduced in a manufacturing environment where optimal throughput is required. The outcome from the research provided manufacturers with the best-operating conditions that can yield efficient throughputs when implemented in a real-life manufacturing environment. The research can transform life, business, and the global economy in a great manner which can promote competitiveness and enhance productivity in an advanced-manufacturing environment. Some of the available complex manufacturing that requires robotic intervention for optimal productivity includes: scheduling, pelletizing, pick and place, packaging, and sorting.

1.7 Thesis Outline and Chapter Overviews

Chapter one presented an introduction to the research work. It outlined the theoretical background of the research, the aim and objectives of the research, the significance of the research, the contribution of the research to the body of knowledge, and the overview of the thesis were presented in chapter one.

Chapter two reviewed the literature on the impact of disruptive technology in an advanced manufacturing environment. Current disruptive technologies were discussed, showcasing their various applications and their impacts on the manufacturing environment.

Chapter three presents the mathematical approach towards achieving the objectives of the research. The Queuing mathematical theory was discussed as well as its features, applications, advantages, and limitations. Newton Raphson's Iteration formula was also discussed and its applications in the research. The Renewal Reward theorem was discussed. Chapter three also presented MATLAB and its applications as simulation software in the manufacturing environment. The engineering Equation Solver used for numerical analysis of the mathematical models was also discussed in chapter three.

Chapter four discussed the mathematical modeling and simulation of the throughput in an automated manufacturing system. The impact of the robot as a disruptive technology on the throughput rate during the pick, and places task was discussed. A suitable model was developed and implemented to achieve optimal throughput. The results were also discussed in the chapter.

Chapter five presented the operational variables of a manipulator's arm for optimal throughput in an advanced manufacturing environment. The chapter discussed the enhanced operational process of a manipulator during a pick and places tasks under standard operating conditions.

The pick and place task were carried out, and the manipulator motion was modified within a selected operational range. Mathematical models were developed and analyzed to obtain the best set of parameters that provided an optimal throughput. The results were also presented in the chapter.

Chapter six discusses the modeling of the design parameters of a conveyor system in order to determine suitable design parameters that yielded optimal throughput during a pick and place task. The results were presented in the chapter

Chapter seven presented the detailed discussions of the research results. And Chapter eight presented the research conclusions and recommendations.

1.8 Conclusion

Chapter one provided an overview of the research on disruptive technology's impact in an advanced manufacturing environment. The background to the research, research objectives, and research contributions to the body of scientific knowledge as was articulated in chapter one.

1.9 Summary

Chapter one introduces the content of the research. The theoretical background of the research was discussed. The aim and objectives to be achieved were clearly stated. Also, the significance of the research in advance, the contribution of the research to the body of knowledge, and the overview of the thesis were presented in chapter one.

CHAPTER TWO

Literature Review

2.0 Introduction

The literature reviewed in chapter two was divided into three sections. The first section discussed disruptive technologies and their possible impact on an advanced manufacturing environment. Applications where robots as a disruptive technology have been used in an advanced manufacturing environment to replace selected traditional manufacturing methods were reviewed in the second section of the literature review. The third section discussed modeling, simulation, and optimization as a viable tool in the study of disruptive technology in an advanced manufacturing environment. The fourth Industrial revolution integrates transparency of information, decentralization of decision-making, technical and operational assistance using artificial intelligence, ease of communication among various types of machinery and devices. The implementation of industry 4.0 enables manufacturers to represent a manufacturing system virtually, which can also replicate the real-life manufacturing scenario. The transparency in information allows manufacturers to decide on the outcome of their proposed manufacturing plant. Industry 4.0 provided a suitable means of communication by connecting manufacturing plants with various distribution systems, outlets, and suppliers. The new communication approach has reduced manufacturing costs. Effective implementation of various disruptive tools adequately increased production performance and machine up-time. Industry 4.0 introduced various disruptive technologies and has supported manufacturers to have outputs at a reduced cost. In recent years, the use of robots has been one of the disruptive tools and has introduced tremendous changes in the advanced manufacturing environment.

2.1 Disruptive Technology

Disruptive technology, as an innovative technology, strengthens the value of existing technology by providing a more effective means of manufacturing by increasing productivity. Disruptive technology can be described as an innovation that can be suitably used to replace an existing technology [5]. Various disruptive technologies have been developed to support and to enhance the smooth running of various stages of the manufacturing processes [26] [11]. The introduction of various disruptive technologies, which include the industrial application of the 3-D printing technology, artificial intelligence, the internet of a thing, near-autonomous and autonomous vehicles, have enhanced the variability in the manufacturing system [27].

Disruptive technologies in an advanced manufacturing environment gave rise to the rapid growth in robotics application to augment tasks at various stages of manufacturing.

2.2 Robots as a Disruptive Technology in an Advanced Manufacturing Environment.

Automating machines in automating tasks or augmenting human activity has increasingly enhanced the efficiency in the manufacturing environment. Industrial robots have been efficient automation tools with higher flexibility and can be programmed to perform various tasks within a short time [20] [28]. Robots are designed to be intelligent. The embedded intelligence in a robot provides capabilities to the robot in performing various tasks in an advanced manufacturing environment. The tasks include; assembling parts, disassembling, welding, packaging and labeling, inspection and testing, pick and place, materials handling, palletizing, etc. [29]. All these were achieved with appreciable high speed, precision, and endurance limit [29] [30]. Manufacturing industries require an automation tool that can be cost-effective and meet up the competitive demand in the labor market.

Industrial robots were used to control the production process through the use of information technology. Implementing industrial robots to execute manufacturing tasks reduces or eliminates human labor in many stages of production [31]. Industrial robots enable the manufacturer to effectively control production cost, enhancing productivity and improving the quality of manufactured outputs [32]. Disruptive technology is often referred to as intelligent technology because of its numerous advantages, leading to the enhancement of manufacturing processes [32]. Robots are classified based on certain criteria such as the type of task it performs (manufacturing), types of motion involved (its degree of freedom), its architecture (parallel or serial), and the manufacturer brand.

Robots as a disruptive technology to replace manual labor is highly efficient, reliable, and highly flexible when performing repetitive tasks in an advanced manufacturing environment [15] [16]. The fourth industrial revolution has led to transforming the complex traditional manufacturing system into a flexible, autonomous system. The fast growth in the industrial revolution has led to the replacement of human labor with high-speed automation tools and machinery. Automation tools in the manufacturing systems ease the task of manufacturers' tasks when high precision and repetitive tasks are required [33]. The increase in the use of automation in the manufacturing environment to perform a complex task has led to the development of various types of robots suitable in an advanced manufacturing environment.

An example of a robot capable of performing complex tasks is the Fanuc M-10i robot. The Fanuc M-10i robot has been effective in a manufacturing environment because of its explicit design characteristics. Fanuc M-10i robot was designed with a high degree of accuracy and capable of performing multiple manufacturing tasks. A typical Fanuc M-10i robot is shown in Figure 2-1. The Fanuc M-10i robot was developed with suitable software that is programmable to perform pick and place many parts within a short period. A vision camera integrated with its operating system senses the arriving parts and promptly sends a signal to the robot for immediate detection to pick up as programmed. The use of a robot to automate a task in an advanced manufacturing environment saves production time, production cost, and assists manufacturers in helping manufacturers achieve increased throughput. An industrial robot such as the kuka robot also has its usefulness in manufacturing industries has a common feature with the Fanuc M-10i robots. Its high degree of accuracy and speeds cannot be underrated

Figure 2-1: A typical Fanuc M-10i robot for a pick and place task

2.3 Optimization as an Approach to System Determination.

In [35], an optimized process can detect various shapes arriving from a conveyor belt in an advanced manufacturing environment [34]. The new vision technology has been efficient in increasing the throughput of the manufacturing station. The research presented in [35] [36] [37], showed how robotic manufacturing systems could be optimized for optimal efficiency and productivity. The positioning of the part to be picked up was an area that affected the performance of the robot in an advanced manufacturing environment. The selection of adequate parameters and the use of a simulation-based optimization approach, an adequate solution was developed. The developed solution can improve throughput by using an automated machining system and considering methods to adjust work position for easy machining [36] [38].

Similarly, another robotic problem was solved using the optimization approach. The problem was optimized by effectively maximizing the operating speed of a bipedal robotic system. The optimization process was based on the function fitting of the system and was used to predict the best parameters that can produce the fastest robot [39]. In [41], the chicken fillet harvesting process was optimized by designing a system with a virtual camera, robotic arm, and gripper to separate the fillet. The developed automated system was capable of separating chicken fillet from the chicken carcass effectively [40].

One of the significant challenges faced by manufacturers was to develop an efficient means of improving the throughput rate in an advanced manufacturing environment. A suitable means of obtaining a higher throughput can be achieved by understanding the various means to manipulate the task of the industrial robot. The operational variation for effective motion planning was required to enhance the robotic efficiency to improve the throughput rate. In [41], the learning process of a robot to adequately interact with available objects was examined. The kernel-based approach was employed to recognize objects to be picked up, while spectral clustering was also used to differentiate the form of interaction required (placing, pushing, inserting) for the machine learning [41]. There a few different types of industrial robots: articulated robots, collaborative robots, selective compliance assembly robots, and automated guided vehicles among others. Advanced robotics are making an impact on manufacturing.

2.4 System Modeling Using Classical Mathematical Theory.

A queue is a common problem that exists at various stages during manufacturing in an advanced manufacturing environment. The occurrence of a queue leads to congestion and the cost of waiting affects the productivity level in an advanced manufacturing environment [42]. Mourtzis et al. [43] deduced that the packaging stage requires a practical measure reduce the time spent from the initial stage of manufacturing to the final stage. Elkhodr et al. [44] confirmed the effectiveness of implementing mathematical modeling to describe a manufacturing system in predicting system behavior at various stages in an advanced manufacturing environment. Mathematical models have been used to solve various problems at different stages of manufacturing before implementation in real-world applications [45]. In the research of Manjurul [46], the Queuing theory was effectively used as an analytical tool for solving the waiting line problem. The queuing theory was helpful in predicting the average waiting time of customers in a restaurant and the expected numbers of servers that can attend to customers at a specific period. In the research carried out by Mohammad et al. [47], a waiting line model consisted of the arrival stage, waiting time, and the service rate, was effectively analyzed using the mathematical queuing theory.

Similarly, in [48], the queuing theory was found to be an efficient tool in predicting the behavior of a manufacturing system. The manufacturing process was further stimulated to attain optimal productivity [48]. The use of queuing modeling theory has been effective in model analysis and in describing the behavior of a virtual manufacturing system. Different approaches using numerical methods and queuing theory have been studied to determine the performance of a manufacturing system. The mathematical queuing theory was used effectively to describe the characteristics of an inventory system modeled mathematically. The queuing theory was practical for system flexibility with improved productivity [49].

In the work of Anupama and Solankin [50], a queuing system with unreliable servers experiencing breakdown was analyzed. The Laplace transformation of the system was used to determine adequate system performance. A numerical method was used to present the outcome of the analysis [50]. Similarly, in [44], a queuing system with an unreliable server was also studied. A backup server was assumed to take up action in case of a server breakdown. Matrix geometric technique was used to determine practical performance measures for the manufacturing line. Laplace- transform was used to illustrate the system performance numerically [51]. In [52] the Markovian queuing theory was implemented during the decision-making stage of a multi-stage production system [52]. The queuing theory was used to research the machine parameters that could yield optimal productivity. The outcome was further analyzed under Bernoulli's condition to obtain the desired results [52].

In [53], queue length at the packaging stage in a virtual manufacturing environment was predicted. Specific parameters were assumed to solve the waiting line model using the mathematical expression developed from the queuing mathematical theory [53]. Describing a manufacturing process using the queuing theory and system, analysis can provide a quick and efficient solution to manufacturing problems [54]. In [57], Newton Raphson's iteration formula served as the simulation tool used to analyze and estimate operating parameters that can yield adequate productivity.

From the research of Kamel et al. [55], mathematical modeling and simulation have been effective in estimating the power control devices and a voltage level of a power system. Their findings suggest that the use of the Newton Raphson method as the simulation tool gave more accurate results when compared with some other related methods [55]. Amaral and Cadosol [56], suggested that the Newton Raphson method was effective in the estimation of the optimal condition of an electrolytic capacitor. Similarly, Montaser et al. [57] studied the behavior of a photovoltaic model and was further analyzed with the Newton Raphson iteration method. Nearly accurate results were obtained when compared with the real-life application [57]. The simulation results from previous studies suggest the Newton-Raphson iteration method as a suitable simulation tool when finding optimal solutions to a manufacturing problem. Also, mathematical models have been used to research various manufacturing processes, to predict certain behaviors of some components that can affect productivity.

Toshiba et al. [58] attempted to solve the long queue that existed in the banking hall. The waiting line model was developed to research the behavior of re-occurring congestion. The queuing theory was used as an analytical tool to suggest a quick solution and analyze waiting line models [58]. Related attempts to solve manufacturing problems using different manufacturing models have been carried out by Seyed Hosseini et al. [49]. The queuing theory was implemented to analyze a mathematical model used to describe an inventory system. The research indicated how effective the queuing theory could be in analyzing a system with substitute flexibility. In [49], the queuing theory was used to analyze the congestion of vessels arriving at a river port. The queuing theory was used to suggest a solution to improve service performance and controlling congestion that can lead to a larger queue [42]. Anupana and Solankin [50], used queuing theory to research and analyze a manufacturing system that often experiences server breakdown [50]. Their research suggested a more effective measure that prevented a further breakdown. The outcome from their research showed the effectiveness of the queue theory in analyzing and finding a solution that can predict an optimal service system that can yield optimal productivity.

Gankjaesh and Manish [59], formulated a time-based mathematical model for solving production scheduling problems. The time-based mathematical model was an effective tool used to control the time spent to get a product to the final stage [59]. Cheol [60] evaluated the performance of a generic algorithm using an integer programming model. The unrelated parallel machine scheduling problem was solved by designing a model that can provide an optimal solution to reducing the total completion time during the manufacturing process [60]. Mohamed [61] established a progressive model that can solve complex and large-scale manufacturing problems. The model proposed in the research was used in applications such as supply chain management, production planning and scheduling, and continuous process improvement. Umar et al. [62] employed a progressive close-loop approach to research the relationship between two types of mathematical modeling (the dependency structure matrix (DSM) and stochastic optimization modeling). The stochastic optimization modeling was improved to yield higher productivity than the dependency structure matrix. Guo et al. [63] developed a Pareto optimization model to solve multi-objective order scheduling problems in the manufacturing industry. The model was effective for solving scheduling processes in the manufacturing line. In the research of Shichang et al. [64], the Markov model was implemented in the decision-making of a multi-stage manufacturing system to understand which machine parameters could yield optimal productivity. The production process was analyzed efficiently under Bernoulli's condition to obtain an optimal output.

A single-server with discouraged arrival of customers, having retention of reneging customers was studied by Kumar and Sharma [65]. Models were developed to describe the system, and the Runge-Kutta method was used alongside the queuing theory to analyze model performance. The MATLAB software was used for numerical computation of their results [65]. In [66], a steady-state equation was derived to find a solution to a Markovian single server queuing system having discouraged arriving customers. The iteration method was implemented to solve the steady-state equation using the parameters used during the description of the model in their research [66]. An attempt to control congestion from arriving customers from joining an existing queue was evaluated by Abdul Rasheed and Manoharan [67]. Service switches were introduced into the discouraged arrival of the Markovian queuing system. MATLAB was also used for analyzing the process for the best optimization parameter [67]. Previous works on queuing systems emphasized system performance.

The reliability of the manufacturing system was a contributing factor that has a significant impact on the production throughput. Reliability test was essential in the early stage of the manufacturing process when considering the equipment life cycle and failure rate. Adequate prediction of equipment reliability assists manufacturers to have a clear understanding of potential degradation that could occur during service and to provide adequate solutions when required. The description of the reliability of a manufacturing system that uses conveyors and robotics in its application was researched in [68]. The manufacturing system was analyzed to understand the system reliability and availability of unexpected failure along the robotic manufacturing line [68].

In [69], a desirable allocation of a buffer was suggested to enhance production throughput in an advanced manufacturing environment [69].

2.5 The benefits of industrial robots.

Industrial robots find their application in some of the stages of manufacturing in an advanced manufacturing environment. It is an essential tool in the present-day manufacturing environment as it offers numerous benefits. The benefits derived from the implementation of robots as a disruptive technology in an advanced manufacturing environment are: [32]

i. An industrial robot is cost-effective in the long term, and tasks can be accomplished quickly when using robots.
ii. Implementing industrial robots in performing a task in an advanced manufacturing environment helps manufacturers in restoring some manufacturing tasks and creating more jobs like programming, management, and equipment maintenance jobs.
iii. The high precision rate of industrial robots reduces and eliminates the wastage of resources in an advanced manufacturing environment.
iv. Robots are capable of carrying out some hazardous tasks which can be dangerous to human health and safety. The use of robots makes work to be done at a faster and safer pace within its operating environment.
v. The deployment of industrial robots to carry out tasks at various manufacturing stages maximizes the use of human skills.
vi. Robots can be implemented into the manufacturing process from the initial stage of material handling to the final stages of labeling and packaging. It creates a smooth working environment with good surface finished and high-quality products.
vii. The robot is capable of continuous operation and allows manufacturers to increase throughput rate and produce in large quantities.
viii. The use of industrial robots in an advanced manufacturing environment creates a clean working environment and helps manufacturers to helps manufacturers control costs by saving some utilities such as lightning and water. They do not depend on climate control.

2.6 Impacts of Disruptive Technology in an Advanced Manufacturing Environment.

Automation in the various manufacturing stages as reshaped the manufacturing environment for higher productivity [10]. There are numerous improvements in productivity in an advanced manufacturing environment through the advent of disruptive manufacturing technologies. Robots are one of the widely used automated tools among manufacturers. Its unique design enables it to be efficient in performing some problematic tasks within the shortest period. Disruptive technologies reinforce and enable competitiveness among manufacturers [70]. Disruptive technologies are innovative because of their advantages. The advantages of disruptive technologies lead to replacing specific manufacturing processes [9].

Various researchers have studied the use of various disruptive technologies in computer-aided design and manufacturing. Computer-Aided Design (CAD) is an advanced manufacturing technology that uses the application of computer systems to support the creation, analysis, optimization, and modification of a specific design [71]. Due to the highly competitive nature of manufactured products, the requirement in the aspect of the functionality of parts with improved quality has been significantly increasing [72]. With the advent of disruptive technology, there exist new designs of components with high complexity in manufacturing. Efficient manufacturing system is required in an advanced manufacturing environment [73]. Advance manufacturing technology transforms the manufacturing sector by using 3D printing to disrupt the traditional methods of manufacturing [74] [13].

2.6.1 3-D Printing Technology.

3-D printing is an advanced manufacturing process that creates components layer upon layer [75]. The manufacturing process involves component design with a computer-aided design package of their choice [76]. The application of applying a laser beam melts the raw materials the part is formed upon solidification [76]. 3-D printing can rapidly manufacture prototypes and transform the design to finished products by skipping many manufacturing steps [77] [78]. 3-D printing as a disruptive technology can yield product outputs at a reduced time with minimal production cost. Selective laser melting (SLM) is a type of 3-D advance manufacturing technology that economically supports the mass production of parts [79] [74].

The customization of parts using 3-D printing technology has introduced a certain level of disruptive technology in an advanced manufacturing environment [79]. Designs can be made and customized into mass production as the exact design chosen by customers within a shorter period [79] [80]. 3-D printing technology facilitates the design of products within the manufacturer's capabilities at a faster rate [79]. The use of 3-D printing in an advanced-manufacturing environment in industrial applications enhances raw materials' maximization the manufacturing process [81]. Adequate control of the manufacturing process during a 3-D printing process has the potential of reducing waste to the minimum in an advanced manufacturing environment [82]. In 3-D printing, the raw material can be re-melted and used for another manufacturing purpose [83].

3-D printing has progressively become a disruptive tool for traditional manufacturing processes with its high degree of productivity. 3-D modeling and printing, as a disruptive innovation positively impact the manufacturing of structured parts at a faster rate and lower production cost [84]. The fabrication of intricate shapes and geometrics has been a problem among traditional manufacturers. The innovative technology of 3-D printing has made it possible to fabricate components of intricate geometrics [85]. The lead time for difficult to machine shapes and parts could be reduced significantly by 3-D printing technology [86] [87]. Figure 2-2 shows an example of a complex geometric structure manufactured through automated 3-D printing [88]. 3-D printing technology eliminates the use of expensive tools as it does not require tooling to carry out the required task [77] [88]. Advance manufacturing processes disrupt the processes involved in changing tools during the manufacturing of parts using traditional methods involves during milling, turning, grooving, etc. [84] [88].

Figure 2-2: Complex Structure Manufactured through Automated and Robotic 3D Printing [88].

Due to the limitations in some engineering materials properties, need for improved properties were required to manufacture certain parts [89]. Composites can be produced to influence specific superior properties into parts during manufacturing. Laser metal technology is a member of 3-D additive manufacturing technology that can produce composite materials with improved physical, chemical-mechanical, and microstructural properties [90] [91]. The composites material parts are useful in industries like aerospace, marine, medical, automobile, etc.

3-D technology is suitable to fabricate functionally graded materials with improved mechanical and chemical properties [31] [92]. The functionally graded materials are used for various industrial applications in an Advanced-manufacturing environment [93] [94]. The portability of 3-D printing manufacturing technology can reduce the time spent to get a product closer to the market [95]. It brings customers closer to products when needed. 3-D printing adequately reduces the supply chain management in the marketing structure of the advanced manufacturing environment [96]. 3-D printing is useful in an advanced manufacturing environment because of its high efficiency of processing, productivity, and quality output production [13] [14].

Laser metal deposition is an advanced manufacturing technology that uses 3-D printing for manufacturing and can be used to repair worn-out parts [97]. The use of laser metal deposition in the repair of parts saves the cost of purchasing new parts and reduces waste in an advanced-manufacturing environment [98]. Damaged and worn-out parts can be repaired and restored to their standard functioning form [99].

2.6.2 Advanced Manufacturing and Human-Robot Collaboration.

An effective transformation of the manufacturing sector into a more flexible and efficient process, enables manufacturing industries to have a competitive value in the advanced manufacturing environment. The increasing competition rate among manufacturing industries across the nation continuously promotes an automation tool to enhance the production process [17]. Figure 2-3 shows the process of using robots as a disruptive technology to collaborate and augment human labor.

Figure 2-3: Robot Workplace with Collaborative with Human Labor [17]

Automation tool adequately improves productivity in an advanced-manufacturing environment. The strategy of industry 4.0 adequately promotes the use of robotics as a disruptive technology in the manufacturing process in an advance-manufacturing environment. Robots as an automation tool can augment human labor in an advance-manufacturing environment [17]. Robots are designed with a high degree of freedom. Robots can rotate about more than one axis and can execute tasks in an advance-manufacturing environment [100] [12]. Robots' design configuration allows effective communication and interpretation of human-related activities in an advanced-manufacturing environment [101].

An example of a Kuka robot was used for an additive manufacturing process of laser metal deposition of composite materials [102]. During the manufacturing process, the Kuka robot played a role in carrying out the various tasks involved during the deposition process. The Kuka robot was attached to the equipment and controlled the delivery of the powders during the fabrication of the composite material [31]. During the fabrication process, the efficiency of the robot enabled the automation of the manufacturing process by adequately disrupting the traditional method of fabrication. The robot enhanced productivity and higher efficiency by carrying out the task within a shorter manufacturing period. The improved technology disrupted the traditional manner of handling molten metal, which can be hazardous to human health [31]. Composites and functionally graded materials produced through the advanced manufacturing process have better material properties and beneficial among industries [31]. Materials are handled adequately and controlled by robots during manufacturing. The use of robots reduces waste and the cost of manufacturing in the advanced manufacturing environment [103].

Human-robot collaboration (HRC) in the advanced manufacturing industry has been effective in a virtual manufacturing environment [104]. Human-robot collaboration ensures there is the adequate handling of collaborative tasks between human beings and robots. The collaborative robot used in an industrial application interacts with data processing, actuators, sensors, and human laborers to support the manufacturing process. The human-robot collaboration disrupts the manufacturing process where manual labor is used in the manufacturing environment. HRC has a significant impact on the reduction of production lead-time and improves overall manufacturing efficiency. In [20], the handover process, removal of adhesive backing strip, and fabric layup in a mold were effectively controlled with the HRC system.

In the HRC, there is enrichment in communication between humans, and robots which prevents collision from occurring during manufacturing in an advanced-manufacturing environment. The proper control of HRC enables an advanced manufacturing technology to be highly effective in an advanced-manufacturing environment [21]. In an advance food processing industry, the production cost was maximized by using robots as an automation tool. Robots carried out food processing stages like picking, palletizing, placing, and packaging carried out packaging. Food processing and handling operations were carried out using a robot as a disruptive tool for human labor and yielded higher precision and reliability [22]. Figure 2-4 shows the application of robots in the food processing industries. Figure 2-5 shows the use of robots in an advanced food processing industry for pick and place tasks, cake decoration, and pizza making. Human-related tasks carried out by robots in the food industries and the productivity levels were increased compared to human beings performing the same tasks [22].

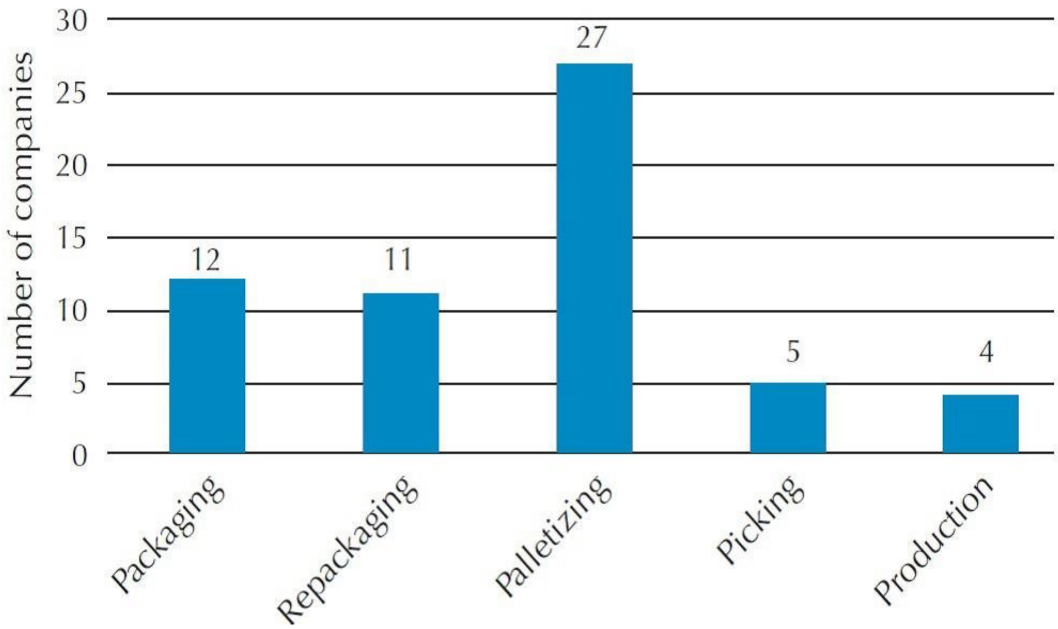

Figure 2-4: Applications of Robots in Food Industries [22]**.**

Figure 2-5: Application of Robots for a Pick and Place task in the food industries [22]**.**

Robots are used as an automation tool in the manufacturing environment to effectively perform human-related tasks reduces manufacturing processing time [20] [28]. Robot as an automation tool can carry out continuous production processes safely, efficiently, and approximately with no error. Robots can perform repetitive tasks during manufacturing processes, which reduces the waste of raw materials during the processing [105]. Robots can handle dangerous tasks and are capable of seeing a tiny object. Robots are useful in areas such as in automobile industries where assembling of parts is required [29]. Effective communication between hybrid robots and other automobile operators enhances the manufacturing process [30].

A hybrid robot using brainwave effectively collaborated with other operators to coordinate collaborative tasks in the automobile industry [106]. Robotics can withstand extreme heat, electric shock, high radiation, toxic chemicals that can be dangerous to human health in an advanced-manufacturing environment [106]. Robots are suitable to be used in the welding of components or parts in automobile industries. The application of robots made the welding of the sheet metal used in making the body of the automobile to be performed at a faster speed [107] [108]. Figure 2-6 shows a typical example of welding using robots in the automobile industry.

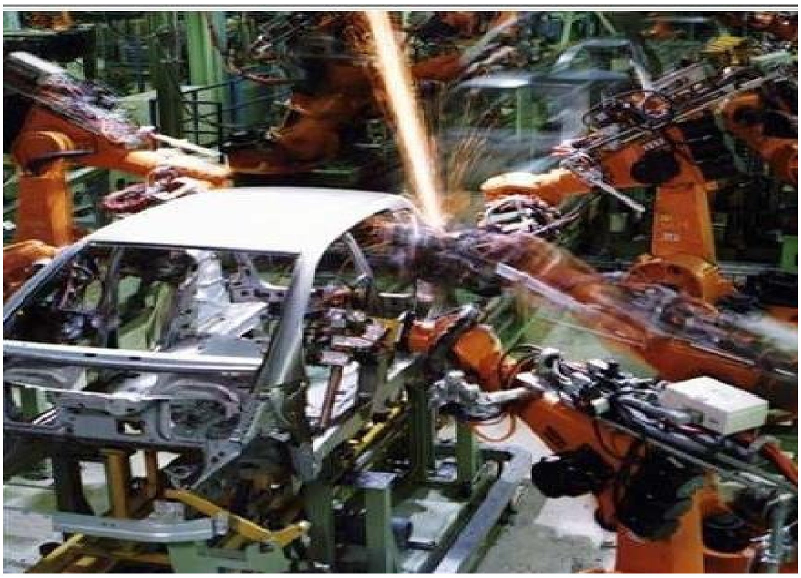

Figure 2-6: Industrial robot welding in the Automobile industry [109].

Fatigue and downtime are significant challenges in a manufacturing environment among human laborers. Convenient control of robots for supporting related manufacturing tasks using mental command was a success [110]. The use of robotics in the assembling process in some automobile industries reduces noise that would have been associated with human-to-human operators. Robot and human collaboration adequately reduce parts assembling time and provides a positive impact on the product, process, and productivity in the advanced-manufacturing environment [110].

The hybrid of different robots can create a changeable advanced manufacturing system. Robots play critical functions in the production and delivery of goods and services [111]. Besides, the hybrid of different robots induces structural changes like scheduling of manufacturing tasks in an advance-manufacturing environment [111]. The addition of new technology to the production line creates a process that reacts to customer specifications and changes in the finished product. [112] [25]. During the manufacturing process, the orientation of robots adequately and effectively controls the manufacturing process since there is no fellow robot that distracts like a human operator. Some waste that may likely set in during the manufacturing process in an Advanced-manufacturing environment can be adequately recycled when using advance-manufacturing technology for manufacturing [113].

Disruptive technology played an essential role in the development of a traffic management system [114]. A convenient parking space needed adequate management among car users to ensure safety and convenience. The innovative idea developed through the internet of things controlled the intelligent parking system. The advanced technology economically displaced the local way of parking that consumed a lot of time. The implementation of an adequate mechanism through the internet of things prevented disputes in the car parking area and adequately managed and controlled the time spent in searching for convenient parking [114].

Industry 4.0 as an emerging technology enhances productivity in the manufacturing environment [115] [116]. Industry 4.0 introduces innovative manufacturing technology such as; smart machining, smart scheduling, intelligent monitoring, and smart decision-making. The disruptive technological tools used in an advanced manufacturing environment enable an effective manufacturing system. The introduction of disruptive technologies facilitates decision-making, satisfies challenging demand, satisfies customer needs, and improves quality. Disruptive technologies provide an enabling platform to produce a customized product at a reduced time and cost [116]. The smart machining process uses robots to to sense and interact with other equipment and machines to accomplish the desired task. The implementation of the internet of things, artificial intelligence, cloud-based solution, and smart machines supports the robot to carry out the manufacturing processes. Adequate decision-making achieved through disruptive technology enhances information communication in an advanced manufacturing environment [116].

The convergence of disruptive knowledge and technology introduces flexibility into the manufacturing process in an advanced-manufacturing environment [117]. The convergence of disruptive technologies enhances the customization of high-quality product in batches [117] [118]. Batch production of commodities introduces a variety of product designs into the global market. An example is the production of women's shoes in customized batches enables various designs to be available in the market compared to the mass production of only one design. Batch production as disruptive technology improves the market value and the level of competitiveness in the market. Disruptive technology in an advance-manufacturing environment also allows customers to relate with manufacturers through internet technologies. The customer manufacturer relationship encourages standard production and diversifies products in an advanced manufacturing environment [117] [119].

Disruptive technologies have an impact on productivity levels in an advanced manufacturing environment [120]. The productivity level of the advanced manufacturing environment increases daily with the implementation of various disruptive technologies into the manufacturing processes. Advanced manufacturing technologies displace the traditional manufacturing process and replace it with manufacturing processes that use disruptive technologies to create value [121].

Advanced manufacturing technology brought various innovations into production methods in an advanced manufacturing environment. The industrial revolution of disruptive technologies has initiated new manufacturing processes that facilitated the replacement of most labor work with machines [122]. Machining processes such as forming, casting, molding, and others, which require substantial processing time, can be performed by the new disruptive technology additive manufacturing technology [123].

During the additive manufacturing processes, disruptive equipment like computers and robots communicate with other advanced manufacturing equipment to fabricate components [124]. Additive manufacturing processes eliminate human intervention during the fabrication process. A computer-based technology sends the design information to the robots, which will carry out the required task and enhances productivity [125]. The additive manufacturing technology enables freedom of design and can facilitate the manufacturing of complex geometries with a high degree of accuracy [126].

2.6.3 Impact of Disruptive Technology in the Manufacture of Medical Equipment.

The health care sector uses disruptive technology as an effective tool to enhance the productivity of medical devices [127]. The health care sector carries out various forms of diagnosis and therapy on patients that require quick and reliable medical solutions. The use of advanced manufacturing technology in the manufacture of medical devices enhances the decision medical devices' manufacture enhances the decision-medical professionals' decision-making process. Visualization-based technology is a disruptive technology used to improve human beings' interaction with machines and various medical equipment. Visualization technologies provide an adequate and compelling view of product, process, and services to improve productivity in the medical sector advanced manufacturing environment.

2.7 Mathematical Modeling, Simulation, and Optimization as a Disruptive Technology.

2.7.1 Mathematical Modeling.

Mathematical modeling can be used as a disruptive technology in the development of a manufacturing process. Mathematical modeling can be used in describing the manufacturing system, process, and behavior [70]. Models are used in the advanced manufacturing environment to represent the real-world application of the manufacturing system/process [128]. Mathematical models facilitate focused research and understanding of the manufacturing application process addict the pattern and behavior of the manufacturing system [128] [9]. The implementation of mathematical models in describing the behavior of the desired manufacturing system/process assists manufacturers in achieving a fast and accurate decision in a given application of a manufacturing process [87]. Mathematical modeling saves reasonable time and materials as the manufacturer may have an insight into how the system would behave in the real-life application.

The application of mathematical modeling in manufacturing involves representing a real-world manufacturing system using quantities and variables that can be examined safely and cost effectively [66]. The disruptive innovation in mathematical modeling provides a platform to test the real-life application of the same manufacturing processes. The manufacturer at each stage can easily change various processes and plans using the simulation tool to achieve his targeted manufacturing output [66].

Production cost is a criterion that can determine a manufacturer's competitiveness in a larger market [128] [129]. Effective manufacturing requires an efficient tool that can be cost effective, accurate, and suitable for effective decision-making [130]. Stages involved during manufacturing are complex, causing manufacturers to develop innovative ideas and products which can adequately compete in the global market [13]. The use of various disruptive innovations affects overall productivity in an advanced manufacturing environment [82]. Mathematical models and simulation software used in developing manufacturing systems ensure manufacturing processes are designed to be flexible and cost-effective [131]. Various disruptive technologies have been developed to support and enhance the smooth running of various stages of the manufacturing processes [67] [78]. Mathematical modeling and its application in the various manufacturing processes enables manufacturers to have adequate planning of their various manufacturing processes [8] [7]. Various stages of manufacturing have been described and analyzed using modeling and simulation tools [132]. Specific long-term applications in the manufacturing process can be described using mathematical models to represent stages and processes involved during manufacturing stages in an advanced manufacturing environment [133].

2.7.2 Simulation.

Simulation as a disruptive tool in manufacturing process development can support decision-making during the manufacturing process. Simulation tool helps manufacturers build a virtual system using different methods before implementing the system. Simulation is a cheap and faster means of solving problems in the manufacturing system by helping the manufacturer enhance decisions. Simulation can be performed using simulation tools such as Discrete Event Simulation (DES), System Dynamics (SD), and Agent-Based (AB) Simulation. Simulations have been used in the design of the manufacturing systems and operations [134]. In [160], A simulation tool was used in analyzing the supply chain management level and enterprise level of a manufacturing system [135]. The numerous advantages of simulation become a challenge and lose effectiveness when too many decision alternatives are to be considered simultaneously.

In [112], a simulation method for changeable manufacturing and its suitability to the manufacturing system was studied. Simulation tools provide the platform on which models can be developed and used to simulate the management of an advanced manufacturing process. A simulation tool to support decision-making during manufacturing allows manufacturers to plan and optimize the manufacturing processes [6].

2.7.3 Benefits of Simulation in an Advanced Manufacturing Environment.

Simulation checks and validates process automation system by using software and training of operators to provide numerous benefits and growth in technology development. The benefits are:

Changing workforce leading to skills gap: With the fast growth in technology, there is a need for well-trained operators that helps minimize human error, reduce material wastage during production, reduce idle time, and enhance providing room for a conducive environment. Operator training simulators (OTS) are used to train operators and used as a tool to refresh the skills of experienced operators.

Simulator justification: The simulator's justification is in the simulator ability to determine the required automation system and provide operators with a better understanding of a new manufacturing process. OTS is typically purchased as part of the significant plant during manufacturing setups.

(i) Simulation offers substantial business benefits: Simulation reduces the production cost, damage to equipment, costs incurred on environmental excursions. Simulation increases saving by reducing the cost incurred in the production process.

(ii) Enhancing human performance through training: Operator training simulators OTSs are the preferred method to train and certify operations staff before plant startup and production. The training of operators before the production process accelerates the learning curve on the new process and the automation system.

(iii) Simulation reduces risk and startup times: The quality of the automation system is an essential tool in the manufacturing process. Simulation ensures that the quality of the automation system and the application software are following the production requirements of the organization.

2.7.4 Relevance of Simulation and Modeling in an Advanced Manufacturing Environment.

The implementation of mathematical measures in an advanced manufacturing environment focuses on using classical models to represent the behavior of the manufacturing processes and systems. An analytical tool can be employed during the approach which further leads to the development of mathematical models [37]. The mathematical models can be solved numerically or by using simulation software to decide [6]. Various results can be compared against each and represented graphically to give a clear description and analysis of the outcome. The manufacturer can use the results from the simulation to obtain optimal productivity [39]. Mathematical modeling and simulations (MS) as a disruptive tool, have been used in an advanced manufacturing system such as in the control of manufacturing processes and systems, supply chains management, inventory and labor control, tools, equipment, machines, information systems, and logistics [95] [74].

Adequate application of mathematical models and simulation in describing manufacturing processes provides manufacturers reliable information required in assessing the future of a business. Modeling and simulation tools enable managers to make accurate decisions when results are compared against each other using simulation software to achieve optimal productivity. The benefits a manufacturer derives from using mathematical models and simulation software in an advanced manufacturing environment are:.

- Modeling and simulation enable manufacturers to determine the behavior and final result of a new production process [33].
- The possibility of manufacturing new products, multi-product, and designs can be evaluated using the modeling and simulation tool [36].
- Modeling and simulation support manufacturers in the development and validation process used in processing data obtained in a manufacturing process.
- The future implication of proposed innovations can be determined using the modeling and simulation tool [74].
- Modeling and simulation can be very effective during the evaluation of resources, allocation of buffers, queue analysis, scheduling, and planning in an advanced manufacturing environment.
- Modeling and simulation can be used to evaluate the impact of a new design and process on the overall performance [131].
- The layout and flow of materials can be analyzed within a manufacturing workstation using the modeling and simulation [67].

- Modeling and simulation can be used in capacity planning, production scheduling, and analysis for proper material handling.
- Modeling and simulation can be a training tool for personnel in new manufacturing systems and processes.
- Modeling and simulation can be used in developing measures for comparing various predicted performances, which allow for continuous improvement of the production process [67].
- Modeling and simulation enable the discovering and analysis of bottlenecks that may occur during production.
- Modeling and simulation can be used in the early detection of manufacturing errors and providing adequate solutions.
- Modeling and simulation can be used to develop measures for controlling congestions and queues in the manufacturing system [67]

2.7.5 Factors inhibiting the use of Mathematical Models and Simulation Tools.

The cost of modeling and simulation technology is the primary factor that affects the adoption of simulation tools in the manufacturing industries. Factors inhibiting the use of simulation tools by manufacturers are:

- Cost of training and retraining current and proposed staff on the use of simulation and modeling techniques.
- The complexity of the targeted area that requires modeling and simulation
- Availability of data required during the process of using the simulation tool
- The risk involved in inventing the new technology without the modeling simulation approach
- Software licensing cost
- Cost of computing, setup up hardware, and related devices
- Cost of translating the company's existing data

2.6.6 Applicable Simulation Software used in an Advanced Manufacturing Environment

The use of modeling and simulation as the disruptive technology in addressing identifiable problems encountered during the manufacturing process has benefits to the manufacturer [24]. Simulation software can be used to describe and represent a manufacturing process virtually. A simulation environment allows manufacturers to have adequate control over their desired output. Modeling and simulation as a disruptive measure provide manufacturers with useful information on the long-term effect of the possible new idea [136].

Examples of software that can be used in modeling and simulating an advanced manufacturing process include:

MATLAB: MATLAB is suitable for computation of technical data, data analysis, and solving complex mathematical models. MATLAB has an iteration tool that can be employed when different classical modeling results are required to be compared against each other. The iteration process provides a more precise outcome which enables the manufacturer to choose the best operating conditions/parameters that can yield higher productivity. The accuracy and speed of achieving optimal and efficient results made the MATLAB is suitable software for model analysis and results computation. MATLAB has an iteration tool that can be employed when different classical modeling results are required to be compared against each other. The iteration process provides a more precise outcome which enables the manufacturer to choose the best operating conditions/parameters that can yield higher productivity. The suitability in term of higher precision made it an efficient tool in the present research.

- **ANYLOGIC:** ANYLOGIC provides a multi-approach solution to simulation which can be used for discrete event, agent-based, discrete event mathematical simulation models. Anylogic can be used to obtain optimal solutions in areas such as manufacturing, traffic management, healthcare industries, aerospace, supply chain management, and business processes.

- **SIMUL8:** SIMUL8 is manufacturing simulation software capable of optimizing production processes, planning, logistics, designing and can be used to effect changes on the production line. SIMUL8 can be used to represent and describe a real-world manufacturing environment. It can help determine plant capacities, the number of operators required for a given task, and the throughput rate in an advanced manufacturing environment.

- **SIMULINK:** SIMULINK software is suitable for analyzing classical models in an advanced manufacturing environment. SIMULINK is integrated with MATLAB SIMULINK is an analytical tool when considering models of dynamic systems.

- **ARENA:** ARENA is automation software that enables the derivation of different experimental mathematical models, which can be used in representing various logics and processes. Arena simulation software can be incorporated with Microsoft excel for efficient result analysis.

- **SIMSCALE:** SIMSCALE computer-aided software is designed to simulate a manufacturing environment when fluids to simulate a manufacturing environment when fluid flow parameters are required to be analyzed. The software is suitable for simulating and optimizing parameters that can improve working parameters to yield optimal results.
- **FLEXIM:** FLEXIM powerful simulation software used for model analysis in an advanced manufacturing environment. It can be used to visualize the long-term implications of manufacturing innovations.
- **ANSYS:** ANSYS used in the design of electrical components and thermal analysis. It is also used in analyzing designs of 3-D parts.
- **PRO MODEL:** PRO MODEL is suitable software that can be used to manufacture parts where the design is required to be altered during the manufacturing process. Modeling and simulation have been an effective approach used in measuring the performance of various manufacturing stages in an advanced manufacturing environment. It saves considerable time and cost and provides insight to projected manufacturing plans.

MATLAB is suitable for computation of technical data, data analysis, and solving complex mathematical models. MATLAB has an iteration tool that can be employed when different classical modeling results are required to be compared against each other. The iteration process provides a more precise outcome which enables the manufacturer to choose the best operating conditions/parameters that can yield higher productivity. The suitability in term of higher precision made it an efficient tool in the present research.

MATLAB was used for computation of data, data analysis, and solving complex mathematical models. MATLAB has an iteration tool that can be employed when different classical modeling results are required to be compared against each other. The iteration process provides a more precise outcome which enables the manufacturer to choose the best operating conditions/parameters that can yield higher productivity.

2.7.7 Applications of Modeling and Simulation in Manufacturing.

Modeling and simulation have been used in addressing problems associated with manufacturing processes in the manufacturing environment. Modeling the manufacturing environment is the virtual representation of the real-world manufacturing system.

Manufacturing problems that can be researched using modeling and simulation are:

- Evaluation of running cost for manufacturing processes

- Planning number of personnel required for a given task
- The decision on the suitable machines and equipment required for a designed objective
- The layout of tools, types of machinery, and equipment
- Implementation of change in design/formulation during production stages
- Evaluating the throughput of a particular manufacturing process
- Analyzing the time spent on each task
- Queue length of products
- Production process planning and scheduling
- Evaluation of the functionality of newly introduced equipment during the manufacturing process
- Controlling of congestions
- Discovering and analysis of bottlenecks that might arise in production.
- Early detection of manufacturing errors and providing adequate solutions.
- The manufacturing problems can be grouped into three broad categories. The broad categories are:

1. Evaluation of the required resources (labor and equipment).

- The number of machines and equipment required for a particular manufacturing task.
- The physical layout of conveyors and other equipment required to support manufacturing processes such as the positioning of pallets and fixtures.
- Allocation of buffer stations and sizes.
- Evaluation of the benefit derived from introducing additional equipment along the line of production.
- Evaluating the effect of changing the product mix ratio.

2. Performance evaluation

- Analysis of throughput
- Evaluating the average time required to accomplish a task.
- Bottleneck identification and analysis

3. Evaluation and management of the operational process.

- Quality control checks
- Reliability of resources and types of machinery
- Personnel and equipment utilization
- Queuing analysis of the size and type of queue in the system.

2.7.8 Simulation Technique

Various simulation techniques can be used as a disruptive tool in analyzing mathematical models for obtaining varying values that can yield optimal results in an advanced manufacturing environment. The types of simulation techniques are discrete event simulation (DES), system dynamic (SD), hybrid, agent-based simulation (ABS), Monte Carlo, Petri-net.

The applications of the simulation techniques are presented in Table 2-1.

Table 2-1: Applications of the Simulation Techniques.

S/no	Type of simulation	Applications	Description of task
1	DES	Allocation of resources	It can allocate equipment to the simulation suit and improve the flow of raw materials and operational processes
2	SD	Model Forecasting	It can be used to compare various available models required for forecasting
3	Hybrid technique	Location of required facilities	Minimizing cost by promptly locating required facilities
4	DES	Balancing of an assembly line	For designing suitable and balanced assembly lines
5	DES	Adequate planning & Scheduling	Production process scheduling, throughput analysis, control of idle time, job sequencing, and reliability of job delivered

6	DES, Monte Carlo	System inventory planning and management	Batch size allocation, holding cost, inventory costs, and stages
7	DES, ABS, Petri-net	Transportation	Traffic control, transport route allocation for moving goods, pricing, moving of finished goods
8	DES, SD	Quality	The overall quality of services and improvement of the production process
9	DES, ABS, Hybrid	Early-stage planning of production requirement	Batch size allocation, scheduling, and future forecasting

The measurement of manufacturing systems is a means of analyzing the overall efficiency of the manufacturing system. Adequate evaluation of the manufacturing system provides information on the long-term behavior of the system. Modeling, Simulation, and optimization have become a useful tool in measuring errors such as bottlenecks in the manufacturing process.

When deciding a manufacturing process, the implementation of mathematical model is an effective approach that is convenient, faster, and reliable in proposing an outcome in an advanced manufacturing environment [137]. A mathematical model provides valuable information that helps the manufacturers select the best manufacturing condition that can yield optimal productivity [138]. The implementation of a simulation tool along with a mathematical model provides manufacturers with the best manufacturing conditions.

The modeling and simulation tool may not yield a satisfactory result if various manufacturing conditions are not varied against each other and compared to select the best operating parameters. Simulation software provides an iteration tool to compare various parameters within a chosen range of values to estimate optimal productivity values [139] [140]. The problems faced by manufacturers include Material handling, inventory control, changing design, manufacturing of complex shapes, inventory control, achieving optimal throughput, which can be solved using modeling, simulation, and optimization tools [139].

High operating costs can affect the competitiveness of products in the marketplace [141]. Modeling and simulation have been used to improve energy efficiency to save manufacturing costs [142] [143]. In [144], operating cost was controlled using information derived from mathematical models used to represent and describe material handling processes and conveyor system management. Suitable mathematical models were derived and analyzed statistically to evaluate and enhance the efficiency of the conveyor system. The conveyor system with improved energy consumption was achieved by controlling all available drives [144].

Motion planning of the robotic arm in the manufacturing environment has become an important area that can determine the efficiency of the manufacturing process [145] [146]. The use of mathematical modeling, simulation, and optimization has successfully obtained the best motion required by manufacturers to obtain optimal throughput [147] [148]. A pick-and-place task is a common task in an advanced manufacturing environment. Proper selection of parameters that can yield efficient productivity can be achieved using the disruptive measures derived from mathematical modeling, simulation, and optimization. Simulation tools have been effectively used to estimate the motion, time, sizing, arrival rate, and maximum speed that can yield optimal throughput during the manufacturing process [149] [150] [151] [152]. The task of a manipulator was evaluated by using classical mathematical models and algorithms to determine the effect of independent and dependent parameters on the time of operation. In [153], an actuator was studied by considering all the electrical components involved in the manipulator motion. A simulation was carried out to determine the best operating conditions and design parameters that enabled the actuator to perform the pick and place task within a short period and with optimal efficiency [153].

Simulation has been used in determining the set of parameters that can be suitable for the development of practical tools used in the robotic manufacturing system. The simulation tool was useful in analyzing a pick and place task to determine various manufacturing conditions, such as the number of robots required for a particular job, positioning of robots, the distribution of materials along the manufacturing line, which also assisted manufacturers to make quick decision of a manufacturing process [154]. In the work of Khalid et al. (2018), optimization and simulation tools were used to analyze series of designed models. A generic algorithm was analyzed and optimized to minimize the total energy consumed by the manipulator. All the joints and angles of rotation were effectively optimized, and the simulation run was done with the MATLAB software to achieve optimal results [155]. Similarly, mathematical measures using simulation and optimization were used to describe a robotic grinding system's layout and operational characteristics to describe a robotic grinding system layout and operational characteristics. The stiffness performance was evaluated along with the production layout. The simulation results were used to determine the best installation position and stiffness performance for the grinding system. The set of parameters and operating conditions were simulated and compared against each other to achieve optimal efficiency. The optimized scenario gave a better output [156].

In [33], a modeled manufacturing environment was analyzed using simulation software to decide on which process can yield optimal productivity [33]. Manufacturing system models can be optimized for variation in production processes [157] [40]. Manufacturing models can introduce additional designs and decisions into the manufacturing process, and the simulation software can be a suitable tool for testing the manufacturing decisions [40]. Various manufacturers have explored modeling and simulation tools and researchers, and different approaches have been implemented toward enhancing productivity in the manufacturing environment. For example, Troels used the simulation-based approach during the optimization of an adaptive robotic manufacturing system that performs pick and place tasks on the deformed part [158].

The effectiveness of the scanner was improved by integrating a lighting system into a robotic system to perform pick and place tasks. The proposed simulation method adequately improves the robotic system performance for higher efficiency. In [18], a numerical optimization approach was developed to research and analyze a suitable process to facilitate robotic handling of delicate manufactured parts [18]. Monostori [159], researched the application of agent-based system (ABS) in engineering design during process planning, production scheduling, production planning and control. In [197], the simulation tools and agent-based concepts were a new technology that was increasingly being used in manufacturing system setup. Modeling and simulation as a disruptive tool were used as an optimizing tool for manufacturing control, scheduling, process planning, and supply chain management. It is also helpful during the scheduling of a particular production process [159].

Branislav and Pavol [160], research the trends in the simulation and planning of manufacturing companies. The research was initiated with an attempt to plan and optimize the manufacturing process through the use of a factory simulation approach. Process analysis was carried out, development of a simulation model was carried out, and a structure for input data (bill of material, operation time, material flow, pallet dimension, tables for data, etc.) was prepared. A Gantt chart was generated after the simulation process, which serves as a basis for monitoring the production stages by identifying any problem and allows corrections to be made on the production plan before final production. The research was able to deduce that using a simulation tool in supporting decisions during the manufacturing process allows the manufacturer to detect a probable fault that may arise on products and helps resolve it before proceeding to the final production stage. In the work of Selim *et al*., [24], a simulation method for changeable manufacturing and their suitability to the manufacturing systems were evaluated. Three different simulation tools were studied: system dynamics, discrete event simulation, an agent-based system. Conclusions were drawn that these three simulation tools were becoming less effective as a decision-making tool. The increase in the complexity of the manufacturing system due to advances in manufacturing technology was rendering the three simulation tools obsolete. Hence, it was suggested that the need for an improved simulation methodology that will enable adequate exploration and evaluation of changes encountered during the manufacturing system is required.

Railsback *et al*., [161] based their research on five agent-based simulation platforms (MASON, Repast JAVA, Swarm, and NetLogo). A review was done to compare their effectiveness in manufacturing. A detailed comparison was done between the platforms to understand their general simulation issues such as the scheduling of action execution, model structure, and general programming experience. It was deduced that NetLogo performed better than the other simulation platforms. NetLogo was recommended for modeling in a complex system. In the study done by Wilson *et al*., [162] the modeling, simulation, and optimization of the material flow in a multiproduct assembly plant was investigated. The study aimed at developing a software that reduces the time spent by a product in the system and to improve the manufacturing system's hourly throughput. An efficient system that accomplishes the task was successfully developed. Arena simulation software was used to develop a generic simulation model based on two products (domestic and commercial furniture as well as industrial timber products). The simulation as a disruptive tool was used to increase the average hourly throughput and creating room for additional storage facilities before the production process at various work stations. The generic software that was developed was compatible with other products in the company and hence suitable for the company production aspect of planning and scheduling. It was suggested that manufacturers should acquire arena simulation software to enhance production.

Further studies were carried out by Crostact *et al.,* [163] in manufacturing process safety using simulation for the assembling process. Tolerance and inspection planning for the assembly process was optimized. Solutions were developed using a simulation tool. The outcome revealed that the simulation tool assisted in the evaluation and investigation of tolerances and inspection planning. The results facilitated the selection of suitable tolerances and inspection strategies without experiencing any risk at the time of actual production. Also, the research improved product quality; cost the time spent during production was reduced. Hence, a simulation tool helps manufacturers achieve various goals that enhance their productivity and support management in justifying their investment in a manufacturing process.

2.7.9 Disruptive Technology and Advance Manufacturing.

Disruptive Technology (DT) has impacted the economic growth of the world positively. It is a technology that brings in a new set of innovations, ideas, and skills into the existing technology to improve the production output. The innovative process creates a new market that benefits the consumers by coming up with cheaper products and even allow them to access goods and services of their choice [164]. The technology requires further research to enable proper research on the impact on products, processes, and productivity in the advanced manufacturing environment. Advanced manufacturing refers to a current technology that uses a computer-aided device to promote the production process. It has excellent potential to manage resources during the production process. The advanced manufacturing process ensures that scraps and unused materials can be recycled for other production processes. Advanced manufacturing can be referred to as smart technology because of its numerous advantages, leading to the replacement of substantial means of manufacturing and processes [164]. Table 2-2 shows how disruptive technological tools influenced the manufacturing settings and their impacts on productivity.

Table 2-2: Top Six disruptors.

Disruptive technologies	Effect on productivity
Mobile internet: Increasingly inexpensive and capable mobile computing devices and Internet connectivity	Enabling more efficient delivery of services and opportunities to increase workforce productivity.
Automation of Knowledge work: **Intelligent software systems that can perform knowledge work tasks involving unstructured commands and subtle Judgments.**	A threat to the service sector, especially with voice recognition allowing computers to interact with customers, is imminent. It will allow for the automation of a lot of knowledge work and make it cheaper and more accessible.

Internet of Things: Networks of low-cost sensors and actuators for data collection, monitoring, decision making, and process optimization.	A positive for the industry because it allows companies to manage assets and optimize the performance of the production processes by having improved sensors and remote monitoring.
Cloud Computing: Use of computer hardware and software resources delivered over a network or the Internet, often as a service.	Negates the need for having lots of hardware equipment because software and hardware are now accessible remotely over the Internet.
Advanced robotics: Increasingly capable robots with enhanced senses, dexterity, and intelligence used to automate tasks or augment humans.	An obvious threat to manufacturing jobs, but can boost productivity and reduce costs. Also, it is a threat to industries such as healthcare as some tasks would be able to be performed by robots and services such as cleaning and maintenance.
Autonomous and Near Autonomous Vehicles: Vehicles that can navigate and operate with reduced or no human intervention. If regulation allows, as early as 2020, autonomous cars, aircraft, and boats can revolutionize transportation.	Reduces the cost of maintenance.

2.7.10 The applications of Disruptive Technology to Enhance Throughput in an Advanced Manufacturing Environment.

Disruptive Technology has been an effective tool in the development of advanced manufacturing technology. The application of disruptive technology in manufacturing enhances productivity by increasing the throughput rate of the various manufacturing processes. The application of mathematical modeling, simulation, and optimization is a disruptive measure that supports manufacturers in the early stage of planning a manufacturing process. The model-based approach has been helpful in obtaining suitable working parameters for a conveyor system. The competition in manufacturing industries requires a practical design that can lower the utilization of operating resources [165] [166] [167].

Therefore, a design that can reduce power utilization is required to lower the overall cost of production. Previous works have been done to research the conveyor system efficiency using various approaches. Shirong and Xiaohua carried out research to improve the energy efficiency of the conveyor belt systems by using modeling and optimization approaches. The analytical modeling was used to describe the stages involved in its operation. Various parameters were assumed to represent the conveyor operation, and the model was simulated and optimized to achieve the best operating efficiency [168]. In the work of Irfan and Sania [169], the energy efficiency of the conveyor system was studied by considering various factors that contributed to the cost of electricity of the conveyor system.

The different stages of the conveyor system operation characteristics were modeled. The driving speed of the conveyor was considered when it was fully loaded, partially loaded, and when there was no load on it. The relationship between the belt loading dynamic, and rate of power consumed during conveyor system operation were determined [169]. Energy reduction has been a significant area of interest to researchers. Energy reduction enables manufacturers to reduce the cost of manufactured parts. An attempt to control the energy consumption of a conveyor system was researched by Halepoto et al. The cost of electricity in electrically and mechanically driven conveyor systems was evaluated by controlling the mechanism's multiple drive system. There were an adequate evaluation and integration of factors that lead to a high electricity consumption rate [170].

A dynamic model was developed and suitable for comparing the driving mechanism of a conveyor belt. The simulation outcome was used to analyze the relationship between the dynamic behavior of a multiple-driven conveyor system and a single conveyor system [171].

Weight of materials is part of the design factor to be considered when designing a conveyor system. In [172] [173], a roller belt conveyor system was redesigned for weight reduction. The optimization of an existing roller was done by redesigning the C-channel that serves as the support for the chassis and modeled using the ANSYS software. The re-designed chassis gave a roller conveyor with minimal weight [173]. The evaluation of materials for the design of a conveyor belt requires the selection of standard design parameters that can be cost-effective, durable, and can be able to withstand load above its limit [165]. Sustainability was an important factor that was considered when designing the conveyor system.

The conveyor system must be able to sustain any environmental factor without affecting its operations. The approach to optimizing the design of a conveyor system leads to more effective manufacturing by reducing the cost of manufacturing. A suitable design was selected for the conveyor chain. The design adequately reduced the energy consumed during the service condition of the conveyor system [6]. In [174], speed control of the conveyor belt was used to reduce its energy consumption. Effective control and simulation or system analysis produce an optimum acceleration time [174]. The rapid growth of technology required conveyor design that can satisfy the transportation of any kind of material. Parameters such as the shaft pitch, number of rollers incorporated were studied to enable the conveyor belt to adequately handle glass materials of different sizes [175].

In [214], a composite system for a conveyor line speed was designed and modeled. The controller was effective in solving some of the existing manufacturing problems [176]. An adaptive observer was effectively implemented in estimating some of the unknown parameters of the conveyor belt system. The model developed gave a reliable output when it was used to measure the angular velocity of the rotor that drove a DC motor as well as the feed rate of the conveyor belt system [177]. Different methods of transporting materials exist in the manufacturing industry, the use of a conveyor belt has been one of the most efficient means of transporting materials and parts from one manufacturing stage to another [178]. The robotic arms are designed with a high degree of freedom and can be a disruptive technology the manufacturing space. The degrees of freedom enable the robotic arm to perform a repetitive task within the shortest period [179] [180].

The multiple degrees of freedom of robotic arms play an important role in various applications of automation [180]. The use of robots provides higher precision in operation as compared to work done manually by human operators [181]. The operational variation of industrial robots can have a great impact on the throughput rate in the manufacturing environment [182]. |During service, the robots imitate the actions of real humans and robots when collectively performing a complicated task in manufacturing industries [183] [184]. The pick-and-place task is the critical activity carried out by robot manipulators in manufacturing environment [22]. The manipulator is designed to be flexible, and the operations can easily be varied for optimal efficiency [185].

In the research of Kowalczyk [229], various obstacles were modeled to understand the convergence of robot motion towards a targeted direction. The algorithm was proposed and the gradient was generated, which gave a significant value that can increase the smooth movement of the robot within its work envelope [186]. Domski et al [229] designed an approach to control mobile manipulator motion along an unknown terrain. An algorithm with various classical models was developed to describe the manufacturing system. The concept of fictitious force was used to research and analyze the developed models and algorithms. A simulation was carried out to achieve an optimal result. [187]. Service robots can improve the operational relationship among customers, and eliminate the human customer's relationship [187].

In [188], a method was developed using a simulation tool to improve the performance of multi-robot operation during a pick and place task. The optimization of an operating process gave rise to the utility rate of the robot [189]. The simulation tool employed gave a more accurate outcome which also follows a similar trend with the real-life situation in the manufacturing sector [189]. The research work presented in the thesis used the Fanuc M-10i robot platform to investigate the impact of disruptive technology in manufacturing processes. The Fanuc M-10i manipulator was available at the mechatronics laboratory of the University of KwaZulu-Natal, Durban, South Africa. The technical specification of the Fanuc M-10i robot showing the joints, motion range, and maximum speed were used developing the mathematical models used in the research The manipulator was-designed with 6 controlled axes, repeatability of $\pm$ 0.03°, a mechanical weight of 130kg, arms reach of 1422 mm, and a maximum load capacity of 10kg [188].

2.8 Conclusion

Disruptive technologies have influence advanced manufacturing positively. The implementation of disruptive technology like 3-D printing, the internet of things, and automation in the manufacturing environment has reshaped the advanced manufacturing environment. Disruptive technologies have significantly made the manufacturing process more effective and productive. There is a need for further improvement in the application of disruptive technology in hand tracking, the layout of products, and scheduling in an Advanced-manufacturing environment.

Subsequently, the mathematical modeling and simulation tool reshaped the ways managers deal with manufacturing problems in an advanced manufacturing environment. Mathematical modeling and simulation as a disruptive tool have assisted manufacturers in various fields in an advanced manufacturing environment. Mathematical models and simulations can describe the prospect of a manufacturing system. It is a good tool for planning each stage in an advanced manufacturing environment. The use of models to represent various stages provides the manufacturers with adequate information and the expected outcome of their proposed plans.

The benefits derived from the use of mathematical models and simulation software in describing a manufacturing process were presented in the chapter. The use of mathematical modeling and simulation to analyze and validate the process of most automation systems provides numerous benefits to manufacturers and assist in improving the production output, process, and overall productivity. The benefits also assist in enhancing the operator's performance in an advanced manufacturing environment.

The goal of a manufacturer is to use innovative ideas that can support improvement, productivity, and throughput. Adequate utilization of an effective manufacturing process and processes to identify and diagnose performance problems in an advanced manufacturing environment are desirable. An essential factor that determines efficient productivity is the time spent during the production stage [190]. Production time requires adequate control measures that can assist manufacturers in obtaining production output at a reduced cost.

The packaging stage of manufacturing is a critical stage in manufacturing where much time is spent. During the packaging phase, products are placed in a queue while waiting to be picked up by the next available server. The long queue can increase the waiting time and increase the overall time of production. A queue on the production line can have a substantial impact on the overall efficiency of the production process. Adequate control of the waiting time has become a major interest area among manufacturers. It is important to understand how to effectively resolve problems associated with queues that exist as a result of products awaiting server operation. The research was focused on determining the effects of performance optimization on waiting time and the application of queuing theory to analyze a packaging stage model that can control the waiting time. The M/M/S queue model was described in this present work; M/M/s model has its servers arranged in a parallel form where the service time at each station is identified following the same exponential law. The focus of the research was also on the use of the robot as a disruptive technology during a pick and place task to improve the operational process, manufacturing process, and overall productivity in an advanced manufacturing environment.

Based on the previous studies, the queuing theory was effective in analyzing various modeling techniques in manufacturing. In the research, the packaging stage of a virtual manufacturing studied was studied to determine the effect of waiting time on productivity. Robots as a disruptive technology were implemented during the packaging stage to research the performance and to determine the optimum service rate required by the server (Robot) to yield optimum productivity. The model analysis was done using the queuing mathematical theory and the numerically analysis and simulation were carried out using the Newton-Raphson iteration method.

2.9 Summary

The review of various disruptive technologies in an advance-manufacturing environment was presented whereby robots and other emerging technologies have been effectively used in the manufacturing environment to enhance productivity. The replacement of some traditional processes of manufacturing with the new disruptive technologies has highly improved manufacturing outputs. A few of the technologies that impact the advanced manufacturing environment include; the use of computer-based technology in manufacturing, the application of the internet in various aspects of manufacturing, the use of robotics to automate or augment human services during the manufacturing process. The applications of modeling, simulation, and optimization processes were thoroughly discussed with the various progresses made towards an efficient manufacturing system.

CHAPTER THREE

The Impact of Disruptive Technology on Manufacturing Process: A Mathematical Approach

3.0 Introduction

A single-server robotic system with parts arriving from various stations for a pick and place task was studied using mathematical models. Assumptions were made to represent the virtual manufacturing scenario. Classical mathematical models were used to describe various stages involved in the virtual manufacturing system. Using the Markovian queuing theory and the renewal reward theorem, an expression was derived for estimating the system throughput. The Engineering equation solver (EES) was used for the numerical analysis, and MATLAB software was used as the simulation tool to derive optimal results. Results obtained were further illustrated graphically and discussed.

Queuing theory and Newton-Raphson iteration strategy were used to analyze and describe classical manufacturing problems and models that are being presented in the chapter. The Newton-Raphson iteration formula was used in finding the approximate values for the roots of the algebraic expressions required in establishing the performance optimization on waiting time. The solutions to the models presented in the chapter were derived using engineering equation solver (EES). The engineering equation solver was used in finding solutions to the numerical expressions described in the models and simulation of throughputs in a robotic manufacturing environment. The Renewal Reward Theorem was also used along with the queuing mathematical theory to analyze the classical models that described the working parameters of a conveyor system. The solutions from the renewal reward theorem provided an optimal efficiency in the advanced manufacturing environment. MATLAB was used as the simulation platform in finding approximate values that can give optimal results.

The performance optimization on waiting time using queuing theory in a virtual manufacturing environment was studied. The impact of a robot as disruptive technology was examined and researched its effects on the waiting time during the packaging stage in a manufacturing system. The working parameters and the design parameters of the conveyor system were also analyzed to determine the time it took arriving parts from machines to the final stage. Classical models were used to describe the working parameters, which were simulated to obtain results. The best set of working parameters were chosen and implemented. The outcome gave a higher efficiency and an optimal throughput. Using the Renewal Reward theorem, a mathematical model was implemented during the manufacturing process to obtain optimal throughput. Specific parameters were implemented to experiment with the accuracy of the derived models. The results obtained gave an optimal throughput. Also, MATLAB was used as the simulation software to compare the various outcomes and varied against each other. The results obtained were presented in the thesis.

3.1 Queuing Mathematical Theory

Queuing theory is one of the most efficient and widely used mathematical techniques to perform research on waiting lines and queues in commercial manufacturing applications [42]. Queuing theory was developed by A. K. Erlang in 1903 in his attempt to solve a congestion problem during a telephone call [44]. His widely used approach towards estimating the queue length and waiting line has always been a success in an advanced manufacturing environment. Queuing theory has been used to estimate the average waiting time of products/services in a queue, the expected time spent within a system, average queue length, the required numbers of customers attended to at a time [47].

Queues and waiting lines are commonly experienced in industries, banking systems, colleges, telephone calls, traffic, hospitals, post offices, and schools [59]. A queue is also experienced among customers waiting to lodge online complaints. Clients would have to wait for so long before they have been attended to by the operator on duty [46] [60] [60]. A queue is a common manufacturing problem that requires adequate control. It delays the manufacturing process and can result in a high cost of production. A queue has significant impact on the throughput rate in an advanced manufacturing environment.

3.1.1 Features of the Queuing Mathematical Theory

The three main components considered when describing the queuing system were the queue, rate of arrival, and the service facility.

a) The queue (waiting line)
b) Rate of arrival (the rate at which customer enter the system)
c) Service (service facility given to customers)

The above components of the queuing theory required adequate examination before an effective mathematical model was developed to analyze queuing problems in an advanced manufacturing environment.

3.1.2 Advantages of Queuing Mathematical Modeling Theory.

The following benefits were derived from applying the queuing mathematical modeling theory in solving problems in an advanced manufacturing environment.

a) Queuing mathematical modeling theory was useful in the situation whereby the manufacturer was required to create a balanced relationship between the optimization of the service costs and the waiting costs.
b) Queuing mathematical modeling theory was used to illustrate, analyze and provide a clear understanding of how a waiting length can be and provide an adequate solution to manage the queue.
c) Queuing mathematical modeling theory was used to develop classical models used to determine the pattern of arriving customers/products in an advanced manufacturing environment.

3.1.3 Limitation of Queuing Theory.

The queuing theory also has its limiting factors which are presented below.

a) Queuing mathematical models are very complex and difficult to analyze due to the presence of uncertainties in the models. The uncertainties are as a result of:

i. The type of probability distribution that was used in the model.
ii. The process parameters are unknown in some cases, although the probability distribution may be known.
iii. If conditions (i) and (ii) are known, the probability distribution can be determined without having an adequate understanding of the real outcome.
iv. There are limitations in some cases when the first in, first-out (FIFO) condition was not applicable. The queuing mathematical model analysis became more complex when FIFO was not applicable.

3.1.4 Applications of Queuing Theory in an Advanced Manufacturing Environment.

Queuing theory was a viable decision-making tool in an advanced manufacturing environment. It can be widely used for a variety of applications. The applications of queuing theory are listed below:

a) Inventory control and analysis.
b) Controlling of a production line.
c) Controlling congestion.
d) Take-off and landing of aircraft at busy airports.

e) Assembling lines for parts control.

f) Issuing and returning tools in assembling plants.

3.1.5 Newton Raphson's Iteration.

The application of Newton-Raphson's iteration was based on finding an approximate value for the root of a valued function of x [57]. The implementation of the Newton-Raphson equation for numerical analysis in the research gave an effective result with minimal error. Newton-Raphson equation was used an iterative tool that was suitable for simulation purposes when finding zeros of an arbitrary function. Newton-Raphson equation has a distinct advantage over some other mathematical tools that can also be used to simulate results in the research carried out on the performance optimization of waiting time using queuing theory in an advanced manufacturing environment. Newton-Raphson's Iteration equation was modeled using the steps described below.

The derivation of the Newton-Raphson iteration equation was expressed in the form below: Given that the root of the arbitrary equation was r, and x_0 represented the approximate value of r, h denoted the approximate value of x_0 from the initial value. Where

$$r = x0 + h, h = r - x0 \qquad (3\text{-}1)$$

h is negligible and its linear approximation was illustrated as:

$0 = (r) = (x0 + h) \approx (x0) + hf'(x0)$ The analysis was valid if, $f'(x0)$ was approximately equals to zero.

$$h \approx \frac{f(x_0)}{f'(x_0)} \qquad (3\text{-}2)$$

$$r = x_0 + h \approx x_0 - \frac{f(x_0)}{f'(x_0)} \qquad (3\text{-}3)$$

Therefore, the estimated value x_1 of r gives:

$$x_1 = x_0 - \frac{f(x_0)}{f'(x_0)} \qquad (3\text{-}4)$$

x_2 also follows the same trend as x_1:

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)} \qquad (3\text{-}5)$$

For a required number of x, x_n is the next approximate value.

Therefore, x_{n+1} are given by:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \tag{3-6}$$

1.6 Renewal Reward Theorem.

The renewal theory is a probability theory that was used to generalize a process that had the characteristics of Poisson such that the model had a random operating time [191]. The renewal reward mathematical process utilized identical time that was evenly distributed with finite mean and was independent of each other. The renewal reward theorem was suitable for the research as it had a function that was effectively related to the expected number of parts arriving from a conveyor with the expected reward outcome which represented the throughput rate. The implementation of the renewal reward theorem along with the queuing mathematical theory was suitable in deriving useful mathematical models that was effective for calculating the throughput rate in an advanced manufacturing environment. The renewal theorem was suitable for analyzing the parts that randomly arrived from a conveyor.

3.2 Mathematical Modeling and Optimization of the Waiting Time using Queuing Theory in an Advanced Manufacturing Environment.

The queuing mathematical theory was used as an analytical tool to estimate the waiting time in an advanced manufacturing environment. Mathematical models were developed to describe the waiting time experienced when robots were implemented to perform a pick and place task. The mathematical models were analyzed using the queuing mathematical theory. Newton.

Raphson's iteration equation was used for numerical analysis and as a simulation tool. A queue is a common phenomenon that exists in various stages of manufacturing systems and some other organizations. The existence of a queue usually reduces the time required by managers and manufacturers to get the desired task accomplished. During a manufacturing process, performance optimization was used as a tool to support the manufacturing decision-making process towards achieving a cost-effective manufacturing system. The performance optimization process involved adequate monitoring and modification of some operating conditions that - enhanced productivity. The practical implementation of optimization tools during a selected manufacturing process was used to improve the financial performance in a competitive environment Ran et al [8]. The Queuing mathematical theory was a viable tool in analyzing the waiting line model.

3.3 Proposed Mathematical Model for Evaluation of System Productivity of a Multiple Manufacturing System.

The multi-stage manufacturing system is a flexible manufacturing process used by manufacturers in an advanced manufacturing environment. The multi-stage manufacturing system is capable of producing multiple products from a single manufacturing line and was selected as the research platform. During the manufacturing process, delays were experienced during the packaging stages of the manufacturing process, which resulted in queues of products. Products were on queue awaiting server during the packaging stage of the manufacturing process. The waiting line process was modeled and researched using the queuing system of Leonard Kleinrock [5]. The queuing theory was effectively used to derive suitable expressions that were used to analyze the waiting line models. Parameters and operating conditions were obtained and evaluated in the virtual manufacturing environment.

The proposed model used in the research described a virtual manufacturing environment with heavy product traffic that resulted from multiple products arriving at the same packaging point. The trade-off point was set between the number of machines required for production and the throughput rate. Server rate and queue time were the two parameters used in determining the trade-off point during the manufacturing process. To adequately control the waiting time in the packaging stage of the manufacturing setup, an alternative solution was provided and used to determine its effectiveness. The robots were assumed to perform at the same rate based on first in first out (FIFO).

The system performance was modeled using a Poisson distribution function where the service times were exponentially distributed. Using queuing theory as an analytical tool, an expression was generated and solved numerically with the Newton-Raphson iteration formula. The performance of the Newton-Raphson iteration tool with the assumed parameters led to an illustration closer to the effective management of the waiting line during the packaging stage of manufacturing.

Classical mathematical models were used to describe and study the manufacturing process and the waiting line. The mathematical models were further analyzed using the queuing mathematical theory. Some parameters with some operating values were assumed to represent various conditions that built up the manufacturing system. The analysis of the model resulted in the development of some suitable mathematical models and expressions. Assumed values were computed into the models and solved numerically using the Newton-Raphson iteration formula. Results obtained were varied against each other to obtain the best operating conditions and parameters which gave a solution to the research problem. Results obtained were presented in thesis.

The steps involved to achieve the aim of the research were summarized as:

Step 1. The manufacturing process was selected (Packaging stage).

Step 2. Classical mathematical models were developed and used to describe and make a decision in the packaging stage of the virtual manufacturing process. The queuing mathematical theory was used to analyze classical models. Parameters were assumed under operating conditions, and values were effectively used to describe the manufacturing system. Parameters that were used within the waiting line model include the cost of waiting per hour (C_w), average number of products in queue (L_s), the cost of robot/hour (C_p), the average number of products arriving from the machine per unit time (λ_i), packaging rate which represents the service rate per unit time measured per hour (μ), utility factor of the server which is the robot (ρ_n).

Step 3. With step 2 above, suitable mathematical models and expressions were developed.

The values assumed were fit into the mathematical model and solved using the Newton-Raphson iteration formula.

Step 4. The Newton-Raphson iteration formula was further used as a simulation tool to achieve close approximate values which were used to obtain optimal results that were represented graphically. The simulation outcome yielded an outcome that validated the approach was suitable for the research problem.

The following parameters were used to describe the behavior of the proposed model.

n = the available numbers of the machines proposed for the production line

λ_i, = the arrival rate of products for the machine, where$i = 1, 2, 3 \ldots \ldots \ldots \ldots, n$.

(t) = the packaging rate of the server (robot) used per unit time, where $j = 1, 2, 3 \ldots . m$.

m = the maximum number of robots required for the production line.

ρ_n = the productivity rate of each robot.

= The utility factor of the server for the manufacturing process.

C_p = the server production cost per hour.

C_w = Cost of each product waiting in the queue.

L_s = the average waiting time for products on queue

(C_p= R2/hour, C_w = R0.1/hour, λ_i = 5 units/hour for 10 machines, μ = 2 unit per hour)

With the assumed parameters and the operating conditions, the mathematical models were analyzed using the queuing theory. The values were implemented into the mathematical models and solved numerically. The iteration results gave varying approximate values from which the best operating parameters were chosen. The outcome was further stimulated with the Newton-Raphson iteration formula. The illustration of the manufacturing process was modeled using equation (3-8) to equation (3-26).

The products arrival rate was presented as:

$$\sum_{i=1}^{n} \lambda_i \,(\mathrm{t}) = n\lambda\,(t) \tag{3-8}$$

The arriving products are expressed as:

$$N = \lambda T \tag{3-9}$$

A discrete value was assumed, the total number of products that arrived during the packaging process per unit time was expressed as:

$$N = n\lambda_t \mathrm{x}\,\mathrm{t} \tag{3-10}$$

The numbers of products that arrived per unit time was as expressed as:

$$t = \frac{N}{\Lambda} \tag{3-11}$$

The production rate for each robot was expressed as:

Production rate: μ_j x t (3-12)

Total product packed by available robots was expressed as:

Total packed product = $\mu_j(t) \times t \times m$ (3-13)

Similarly, the performance optimization in the manufacturing process was determined using models presented in equation $(3-14)$ to equation $(3-26)$. For, $\eta \geq s$, during the packaging stage and the product on the queue was expressed as : $\eta - s$ Then,

$$\mu_n = s\mu \tag{3-14}$$

The utilization factor of the system denoted by ρ represented the ratio of the rate at which work enters the system to the maximum rate at which the system can perform the task. For a single server case, it was expressed as:

$$\rho = \lambda\ \mu \tag{3-15}$$

During the packaging phase, the utility factor of robots was expressed as:

$$\rho_n(t) = \frac{\lambda_i(\mathrm{t})}{\mu_j\,(t)} \tag{3-16}$$

The mean queue time required by each robot and the production rate of each robot was expressed as:

$$p_j(t) = (\lambda_i + \mu_j)\rho_n(t) + \lambda_i \rho_{n-1}\,(t) + \rho_{n+1}\,(t) \tag{3-17}$$

The total productivity of the system $\rho_n(t)$ was modeled as:

$$\rho_n(t) = \left(\sum_{i=1}^{n} \lambda_i + \sum_{j=1}^{n} \lambda_i\, \mu_j\right) \rho_n(t) + \sum_{i=1}^{n} \lambda\, \rho_{n-1}\,(t) + \sum_{j=1}^{m} \mu_j \rho_{n+1}\,(t)\, for \quad t \to \infty$$

(3-18)

For a discrete value of time t;

$$\rho_n(t) = \rho_n(\mathrm{t}) + \ \lambda n \rho_{n-1}\,(t) + \mu(t)\rho_{n+1}\,(t) \tag{3-19}$$

The waiting time was expressed as:

$$W\ = \sum\nolimits_{j=1}^{m} \mu_j - \textstyle\sum_{j=1}^{m} \lambda_i\,, \quad \mathrm{w}\ = \frac{1}{\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i}} \tag{3-20}$$

The total cost of production was determined given that the time spent by the robot during the manufacturing process production was represented as C_p and the cost of waiting for each product to be packaged = (t). The average waiting time of products on a queue was modeled as:

$$L_s = \frac{1}{\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i}} \times \mathrm{t} \tag{3-21}$$

Waiting time per unit hour was expressed as:

$$L_s = \frac{\mathrm{n}_{\lambda i}}{\mathrm{n}_{\lambda t - \mathrm{m}_{\mu_j}}} \quad (3\text{-}22)$$

The cost of production T was expressed in terms of waiting time and modeled as:

$$T = mcp\mu_j + c_w \rho_n w L_s \quad (3\text{-}23)$$

After substituting the parameters into (3-23); the production cost was expressed as:

$$T = mC_p\mu_j + c_w \left(\frac{\lambda_i}{\mu_j}\right)\left(\frac{1}{\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i}}\right)\left(\frac{\mathrm{n}_{\lambda i}}{\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i}}\right) \quad (3\text{-}24)$$

Production cost yielded:

$$T = mC_p\mu_j + C_w \left(\frac{{\lambda_i}^2}{(\mu_j(\mathrm{m}_{\mu_j} - \mathrm{n}_{\lambda i})^2}\right) \quad (3\text{-}25)$$

The performance of the system was optimized using the waiting time model expressed in (3-22). The solution to the optimization problem was derived by differentiating the model with respect to the service rate of each robot.

$$C_p + \frac{\lambda^2[(\mu-\lambda)^2 + 2\mu(\mu-\lambda)]}{\mu^2(\mu-\lambda)^4} = 0 \quad (3\text{-}26)$$

the model for optimal service was modeled as:

$$C_p\mu^5 - 3C_p\mu^4\lambda + 3C_p\mu^3\lambda^2 - C_p\mu^2\lambda^3 + 3\mu\lambda^2 C_w - C_w\lambda^3 = 0 \quad (3\text{-}27)$$

3.4 Model Simulation Using Newton-Raphson's Method.

The Newton-Raphson Iteration method was to determine the approximate values used in the simulation of the models presented the thesis. Newton-Raphson iteration method based its strategy on finding an approximate value for the root of a valued function of x. Using the Newton-Raphson equation reduced the errors that were likely to set in when calculating the roots of functions. The efficiency of the Newton Raphson method was the advantage it has over other methods. The Newton-Raphson iteration method was used to find the zeros of the arbitrary equations that were developed during the research, whereby the specific root of a function depended on the initial value. The Newton-Raphson's iteration strategy was utilized in the research to determine the server rate that can produce an optimal throughput.

Given that the root of the derived equation was r, let x_0 be the estimated value of r, h represented a measure of the approximate value of x_0 from the exact value. Where

$$r = x_0 + h, h = r - x_0 \quad (3\text{-}28)$$

h was very small and its linear approximation was represented as:

$$0 = f(r) = f(x_0 + h) \approx f(x_0) + hf'(x_0) \quad (3\text{-}29)$$

The mathematical model was valid if, $f'(x_0)$ was approximately equals to zero.

$$h \approx \frac{f(x_0)}{f'(x_0)} \quad (3\text{-}30)$$

$$r = x_0 + h \approx x_0 - \frac{f(x_0)}{f'(x_0)} \quad (3\text{-}31)$$

Therefore, the estimated value x_1 of r yielded: $x_1 = x_0 - \frac{f(x_0)}{f'(x_0)}$ (3-32)

Similarly, x_2 was derived as a function of

$$x_2 = x_1 - \frac{f(x_1)}{f'(x_1)} \quad (3\text{-}33)$$

For a required number of x, x_n is the next approximate value.

Therefore, x_{n+1} were modeled as:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}, \quad (3\text{-}34)$$

The service rate of the server (μ), the Newton-Raphson Iteration for analyzing the service rate was modeled as:

$$\mu_{n+1} = \mu_n - \frac{f(\mu_n)}{f'(\mu_n)} \quad (3\text{-}35)$$

Equation (3-36) and equation (3-37) represented the first and second order of the Newton-Raphson iteration model of the production system [192].

$$f(\mu) = C_p\mu^5 - 3C_p\mu^4\lambda + 3C_p\mu^3\lambda^2 - C_p\mu^2\lambda^3 + 3\mu\lambda^2C_w - C_w\lambda^3 \quad (3\text{-}36)$$

$$f'(\mu) = 5C_p\mu^4 - 12C_p\mu^3\lambda + 9C_p\mu^2\lambda^2 - 2C_p\mu\lambda^3 + 3\lambda^2C_w \quad (3\text{-}37)$$

The assumed values for the manufacturing scenario were (C_p= R2/hour, C_w = R0.1/hour, λ_i = 5 units/hour for 10 machines, μ = 2 units per hour). The values were implemented to solve and analyze the mathematical models. Outcomes were iterated and close approximate values obtained.

3.5 MATLAB & Engineering Equation Solver.

MATLAB (Matrix Laboratory) is a computer programming language developed by Math Works and commonly used by managers in an advanced manufacturing environment. It is suitable for the computation of technical data, analysis of data, solving complex mathematical equations [193]. MATLAB is a good iteration tool that can be employed when different classical modeling results are required to be compared against each other. The iteration process provides a clearer outcome which enables the manufacturer to choose the best operating conditions/parameters that can higher productivity [194]. The MATLAB software was used as an iteration tool in obtaining closer approximate values that were simulated against each other to obtain efficient values that yielded optimal throughput in the present work.

3.6 Engineering Equation Solver.

The engineering equation solver (EES) is a numerical tool suitable for solving non-linear algebraic, integral, and differential equations [195]. The EES tool was used in the research for optimization of results, analysis of results, unit conversion of different kinds, verification of unit's consistency, and was effectively used to generate quality graphs. Its high degree of accuracy made it a suitable tool for solving the complex mathematical expressions used in modeling the problems researched and presented in the thesis. Some of the basic features of the engineering equation solver is summarized below.

- Engineering Equations Solver is compatible with Windows operating system
- EES is suitable to solve thousands of non-linear simultaneous equations
- The computational speed of EES is extremely high
- It is suitable for generating 3-D and 2-D contours and plots
- It can carry out the optimization of multi-variable functions
- It can effectively analyze uncertainties
- EES tool is suitable for parametric studies.

3.7 Results and Discussion.

The queuing mathematical model was used to determine the performance of a manufacturing system and conditions for optimal productivity. Simulation results yielded suitable values that were used in determining the utility factor and the performance of the production process. The graph plotted along with the set of operating parameters and conditions, gave an efficient output was implemented in a real-life manufacturing scenario. Figure 3-2 illustrated the performance of the robots in the packaging stage of manufacturing against the arrival rate of the products. In figure 3-2, the packaging rates increased as the arrival rate increased. The result indicated that the number of robots assumed in the decision-making process in the proposed model was suitable to solve the waiting line model. There was no congestion and there was an easy flow of arriving parts. The available numbers of servers were able to give adequate productivity. Similarly, figure 3-3 the waiting time was investigated against the number of robots implemented during the packaging of products. The outcome showed that the average waiting time reduced with the availability of an increased number of servers (robots). In figure 3-4, the relationship between the utility factor and the number of robots used was also investigated. The result showed that the ratio of the maximum demand for the robot during the packaging stage corresponds to the available number of robots to yield achieves an optimal output. The outcome shows a smooth behavior of the proposed models.

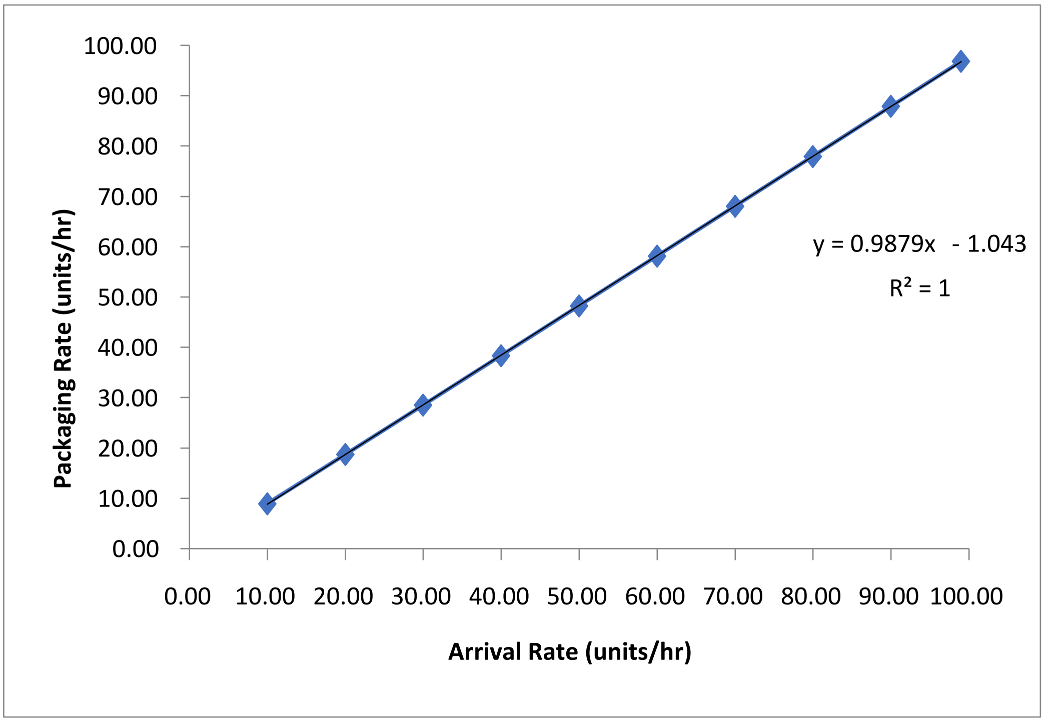

Figure 3-1: Packaging rates of products against the arrival rate

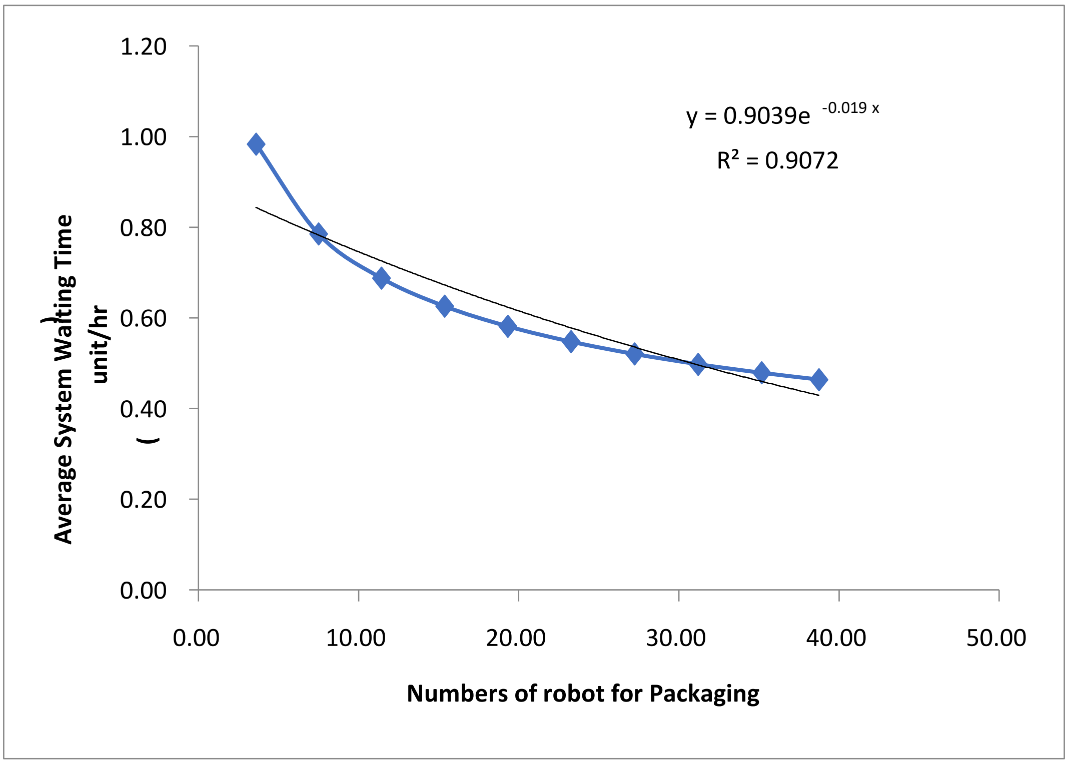

Figure 3-2 Average waiting time against numbers of robot used for packaging

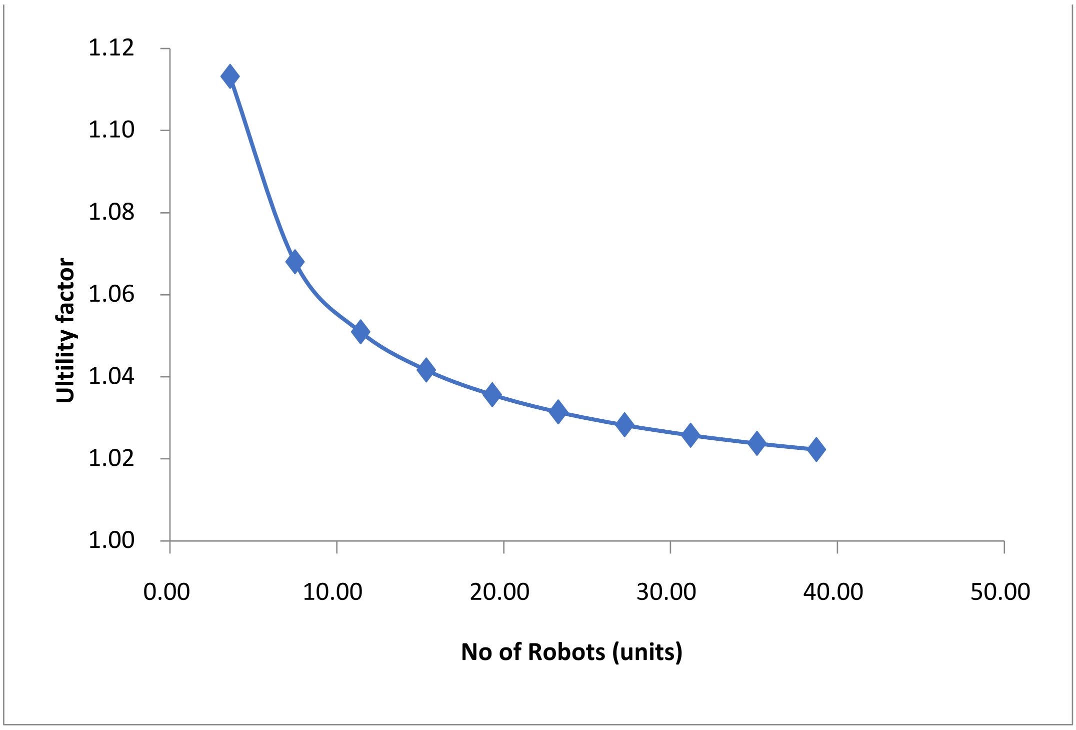

Figure 3-3: The utility factor against numbers of robots utilized.

3.8 Conclusions

Mathematical models were used to describe the production process of goods from the product arriving stage to the packaging stage in a virtual manufacturing environment. The description of the production process provided an initial structure of the service facility required for the arrival stage modeling. An adequate control measure of the waiting time was employed and was used to control and analyze the waiting line model.

The manufacturing environment was modeled and the average queue time was determined from the simulation of the models. The average queue time was further differentiated to optimize the performance of the robot with the corresponding queue. The outcome yielded models that were further analyzed using the Newton-Raphson iteration method. The outcome gave an output free of the queue with minimal waiting time as shown the results a. The results indicated that the suggested model can be suitable for use when the queue time is required to be controlled during the packaging stage in a real-life manufacturing scenario.

3.9 Summary

In chapter three, the Queuing mathematical theory with the Newton-Raphson iteration formula were used to determine the performance optimization of waiting time. A virtual manufacturing scenario was considered where robots as a disruptive technology were implemented during the packaging stage. Classical mathematical models were used to describe each stage involved. The throughput rates were examined to determine the impact of using robots as server during the packaging stage. The mathematical models were further analyzed using the queuing theory along with the renewal reward theorem. The outcome was numerically solved using the engineering equation solver (EES). The results obtained were varied against each other using MATLAB simulation tool. The results from the simulations yielded an effective outcome which gave an improved throughput rate.

CHAPTER FOUR

Modeling and Simulation of Throughput in an Automated Manufacturing System.

4.1 Introduction

Classical mathematical modeling and simulation was useful at the decision-making stage of the manufacturing process to predict the long-term prospect of a manufacturing system. Mathematical modeling was essential to the research in order to determine the best process that can be implemented to yield optimal productivity in an advanced manufacturing environment. Effective optimization of the manufacturing process made use of sequences of automation to improve product quality, reduce time spent, and to increased throughput in in the manufacturing system [18]. Mathematical modeling and simulation was used to research the effects of using a robot as a disruptive technology on the throughput rate during pick and place tasks in an advanced-manufacturing environment. Classical models were used to describe the virtual robotic manufacturing environment. Parts arriving from various stations were transported via a conveyor and a vision camera attached to a robot's senses and sends a signal to the robots. The robots functioned as a disruptive technology a traditional pick and randomly place tasks manufacturing system. Considering the competitive manufacturing environment, the need to increase throughput to reduce the cost of production was of the highest interest in the research. Various mathematical models were derived and a unique expression was implemented to calculate the optimal throughput in an advanced-manufacturing environment.

4.2 Methodological Approach

The system model used a single server queue where parts arrived via conveyor belt from multiple stations to a buffer station. The arriving parts joined another conveyor where parts were transported to be picked up and placed by a robot in a virtual manufacturing environment. The arrival behavior randomly following a Poisson process with varying with mean arrival rate λ, which was a case of inter-arrival time (the difference between two consecutive arrivals). The arrival of the parts from the buffer station took the form of a negative exponential distribution and followed the manner of impatient behavior of customers in the M/G/I queuing system. The M/G/I queuing system follows a Poisson process with varying with mean arrival rate λ with a general distribution of service time. The repeatability motion of the robotic arm makes the system to experience a deterministic feeding time μ (mean service time). Parts that were not picked up were redirected and returned for service in the next cycle. The process characteristics in queuing theory was also referred to as the reneging characteristics of manufacturing process. The flow chart in Figure 4-1 illustrated the steps involved during the modeling stage of a pick and place task in a virtual manufacturing environment.

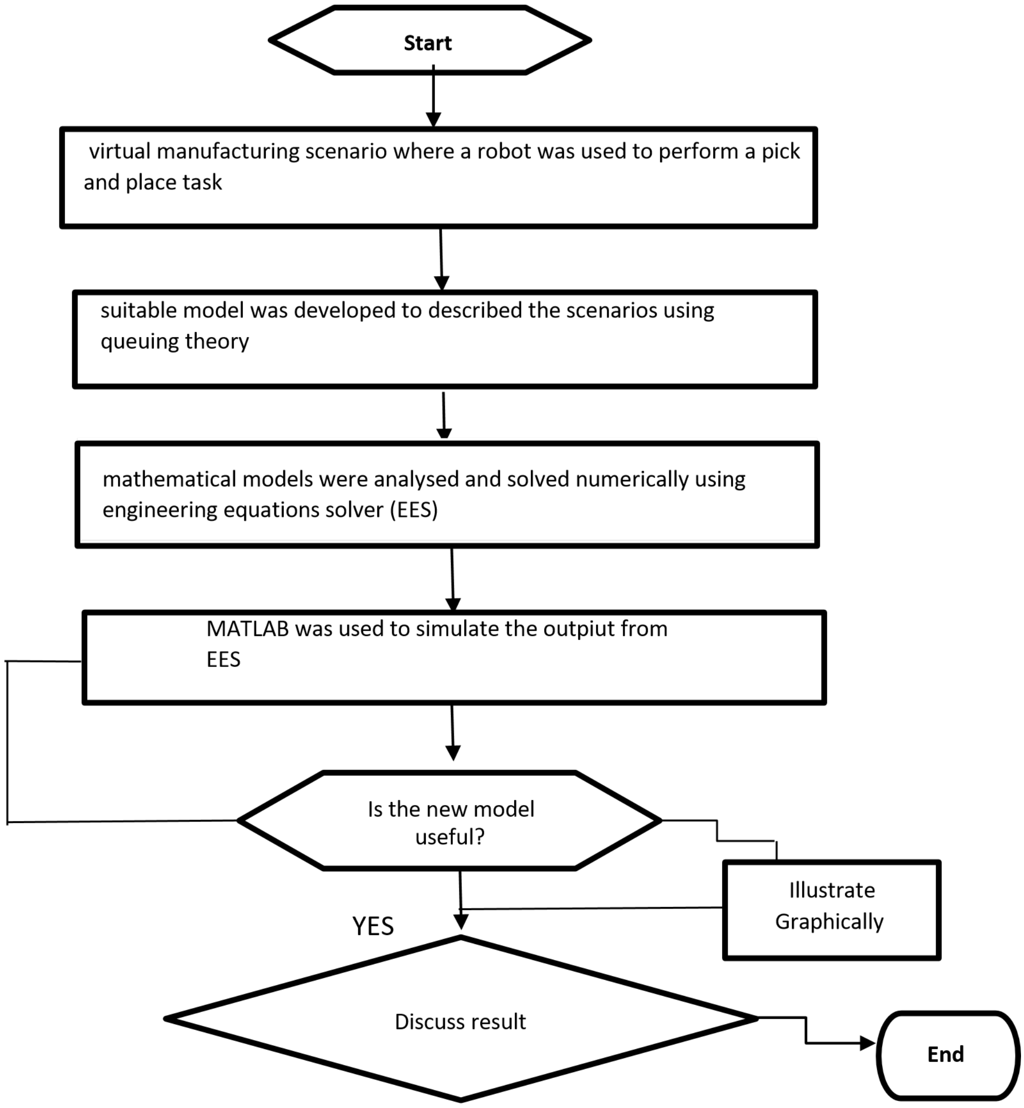

Figure 4-1: Flow Chart for the Proposed Model

Consequently, the total cycle time t_c required for the robot to complete a cycle was calculated using the total duration that was associated with the pick and place operation. It was assumed that the conveyor was neither starved nor saturated. Following the inter-arrival of parts, the total cycle time t_c was obtained by summing together the time involved in the manufacturing scenario that was studied. Given that t_m was the time at which the parts passed the conveyor, t_{vis} represented the camera vision time, t_p represented the pick and place time, t_t was the time taken to change tool, and t_r equals the time taken by the un-picked parts to re-circulate and join the next queue. The total cycle time was calculated using the model presented in (4-1).

4.3 Analysis of the required mathematical models.

$$t_c(s) = t_m + t_{vis} + t_{pp} + t_r + t_t \quad (4\text{-}1)$$

Assuming the values as: $t_m = 0.13s$, $t_{vis} = 0.1s$, $t_p = 0.12s$, $t_r = 0.125s$, $t_t = 0.15s$.

The notations and parameters presented were used to develop a model that described the behavior of a robot as a disruptive tool during the pick and place scenario in a virtual manufacturing environment.

Parameters

$\lambda = The\ mean\ arrival\ rate\ of\ parts\ from\ machines.$

$\mu = The\ mean\ service\ rate\ of\ product\ also\ called\ inter - arrival\ time.$

$p_n = probability\ of\ having\ n\ part\ in\ queue.$

$\rho\ = utilization\ or\ traffic\ intensity.$

L_q = Average number of parts in the queue

$L = Average\ number\ of\ parts\ in\ the\ system$

w_q = Average $waiting\ time\ of\ parts\ on\ a\ conveyor$ before being served

= Average time apart spent in the whole system

$t_c = Total\ cycle\ arrival\ time$

$t_{vis} = time\ taken\ by\ a\ camera\ to\ visualize\ part\ and\ send\ signal\ to\ robot$

$t_p = time\ taken\ by\ the\ robot\ to\ feed\ and\ pick\ a\ part$

Using the above notations from the queuing mathematical theory, a single server system was considered whereby the arriving parts are served by a single robot that identifies and pick up the required part. The probability functions of a negative exponential distribution with inter-arrival time μ, having a mean number of arrivals of parts from available stations.

The probability Pr that one product arrive at a time (t) is given as $\lambda x = (t, t + x)$ for $x \rightarrow 0$. Similarly, the probability Pr that more than one part arrive is given as $\rho_n\{(t + x), x \rightarrow 0\}$. Let $x(t)\ at\ t \geq 0$ denote the available product present to be served at a given time t.

Therefore, the system behavior can be represented mathematically using a probability function.

$$f(x) = \frac{e^{-\lambda}\ \lambda x}{x!} \quad (4\text{-}2)$$

$\rho_n\ (t) = [n\ part\ arrival\ at\ a\ specific\ time\ (0, t)]$

With the set of asumption presented, $\rho_n\ (t + x)$, x $\rightarrow$ 0, can be expressed as

$$\rho_n\ (t + x) = \ \rho_n\ (t)\ [1 - \lambda x] + \ \rho_{n-1}\ (t)\lambda x \quad (4\text{-}3)$$

The probability above represent the poisson arrival condition of parts.

$$\rho_0\ (t + x) = \ \rho_0\ (t)[1 - \lambda x] \quad (4\text{-}4)$$

This can also be expressed using h to denote the inter- arrival time

$$\frac{\rho_n\ (t+h) - \rho_n\ (t)}{h} = \ -\lambda \rho_n\ (t) - \lambda\ \rho_{n-1}\ (t) \quad (4\text{-}5)$$

Similrly,

$$\frac{\rho_0\ (t+h) - \rho_0\ (t)}{h} = \ -\lambda \rho_0\ (t) \quad (4\text{-}6)$$

Diferentiation of 5 & 6 gives

$$\frac{d\rho_n\ (t)}{dt} = -\lambda p_n\ (t) + \ \lambda \rho_{n-1}\ (t), \quad (4\text{-}7)$$

$$\frac{d\rho_0\ (t)}{dt} = -\lambda \rho_0\ (t) \quad (4\text{-}8)$$

Equation 7 and 8 gives the set of the differential equation solving with respect to

$$\rho_0\ (t) = \ e^{-\lambda t} \quad (4\text{-}9)$$

To proof the above, the derivative of $\rho_0(t)$ is computed and compared with equation (4-7) & (4-8) to obtain $\rho_1(t)$,

$$\rho_1(t) = \ \lambda t e^{-\lambda t} \quad (4\text{-}10)$$

Equation 4-7 can be written as

$$\rho_n(t) = \ \frac{(\lambda t)^n}{n!} \times \ e^{-\lambda t}\ , when\ n\ = 0,1,2,3,4 \ldots \quad (4\text{-}11)$$

For an efficient productivity, $\rho = \frac{product\ arrival\ rate\ (\lambda)}{service\ rate\ (\mu)} < \ 1$

For a discrete time, $\rho_n\ (t) = \ \frac{mean\ arrival\ rate}{mean\ service\ rate} = \ \frac{\lambda(t)}{\mu(t)}$ (4-12)

Equation (4-13) was used to obtain the probability that parts have been cleared from the work envelope. Equation (4-13) expressed the relationship between the arrival rate and the server rate which was used to obtain the utility rate of the server.

Similarly, using notations from the queuing system (M/G/1) with single server, the average numbers of parts in the queue, the average number of parts in the system, average time spent before served, and average time spent in the system was expressed in equations (4-14) and (4-15).

The average number of parts in the queue was modeled as:

$$L_q = \frac{\lambda^2}{\mu(\mu-\lambda)} \qquad (4\text{-}13)$$

Average number of parts in the system

$$L = L_q + \frac{\lambda}{\mu} \qquad (4\text{-}14)$$

Average time a part that waits before being served

$$w_q = \frac{L_q}{\lambda} \qquad (4\text{-}15)$$

Average time a part spent in the system

$$w = w_q + \frac{1}{\mu} \qquad (4\text{-}16)$$

To predict a production optimal throughput, the cost involve during the pick and place task must also be considered by taking into consideration the average time spent and average number of parts in the system.

Given that;

Cost of server (robot) = C_s ,Cost of parts wating before picked up = C_w, Cost of busy robot = C_b, Cost of idle robot = C_i ,Cost of part returning to be picked = C_r .

The expression given in equation 16 can be considered to arrive at a total cost for the process,

$$C_p = C_w \times \mathrm{L} + C_b \times \mathrm{w} + C_r \times w_q + C_i \times L_q + C_s\, s \qquad (4\text{-}17)$$

During the pick and place task, the robot does not pick up all arriving part as the conveyor move past the vision camera. Other parts parts were recycled to join the next arriving parts. During the travelling period of parts, there exists a continuous movement of part whereby a minimum distance/gapα, exist between the work envelope and the clear part boundaries. For effective throughput computation, the distance between two arriving part must not be less than α for the robotic arm gripper to easily pick-up parts. Assuming the number of visible parts fed along the work envelope is N_f, the center point of the arriving part must be known. This can be obtained by considering the fact that the height and width of work envelope is the same. The diameter of the part fed in this model was assumed to be less than 20mm. Assuming both belts has the same velocity, the throughput equation can be easily obtained with the set of parameters and assumption made.

Assumptions

- System is not saturated or starved.
- There exist continious motion of buffer belt
- The width and height of work envelope is assumed to be equal
- All part are well secured to avoid falling off

Using the following notations and working parameters, suitable equations were derived.

Notation/parmeters

$N_f = number\ of\ part\ fed\ through\ the\ work\ envelope$

$c = expected\ number\ of\ cleared\ parts$

$d = diameter\ of\ fed\ part$

$a = minimun\ clearance\ required = d/2$

$w = Height\ and\ width\ of\ workpiece$

$P_b = proability\ that\ a\ work\ has\ been\ cleared\ from\ boundry\ of\ the\ work\ envelope$

$v = velocity\ of\ belt$

$T_r = throughput\ rate\ of\ robot$

$r_b = rate\ of\ arrival\ of\ parts\ from\ conveyor\ to\ server\ in\ Parts/mm2$

The renewal theorem of impatient customer is implemented for deriving a suitale equation for optimal throughput. The velocity of the conveyor belt is asuumed to be the same and represented with v, using equation 17, the conveyor speed was determined. Where D is the diameter of the motor pulley, and n represent the number of revolutions per seconds.

$$V = \frac{\pi D n}{60} \tag{4-18}$$

$$p_b = \frac{(w-d-2\alpha)^2}{(w-d)^2} \tag{4-19}$$

Given the centre of the work envelope as c, to obtain the centre of work envelope, the width and height of the work envelope was assumed to be equal. The diameter of the conveyor belt with the speed (v) was considered in equation 19.

$$c = \frac{w\pi(\alpha+d)^2}{(w-d)^2\, v} \tag{4-20}$$

Similarly, there exist another arrival rate denoted as r_b which represents the arrival of parts from coveyor to the server (robot). Equation 20 was used to calculate the value for r_b.

$$r_b = \frac{1}{c}\,\frac{(w-d)^2 v}{w\pi(\alpha+d)^2} \tag{4-21}$$

Also, the number of parts fed through the work envelope can be obtained by considering the width and height of work envelope, the velocity of conveyor, the probability of cleared work from work envelope, centre of work envelope, and the arrival rate of parts from buffer station to the pick up point. This is illustrated in equation 21. Equation 22 can be used to obtain the number of arrivin parts fed through the conveyor to the robotic system.

$$[N_f] = \left(\frac{w}{v}\right) r_b p_b\, e^{-rbc} \tag{4-22}$$

The throughput rate can be obtained using equation (23).

$$T_r = \frac{N_f}{[\left(\frac{w}{v}\right) + t_p + [N_f]\, t_c]} \tag{4-23}$$

The Engineering equation solver (EES) was used to solve the equations numerically and the results of the analysis were simulated using MATLAB software to achieve the best set of parameters for the system. With the set of equations and parameters assumed, optimal throughput was derived for a pick and place task.

Assumed values; $d = 14.4$, $W = 250m, V = 256\, rev\ per\ minutes, T_c = 0.625, n = 340\, rev\ per\ minutes, a = \frac{d}{2} = 7.2mm$,

Lambda$\lambda = 0.5 parts\ per\ sec, \mu = 0.4$, c_w =50, c_b= 0.1,

$c_r = 60$, $c_i = 10$, $c_s = 0.5$, $t_m = 0.13s, t_{vis} = 0.1s, t_p = 0.12s, t_r = 0.125s, t_t = 0.15s.\ from\ calculations, t_c = 0.625$secs

4.4 Results and Discussion

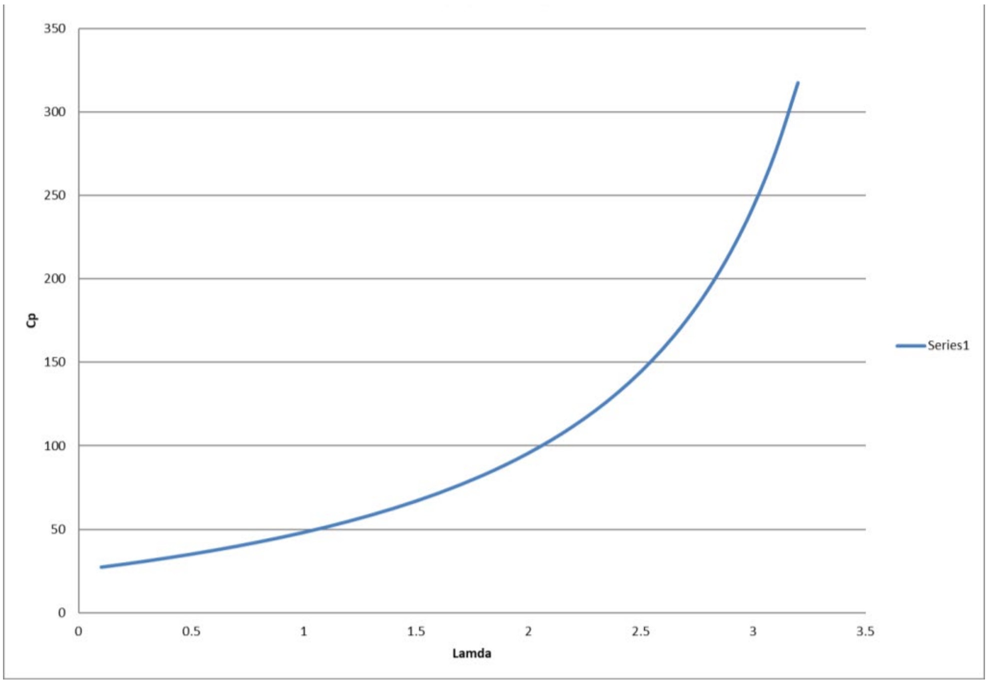

Figure 4-2 Cost of production against arrival rates.

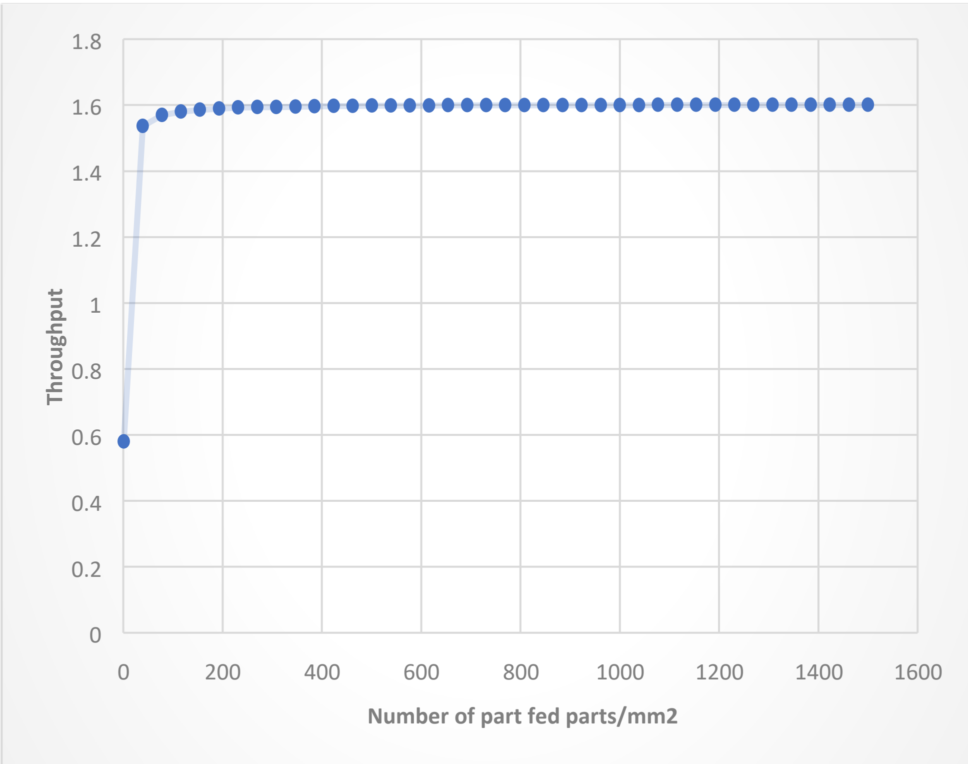

Figure 4-3: Throughput against the numbers of parts fed through the Conveyor.

Considering the outcome from the analytical solutions, an expression that can be used to obtain optimal throughput in a robotic manufacturing scenario was developed. By computing the assumed parameters into the developed models, the various outcomes were obtained. The graph of Figure 4-2 illustrated the relationship between the mean inter-arrival rate and the cost of production. The outcome shows that the longer it takes the parts to arrive at the robotic system the higher the cost of production. Also, the numbers of parts fed through the conveyor to the server (robot) were plotted against the throughput rate in Figure 4-3. The result shows that with the model and some assumed parameters used, an optimal throughput was obtained when the arrival rate was constant at 1.63 parts/mm^2.

4.5 Conclusion.

A mathematical model that gave an expression that could increase the throughput rate of a conveyor system during a pick and place task in a robotic manufacturing system was developed. The classical models that described a virtual robotic manufacturing scenario were studied. Parts arriving from various stations were transported via a conveyor and vision cameras attached to a robot's senses and send a signal to the robots. The robots picked and randomly place tasks and other parts that were not picked up have to recirculate and join the next arriving parts. Considering the competitive manufacturing environment, the need to increase throughput to reduce the cost of production is of the highest interest among modern manufacturers. Various mathematical models were derived and a mathematical expression for optimal throughput was developed. The expressions were tested to determine the efficiency of the mathematical models.

The results showed that the developed model can be used in the real-life manufacturing system when optimal throughput is required to be obtained. With the set of assumed parameters, the engineering equation solver (EES) was used for the numerical analysis, and MATLAB was used to simulate the parameters against each other to obtain optimal outputs. From the classical models formulated, the results from the model analysis suggested that the expression for optimal throughput was effective. The graphical illustration compared the mean arrival rate and the cost of production. Outcomes showed that the slower the arrival rate of parts, the higher the cost of production. Also, the graph of throughput against the arrival of the part showed that an optimal throughput was achieved at 1.6 parts/mm^2. The model can be useful among manufacturers when optimal throughput is required to be obtained in an advanced manufacturing environment.

4.6 Summary

The design parameters of a conveyor system were studied using classical mathematical models to determine the best working parameter that can give optimal throughput during a pick and place task. A virtual manufacturing scenario was studied whereby industrial robot performed a pick and place task. Parts arriving from various stations were transported via a conveyor and vision cameras attached to a robot's senses and send a signal to the robots to perform its task. The arrival behavior randomly followed a Poisson process with varying mean arrival rate λ which took the form of impatient behavior of customers in the M/G/I queuing system. Parts that were not picked up were redirected and returned for service in the next cycle. Classical mathematical models were developed with some assumed parameters to study the effect of varying the loads below and above the rated speed of the electric motor. Equations were developed using some notations to represent operating parameters of a conveyor belt system. MATLAB software was adopted to build simulic mathematical equations and solved using the engineering equation solver (EES). Results obtained were simulated to obtain and select suitable results that gave us optimal design parameters. For the selected design parameters, at 390m/secs, the optimal operating time was 0.4secs at a power consumption of 12700W. The outcome from the research gave a suitable design parameter that can be used to design a conveyor system when an optimal speed is required for efficient throughput.

CHAPTER FIVE

Operational Variation of a Manipulator Arm for an optimal Throughput in an Advanced Manufacturing Environment.

5.0 Introduction.

The variation in the motion of the robotic manipulator during service was a clear research area of interest. The selection and control of the manufacturing process has an impact on the productivity rate of the manufacturing process. Disruptive technology has endowed the manufacturing sector with various automation tools that can be implemented at various stages to enhance manufacturing processes to yield high productive throughput. Industry 4.0 focused on the proper application of emerging technologies as a disruptive tool to improve throughput in an advanced manufacturing environment. The implementation of disruptive technologies, such as the use of a manipulator as an automation tool in the manufacturing environment has a great impact on its productivity level. The motion planning for a robotic manipulator can be referred to as the generation of angular velocity to control the robotic manipulator to trace its path to a targeted destination from its home pose. Effective trajectory motion planning assisted to avoid collision around the work envelope of the robotic arm [196]. The process was achieved by implementing the following strategies. a). A Cartesian space as a set of paths to reach the manipulator's targeted destination was created b). An inverse kinematics algorithm was used to convert the Cartesian coordinate waypoint into an angular motion. c). the operational controller was used to transfer and navigate the joint trajectory into necessary actions by the robotic manipulator. d). A collision detection mechanism was implemented to ensure free path-way around the robotic work envelope.

The reliability of grasping of objects by the end-effector cannot be fully determined without adequate operational planning. The manipulator moves through 6 degree of freedom (DOF) during a pick and place task before grasping an object [196]. The motion planning was used to analyze the sequence of the motion events from the starting point to the endpoint [197]. Motion planning enabled manufacturers to understand the best position that yielded maximum throughput in an advanced-manufacturing environment. The block diagram of a robotic motion manipulator for a pick and place task is shown in Figure 5-4.

The study presents the research on the improved operational process of a manipulator during a pick and places tasks under standard operating conditions. The pick and place task were carried out and the manipulator motion was modified within a selected operational range.

Mathematical models were developed and analyzed to obtain the best set of parameters that provided optimal throughput. The outcome was compared and simulated using MATLAB to obtain optimal results.

5.1 The Operation of the Fanuc M-10i Robot for a Pick-Place Task.

The Fanuc M-10i robot was used in the research to investigate the operational variation of an end effector or manipulator on a robot. The Fanuc M-10i robot has 6 axes of rotation capable of rotating in various degrees with the highest repeatability and rotational speed of axes. The material handling operations of the Fanuc M-10i robot was not limited to assembling of parts, molding operations, coating, cutting, and machine tending. The Fanuc M-10i robot was capable of performing the pick and place task efficiently [198]. The Fanuc M-10i robot was designed to have the best payload and inertia which enhanced its operation to be efficient and was manipulated to obtain an improved output. The Fanuc M-10i c robot was integrated with a visual detection device that allowed the robot to sense and manages production set-ups effectively. The visual device promptly sensed the positioned part for the manipulator to pick and place as expected by the manufacturer. When the robot was assigned with the task of pick and place, it was assumed not to be familiar with the workplace and faced certain challenges when assigned to work in the environment for the first time. Some of the challenges included:

a. The ability to suitably identify the locations where parts were placed, manner of placement (vertical, horizontal, hanged on a hook, placed on each other, etc.). Determining the location of the parts enabled the robot and the manipulator to determine its operations and motion manipulation.

b. The ability to reach its point of placement. It required the robotic arm planning within its work envelope.

c. The challenge of object stability, other obstacles, and collision with human operators was faced when the operation was not well planned.

5.1.1 The Robotic Motion Component.

The motion component of the robotic system comprised of three motion actuation sub-systems. The manipulator, end effector, and the actuator.

Manipulator: It was made up of various joints and links connected serially and capable of moving around its wrist, arm, and hand. The manipulator’s arm positioned the object in the desired location in a 3-D plane while the wrists assisted with the orientation. The robotic arm was formed from the first 3 links, while the last 3 links formed the wrist.

End Effector: The end effector was attached to the manipulator end. It was the mechanical hand of the robot that assisted to manipulate and hold the part before it was fully moved by the robotic arm. Also, some specialized mechanical tools were attached to the manipulator end to perform some required functions were considered to be part of the end effector.

Actuator: the actuator was designed to provide the manipulator with the desired motion along with the end-effector. The actuator was a motor as the motion provided was without a transmission element. The actuators were classified according to their manner of operation (electrical, hydraulic, and pneumatic).

The Fanuc M-10i robot was designed with a mechanical structure, which was controlled to perform dedicated tasks. The robot motion control involved three different phases; the perception phase, processing phase, and the action phase. The sensing device on the robot provided information on the robot and its operating environment. The information was processed and sent to the actuator which further creates the mechanical action that controlled the robot motion [199].

5.2 Operational Motion of the Robot Manipulator during a Pick and Place Task.

During the pick and place task, three different types of grasps were used: the pre-grasp, the grasp, and the post grasp. The pre-grasp positioned the end-effector away from the object position. Pre-grasp allowed for the trajectory motion planning to avoid a collision in operations, grasp was when the end-effector with its fingers positioned and ready to grip the object for the pick-up task, and the post-grasp was when the end-effector moved away from the position where the object was grasped. The operation was controlled by computing the desired action for the end-effector to perform the placing down task [200].

A mechanically designed gripper with a mechanically operated finger was attached to an end effector component of the manipulator for grasping parts during operational processes [200]. Input power was produced through the gripper which allows the finger to react by opening and closing for the desired task. The gripper was equipped with pads to create sufficient force to hold the object [200].

5.3 Kinematic Analysis of the 6-DOF Robot Manipulator.

The kinematic analysis of the 6-DOF links was calculated without taking into consideration the effective forces that caused the motion. The direct and inverse kinematics of the manipulator motion provided valuable information on the robot manipulator mechanism movement. The performance of the manipulator for a pick and place task was achieved by the movement within the linkages of the arms. Denavit-Hartenburg (D-H) developed a kinematic model that was used to derive mathematical models for the robot motion manipulator as proposed by Oscar E.R [183]**.** The application D-H model was useful when links and joints were modeled and also in applications where robotic arm configuration was required regardless of the robot complexity [188]. The 6-DOF Fanuc M-10iA in Figure 2-2, shows the frame positioning while Table 5-2 provided the D-H parametric values of the manipulator. The Θ (°) represented the angle of rotation of each joint, d (mm) represented the distance along the Z-axis, **α** (°) represented the twisted angle that existed between the successive joint, and **a** (mm) represented the twisted length between successive joints.

From the D-H representation in Table 1, the homogeneous transformation matrix of the motion manipulator is given below. Each frame has a homogeneous transformation with respect to the previous frame joints. Each *T* is a dependent of a single variable joint. The forward kinematics models of frame n with respect that of frame 0.

$$T01 = 0_{T1}(q_1) = \begin{bmatrix} -\cos(q_1) & 0 & -\sin(q_1) & 150\cos(q_1) \\ -\sin(q_1) & 0 & \cos(q_1) & 150\sin(q_1) \\ 0 & 1 & 1 & 450 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}1)$$

$$T12 = 1_{T2}(q_2) = \begin{bmatrix} -\sin(q_2) & -\cos(q_2) & 0 & -600\sin(q_2) \\ -\cos(q_2) & -\sin(q_2) & 0 & 600\cos(q_2) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}2)$$

$$T23 = 2_{T3}(q_3) = \begin{bmatrix} -\cos(q_3) & 0 & -\sin(q_3) & 200\cos(q_3) \\ -\sin(q_3) & 0 & \cos(q_3) & 200\sin(q_3) \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}3)$$

$$T34 = 3_{T4}(q_4) = \begin{bmatrix} -\cos(q_4) & 0 & -\sin(q_4) & 0 \\ -\sin(q_4) & 0 & \cos(q_4) & 0 \\ 0 & 1 & 0 & 640 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}4)$$

$$T45 = 4_{T5}(q_5) = \begin{bmatrix} -\cos(q_5) & 0 & -\sin(q_5) & 0 \\ -\sin(q_5) & 0 & \cos(q_5) & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}5)$$

$$T56 = 5_{T6}(q_6) = \begin{bmatrix} \cos(q_6) & -\sin(q_6) & 0 & 0 \\ \sin(q_6) & \cos(q_6) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}6)$$

Therefore, the base end effector gives

$$0_{T_6} = (0_{T_1})\,(1_{T_2})(2_{T_3})(3_{T_4})(4_{T_5})(5_{T_6}) \quad (5\text{-}7)$$

Considering all the matrixes, initial configuration,

$$0_{T_6} = \begin{bmatrix} 0 & 0 & 1 & 790 \\ 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 1250 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5\text{-}8)$$

The matrix presented in equation (5-1) to equation (5-8) can be verified from the links shown in Figure 5-3.

5.4 Production Description for The Pick and Place Task

The pick and place of tasks were successfully carried out in the mechatronics and robotics laboratory of the University of KwaZulu-Natal in Durban, South Africa. The operational flow chart for the pick and place task is presented in Figure 5 - 1.

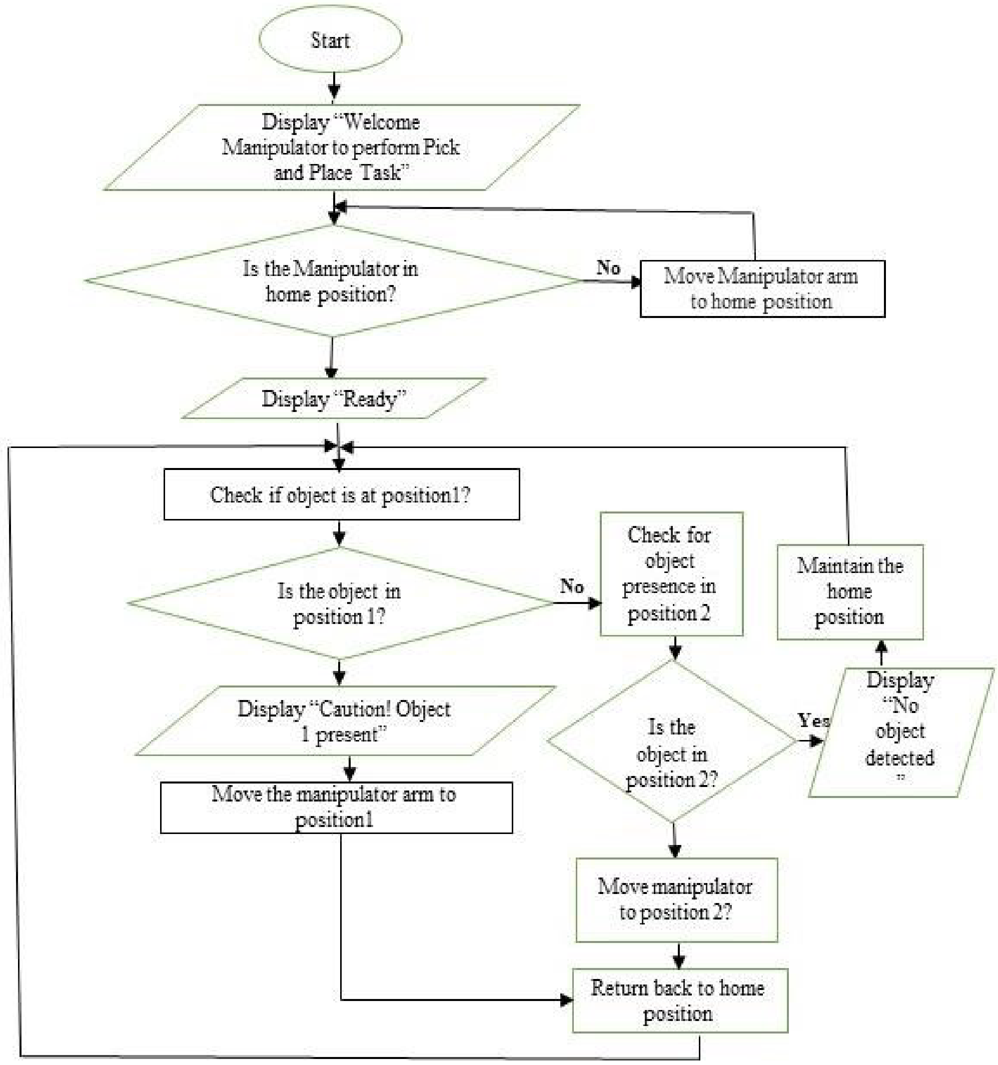

Figure 5-1: Flow Chart for the Pick and Place task

Considering the N number of items flowing through the conveyor belt system in a Poisson manner, at a constant belt velocity. Arriving parts from the conveyor were picked up randomly by the manipulator following the first in first out order (FIFO). The parts were then positioned on a rack for further manufacturing processes. The average time for each task was presented in Table 5-1.

Table 5-1: The Average Time spent for Pick-Place Task.

S/no	Motion	Description of task	Time taken (Seconds)
1	Motion 1	The home poses to view the object on the conveyor.	4.5
2	Motion 2	Reach an object to grasp an object.	3.2
3	Motion 3	Moving to the object drop pose.	3.0
4	Motion 4	Moving from object dropped pose back to home pose.	3.41

Subsequently, an operational variation of the manipulator motion was achieved by varying various manufacturing conditions that were involved during the pick and place task. The angle which was the area of interest was varied between 81 degrees to 96 degrees. The effects of varying the angle and other operating parameters were used to determine the impact on the throughput rate of the manipulator. The task described in the research consists of parts randomly arriving from a conveyor system. It follows the first in first out order (FIFO). The vision camera determined the position of the object that first gets to the robot workspace for immediate pick up by the gripper. For effective productivity, the product's present position was required to be determined. The pick-up position was used to analyze the parts' current position using the illustration in Figure 5-2, and calculated using equation (6-9).

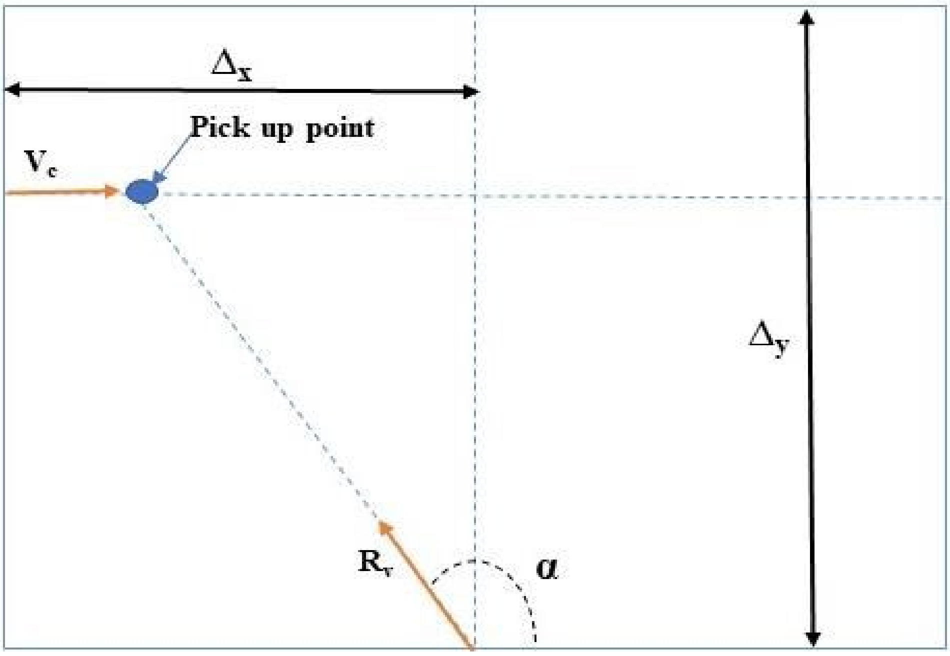

Figure 5-2: Analysis of the Pick-up Position.

The average speed of the robot (R_v), robot current position ($r_{x,}$), product position ($p_{x)}$, and the manipulator angle (α) were considered in order to obtain the current position of the part arriving from the conveyor. The position model is presented in equation (5-9).

$$p_x = \Delta x + R_v \cos\ (\alpha). t_{pick} \qquad (5-9)$$

Where,

$p_x =$ *The product position*

$v_c =$ *Conveyor belt speed*

$R_v =$ *Average speed of robot*

$\Delta_y =$ *distance between product*

$\Delta_x =$ *distance from pick position to drop position*

$t_{pick} =$ *time of pick*

Also, in order to obtain the pick and place rate per second, a mathematical model that relates the time of pick-up, time of placement, conveyor belt speed, and time taken by the vision camera to sense the arriving part, was proposed. The mathematical model is presented in equation (5-10).

$$pp_r = \frac{v_c}{t_{pick} + t_{place} + t_v} \qquad (5\text{-}10)$$

5.5 Conditions of operation using a single robot for the pick and place task.

The operating condition for achieving the pick and place task was summarized as:.

- Number of robots = 1
- The pick and place task follow a FIFO (First in first out)
- The positioning of the robot is closer to the conveyor system
- The angle of placement varied between 81°-96°
- Conveyor belt speed = 0.5m/sec
- Distance from the pick position to the drop position (Δx) = 230mm
- Conveyor width = 600mm
- Distance between product (Δy) = 30mm
- The velocity of belt 256 rev/minutes
- Total production time = 14.11secs
- The diameter of the fed part = 14.4mm

- a= d/2= 7.2mm
- Workspace radius = 600mm
- The average speed of the robot = $100m/sec$
- Total product = 200 objects
- $R_v = 100m/sec$

For effective motion manipulation, the robotic workload, angle of placement, distance between each manipulator position, workspace envelope, conveyor belt speed, product size, product flow rate, were determined.

Parameters/Notations

W = Conveyor width

$V = Velocity\ of\ belt\ drive$

$T_r = throughput$

$d = diameter\ of\ fed\ part$

$p_b = Probability\ of\ of\ work\ cleard\ from\ conveyor$

$r_b = Arriving\ rate\ of\ parts\ from\ the\ conveyor$

α = Angle of placement

$t_c = Product\ cycle\ time$

P_t = $Production\ time$

$pp_r = pick\ up\ rate$

The probability that work was cleared indicated that the proposed mathematical model in equation (5-12), was effective for the pick and place task to decide its productivity rate. Equation (5-11) was used to determine the probability that the work is been cleared from the conveyor system upon arrival.

$$p_b = \frac{(w - \Delta_y - 2\alpha)}{(w - \Delta_y)^2} \quad (5\text{-}11)$$

$$r_b = \frac{1}{v} \frac{(w - \Delta_y)^2 v}{w\pi(a + \Delta_y)^2} \quad (5\text{-}12)$$

$$T_r = \frac{r_b}{\left(\frac{w}{v}\right) + t_{pick} + [r_b] \times t_{place}} \quad (5\text{-}13)$$

$$t_c = \frac{total\ product}{production\ time} \quad (5\text{-}14)$$

Considering the mathematical models in equation (5-11) to equation (5-14), the motion of the manipulator was altered by varying the angle of placement from 85 degrees to 95 degrees in order to analyze its effect on the throughput rate. The values from the experiment are given below.

$w = 600mm$, $\Delta_y = 30mm$, $\Delta_x = 230mm$, $v = 256\ rev/minute$, $v_c = 0.5m/sec$, $\alpha = 90\ degrees$, $R_v = 100m/secs$.

The Parameters obtained from the experimentation as stated above were computed to describe the mathematical models and results were presented graphically.

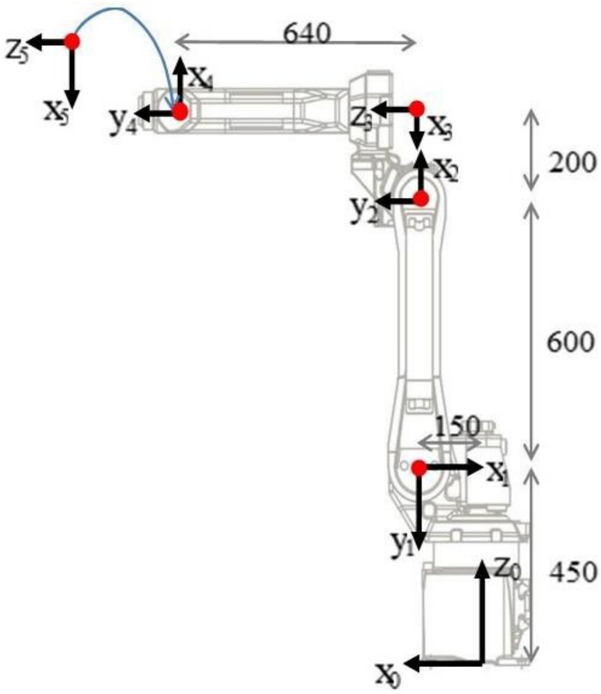

Figure 5-3: Fanuc M-10i **Manipulator for 6-DOF Joints and Frames [20].**

Table 5-2: The D-H Representation for the 6-DOF Robotic Motion

Links	Θ (°)	d(mm)	a (mm)	**α** (°)
1	$180 + q1$	**450**	-150	**90**
2	$90 + q2$	**0**	**600**	**0**
3	$180 + q3$	**0**	-200	**90**
4	$180 + q4$	**0**	**0**	**90**
5	$180 + q5$	**640**	**0**	**90**
6	$q6$	**0**	**0**	**0**

Table 5-3: Specification of the Fanuc M-10ia Robot with 6-Dof

Joints	Motion Range	Maximum speed
J1	360	225
J2	250	205
J3	445	225
J4	400	420
J5	280	420
J6	720	700

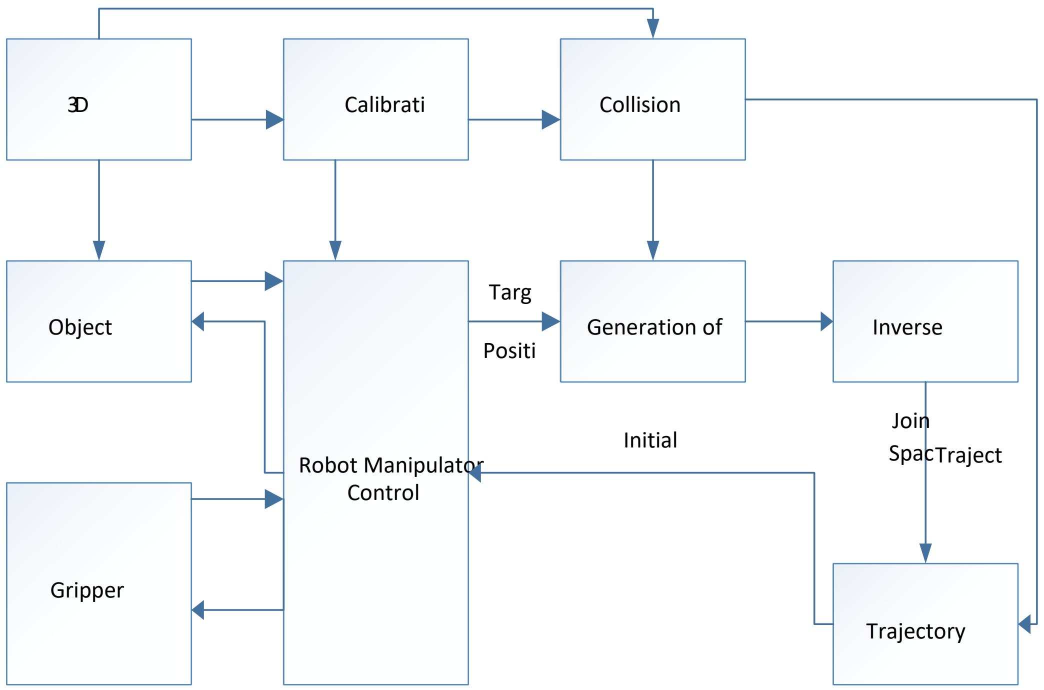

Figure 5-4. Block Diagram of the Robotic Motion Manipulator for a Pick and Place Task.

5.6 Results and Discussion.

The pick and place tasks were carried out in an attempt to vary the angle of the manipulator and research its effect on the throughput rate. Figure 5-3 gave the various links and frames of the Fanuc M-10i robot was used as the basis of the matrix mathematical model described in equation (5-1) to equation (5-8). The flow chart in Figure 5-1 described the steps followed to achieve the pick and place task by the manipulator. Figure 5-5 presented the relationship between the throughput rate and the angle of placement. The outcome showed a steady increase in the throughput values between 80 degrees and 96 degrees. T = There exists a sudden increase in the throughput rate at an angle of 88 degrees. When the angle was further increased beyond 88 degrees, there was a reduction in the throughput value. The simulation results indicated that an optimal throughput was obtained when the pick-up and place angle was allowed to remain at 88 degrees provided the same set of parameters and operating conditions were implemented.

Subsequently, the graph of the product arrival rate against the throughput rate was presented in Figure 5-6. It was observed from the graph that the throughput rate oscillated back and forth from increase to decrease and vice versa until there was a progressive increase in throughput rate. The outcome has a boundary with maximum and minimum value. In other words, a sort of self-regulation of the robotic motion when an angle was set to be at the optimal range. Therefore, the rate of arrival of parts increased progressively with a consistent increase in the throughput rate. The graph of Figure 5-7 showed the relationship between the product present position and the optimal result. There existed a concurrent and stable pick-up rate as the products arrived at their position from the moving conveyor system. It was also an indication that the conveyor area was cleared by the manipulator as parts arrive at its work envelope. Therefore, the suggested mathematical models for product positioning were suitable to give effective productivity during the pick and place task. Figure 5-10 to figure 5-12 showed the efficiency of the angle of placement that was used in the research.

The relationship between the probabilities that work was cleared from the conveyor by the manipulator against the throughput rate was presented in Figure 5-8. The result showed a steady increase in the throughput rate as the probability curve increases steadily showing that the parts arriving at the conveyor were cleared upon arrival. It was also an indication that no congestion could lead to the queue up of parts. The graph of Figure 5-9 showed the relationship between the throughput rate and the pick-up rate. The representation showed a progressive increase in the throughput rate as the pick-up rate also increased. With the set of operating conditions and parameters used in the research work, the results obtained yielded optimal productivity. Therefore, the range of values used for the experimental work was effectively used when the throughput rate was required to be improved during a pick and place the task in an advanced manufacturing environment.

The pick and place of tasks were carried out in the mechatronics and robotics research laboratory of the University of KwaZulu-Natal in Durban, South Africa. The operational flow chart for the pick and place task was presented in Figure 5-1. Considering N number of items flowing through the conveyor belt system in a Poisson manner, and at a constant belt velocity. Arriving parts from the conveyor were picked up randomly by a manipulator following the first in first out order (FIFO). The parts were then positioned on a rack for further manufacturing processes. The part arrival time was studied and the average time for each task was presented in Table 5-1. Subsequently, an operational variation of the manipulator motion was achieved by varying various manufacturing conditions that were involved during the pick and place task.

The angle which was the area of interest was varied between 81 degrees to 96 degrees. The effects of varying the angle and other operating parameters were studied to determine their impacts on the throughput rate of the system. The vision camera determined the position of the part that first gets to the robot workspace for immediate pick up by the gripper. For effective productivity, the part's present position was determined. The pick-up position was used to analyze the part's present position using the illustration in Figure 5-2, and calculated using equation (5-9). The average speed of the robot (Rv), robot current position (rx, ry), product position (Px), and the manipulator angle (α) were used to obtain the current position of the part arriving from the conveyor.

The angle of pick-up and placement of the manipulator was varied within the range of 80 degrees to 96 degrees to study its effect on the throughput rate. Equations were developed which served as a basis for analyzing some selected manufacturing conditions.

The parameters used were implemented into the developed equations to arrive at suitable optimal values. Standard results were obtained and simulated using MATLAB and compared with a range of values against each other to obtain optimal results. From the set of operating conditions and parameters used in the research, it was observed that an optimal throughput was obtained when the angle of placement was set at 88 degrees. Furthermore, the graphical presentation showed that when a speed of 96m/secs was used, a higher throughput was recorded. The research work was able to provide adequate operating conditions, with suitable equations, yielded optimal throughput during a pick and place task. The results obtained in the research enhanced productivity in an advanced manufacturing environment and created an effective manufacturing system that was capable being competitive.

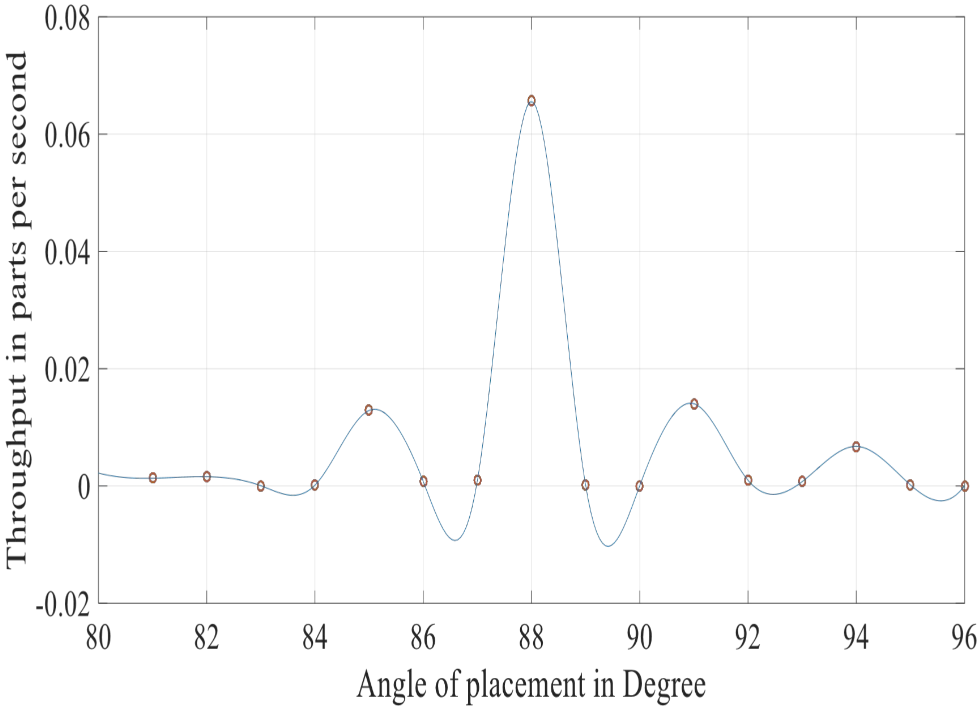

Figure 5-5: Throughput (Parts/secs) under a varying angle of placement ($\alpha°$)

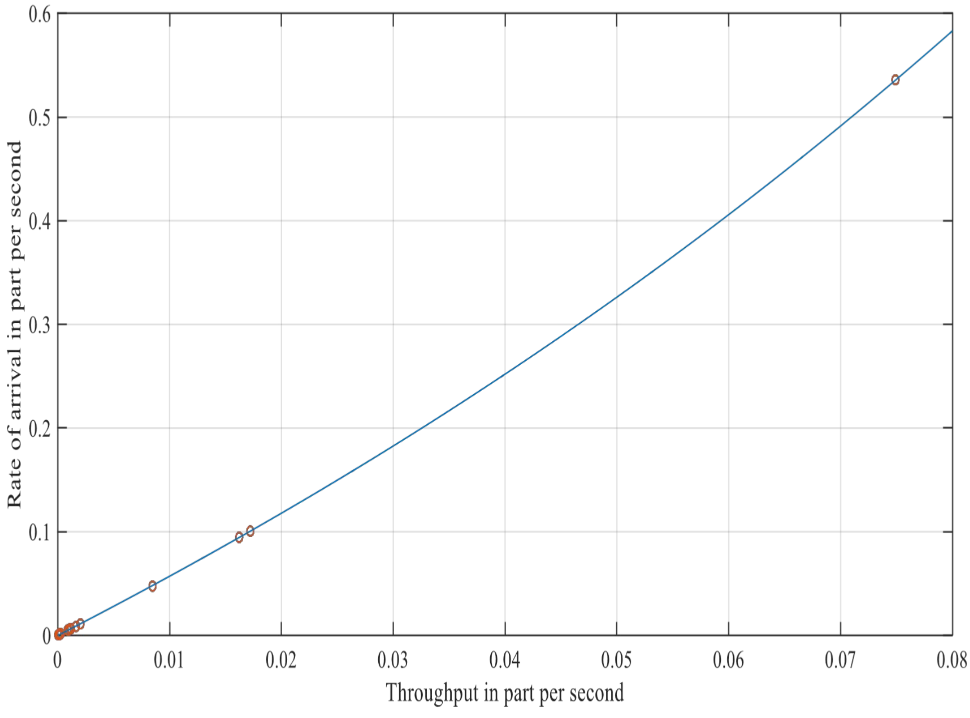

Figure. 5-6: Products arrival rates RB against throughput T_r (Parts/secs).

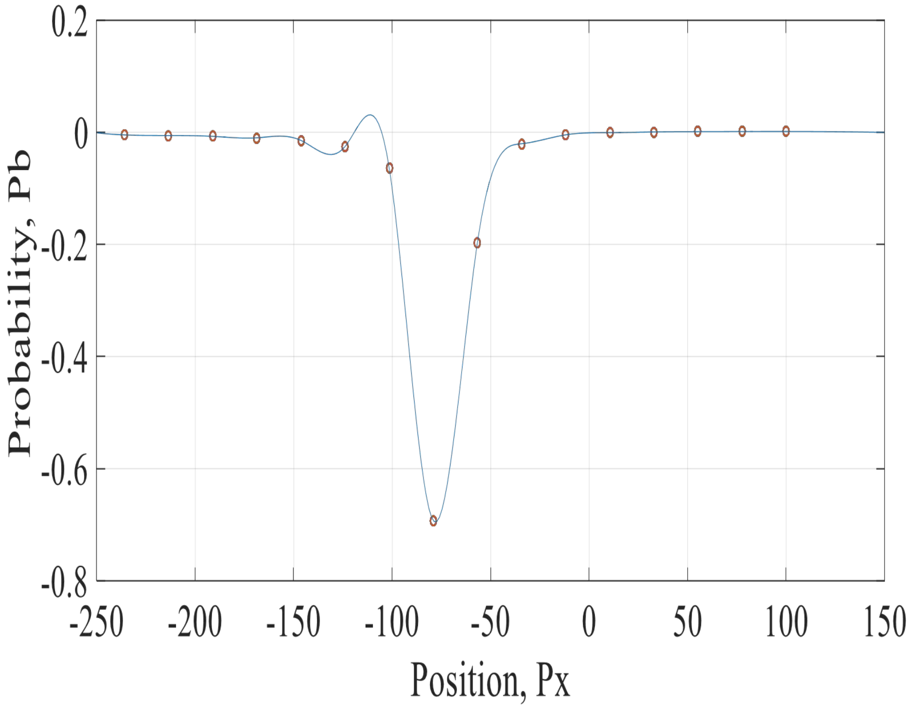

Figure 5-7: Graph of probability that works is been cleared from conveyor Pb against product position Px.

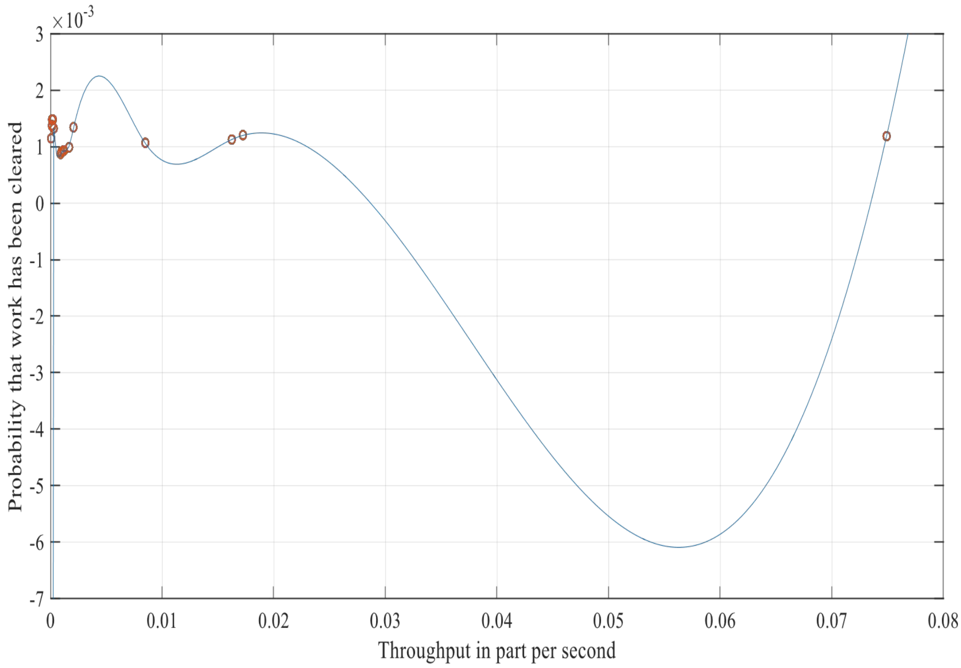

Figure 5-8: Graph of Probability of Cleared Work (Pb) against Throughput Rate (Tr) (Parts/secs)

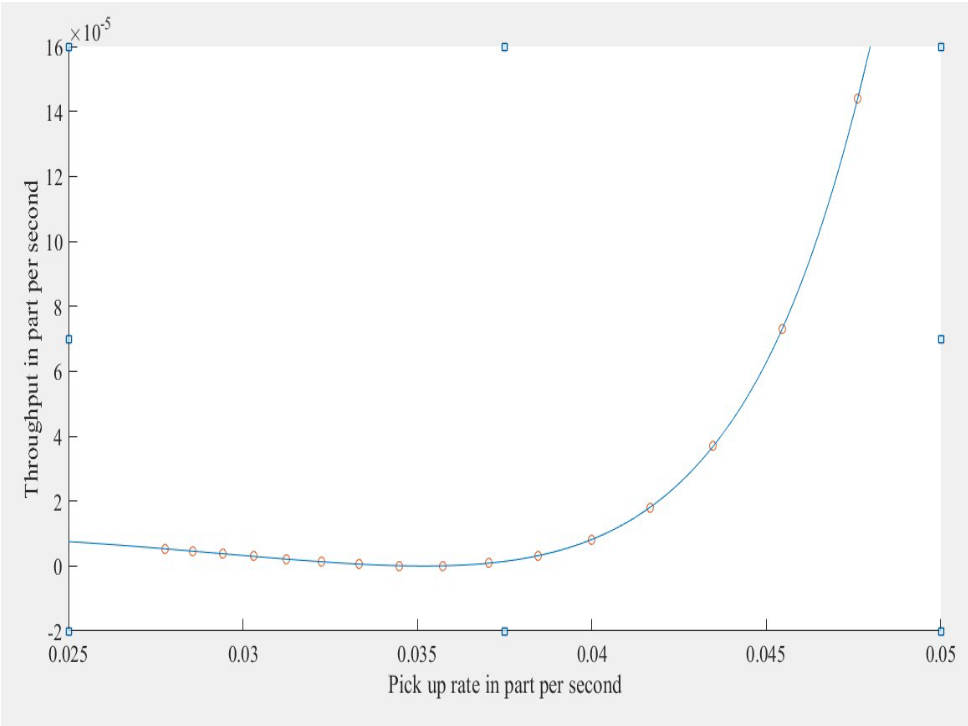

Figure 5-9: The Relationship between the Throughput Rate (parts/sec and the Pickup rate (parts/sec).

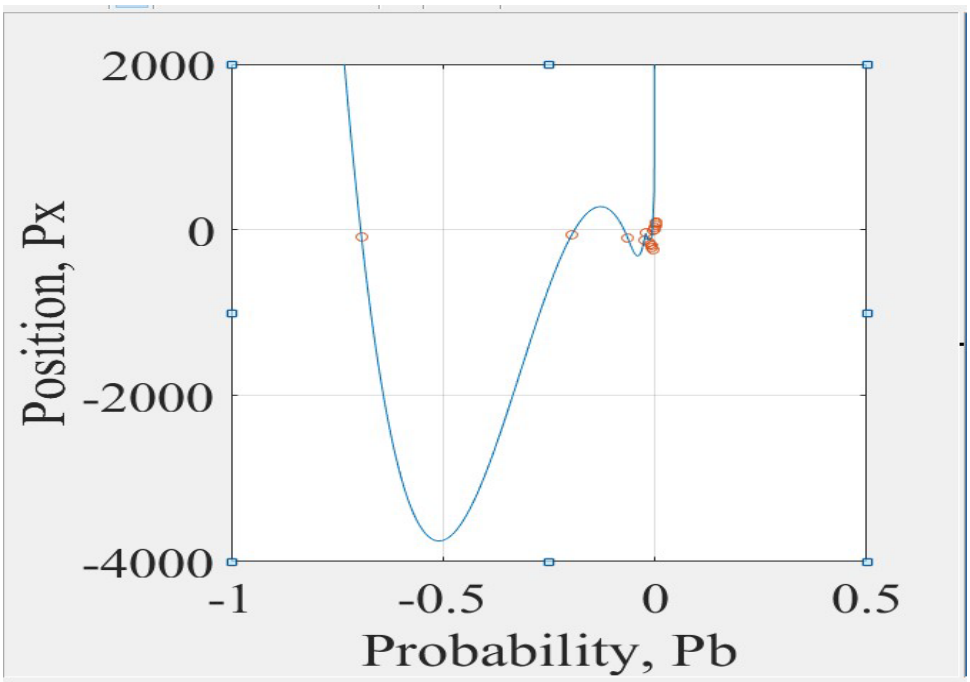

Figure 5-10: Relationship between product position and probability that work has been cleared.

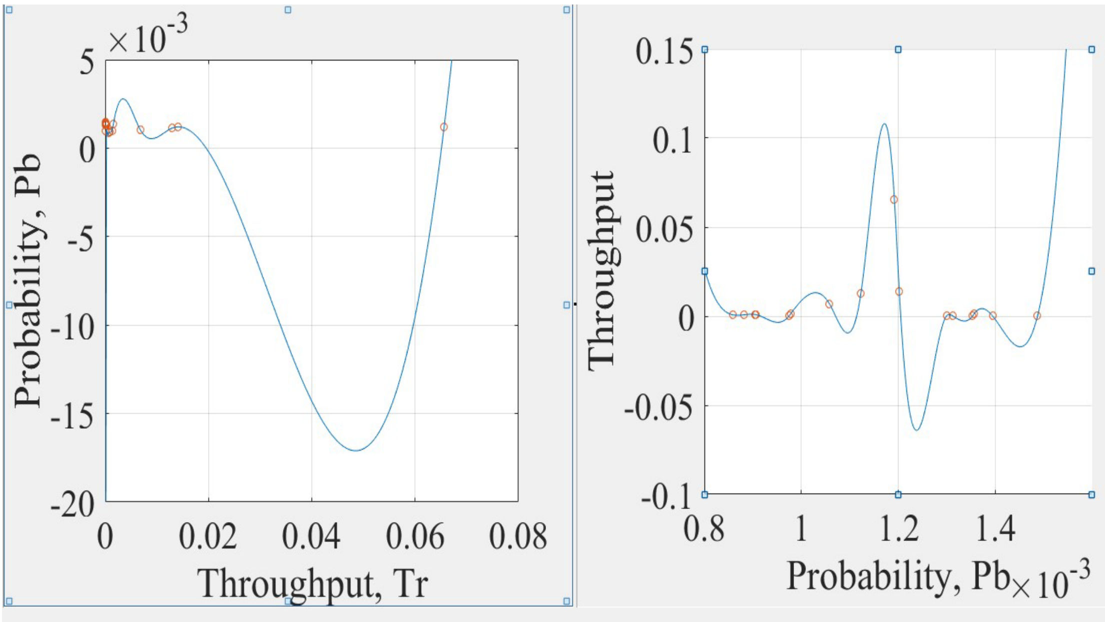

Figure 5-11: Relationship between the Probability that work is been Cleared and the Throughput Rates.

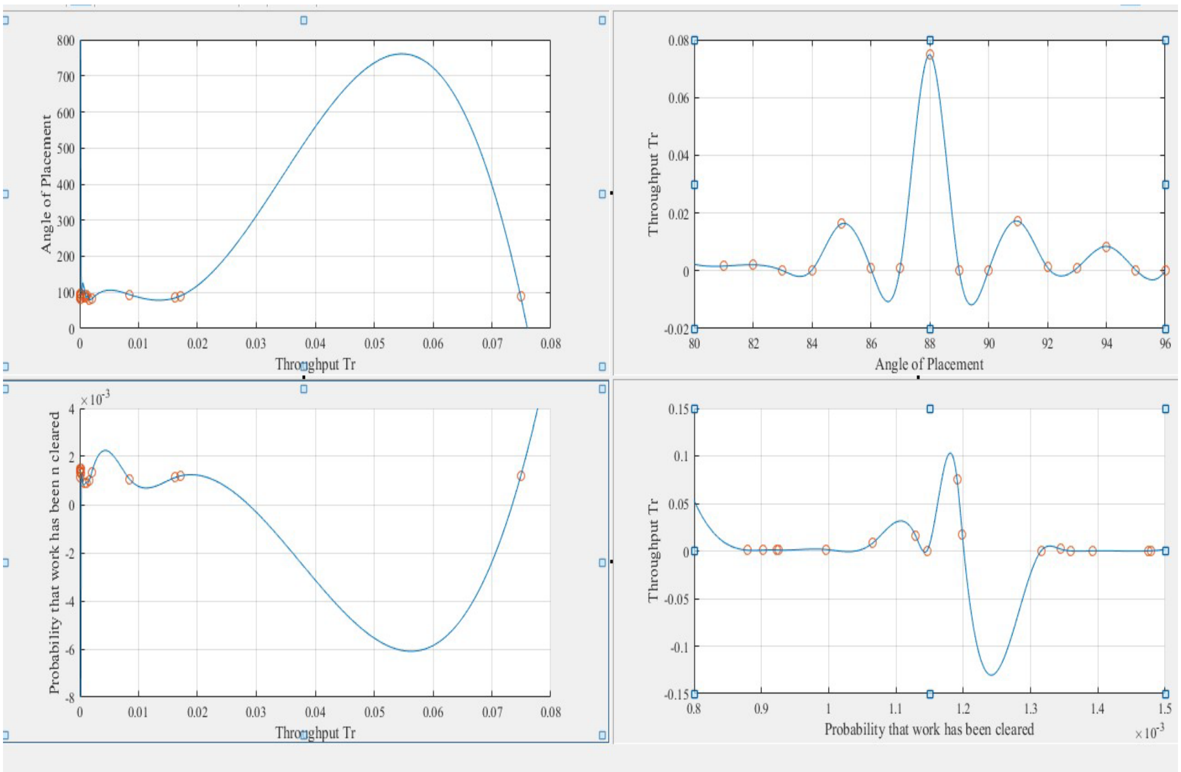

Figure 5-12: Relationship showing the angle of placement against the throughput rate.

5.7 Conclusion

The operation of the robot was varied in an attempt to research the best operational condition that can yield optimal throughput. A pick and place task were carried out using a single robot to pick up arriving parts on a moving conveyor system. The angle of pick-up and placement of the manipulator was varied within the range of 80 degrees to 90 degrees to research its effect on the throughput rate. Mathematical models were developed and served as the basis for analyzing the selected manufacturing conditions. The parameters used were implemented into the developed mathematical models to arrive at suitable experimental values. Standard results were obtained and simulated using MATLAB to compare ranges of values against each other to obtain optimal results. From the set of operating conditions and parameters used for the research, it was observed that an optimal throughput can be obtained if the angle of placement was set at 88 degrees. The graphical presentation showed that when a speed of 96m/secs was used, a higher throughput was recorded. The research work was able to provide adequate operating conditions, with suitable mathematical models, which yielded optimal throughput during a pick and place task. The results enhanced the productivity in an advanced manufacturing environment and created an effective manufacturing environment that was capable of providing a competitive edge and a lead in the competitive market.

Engineering equation solver (EES), and the Renewal Reward theorem, were used to analyze the derived classical models. MATLAB software was used as the simulation platform. The results from the simulation were used to compare and select the optimal operating conditions that yielded optimal throughput. Robot as a trending disruptive technology was implemented to carry out a pick and place task to determine its effects on the production process, and productivity, in an advanced manufacturing environment.

5.8 Summary

The robotic arm motion was varied within a selected operational range to determine its effect on the throughput rate during a pick and place task. The operational variation of the manipulator motion was achieved by varying various manufacturing conditions that were involved during the pick and place task. The angle which was the area of interest was varied between 81 degrees to 96 degrees. Considering N number of items flowing through a conveyor belt system in a Poisson manner, and at a constant belt velocity. Arriving parts from a conveyor were been picked up randomly by a manipulator following the first in first out order (FIFO). The parts were then positioned on a rack for further manufacturing processes. The time spent for the task was studied and the average time for each task was noted. Mathematical equations were developed and analyzed to obtain the best set of parameters that can provide optimal throughput. The outcome was compared and simulated using MATLAB to obtain efficient results. With the set of operating parameters used in this study, an optimal throughput was obtained at an angle of placement of 88 degree. The analysis gave a manipulator speed of 96m/sec which provided the highest throughput during service. The research presented effective operating parameters for a manipulator, which can adequately be implemented in a manufacturing system to improve the throughput rate during a pick and place task in an advanced manufacturing environment.

CHAPTER SIX

The Design Parameters of a Conveyor System for an Optimal Throughput Determination: A Mathematical Approach

6.0 Introduction

The classical mathematical modeling approach was used to research the working parameters of the conveyor system when performing a pick and place task. The best design and working parameters that ensured there were measurable performances of the conveyor system towards achieving optimal efficiency were determined. Achieving optimal throughput in the conveyor system required the determination of adequate working parameters that enhanced its efficiency and optimal production output. With recent advancement in the development of the conveyor system, operational performance of the conveyor assists manufacturers to improve the production process. Suitable and highly effective design parameters that can yield optimal productivity was required to be determined in order to improve the efficiency of the conveyor system during the packaging stage of manufacturing. Adequate material handling equipment in the manufacturing environment was critical in the improvement of the overall production costs. Operating the conveyor belt system at optimal conditions can assist manufacturers to obtain a higher productivity during manufacturing and material handling stages [201]. Conveyor belts are important equipment in an advanced manufacturing environment for the transportation of raw materials from the initial stage to the stage of the finished product [202]. Figure 6-1 shows a simple diagram of the conveyor belt system. The different components of the conveyor belt system were mainly the electric drives, pulleys, idlers, and a long belt. The energy consumption of the conveyor belt when added up to the expenditure in manufacturing industries led to an increase in operating cost [165].

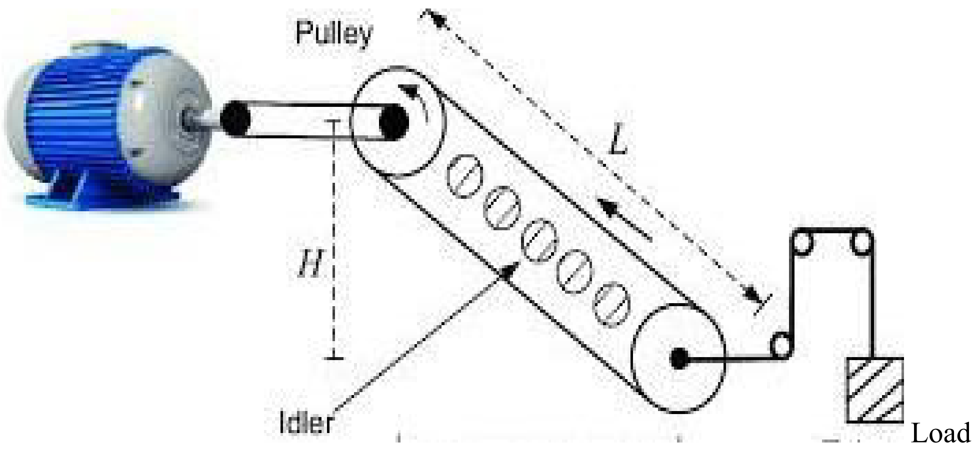

Figure 6-1: Typical diagram of a conveyor belt system

The need for adequate selection of parameters was a factor that was used to determine the efficiency of the conveyor system. The conveyor belt system was configured to operate below and above-rated speed. The normal working parameters of the conveyor system were used to determine suitable and highly effective parameters that were used to configure the conveyor system in order to obtain an optimal throughput in the advanced manufacturing environment. The system was modeled using notable parameters to generate mathematical models that were solved using an engineering equation solver. The model-based design was simulated using MATLAB and the simulation results gave an optimal operating speed that was implemented in order to obtain optimal throughput.

6.1 Model Based Design of the Conveyor System for Optimal Productivity.

The model-based design considered the conveyor belt system that can operate under varying loads within a reduced operating time. The conveyor belt was assumed to be operating within a speed reduction loss of 5%. By considering the design parameters and using some notations, an operating conveyor system with optimal efficiency was developed. The model considered the application of the conveyor belt system in transporting materials and goods from one manufacturing stage to the other. During operation, the conveyor belt experienced a tensile effect as a result of the weight of the loads that passed through it. The loads can be categorized into:

1) Load due to the conveyed materials $\boldsymbol{L_c}$ $(\boldsymbol{kg/m})$
2) Load due to the idler that guides the belt movement $\boldsymbol{L_i}$ $(\boldsymbol{kg/m})$
3) Load due to the rotational effect of the belt drives $\boldsymbol{L_b}$ $(\boldsymbol{kg/m})$

The design of the conveyor belt system considered adequate selection of the idler. The selection considered the optimum weight carrying capacity and to have a design that will not fail during operation. Equation (6-1) was used to calculate the idler load.

$$L_i = \frac{mass\ of\ idlers\ (m_i)}{spacing\ between\ idlers\ (I)} \qquad (6\text{-}1)$$

The load due to the conveyed materials was part of the factors that was used when the tensile effect was calculated. It was expressed as the ratio of the capacity of the conveyor to the speed of the rotating belt and represented in equation (6-2)

$$L_C = \frac{c_c}{v} \qquad (6\text{-}2)$$

The tension of the conveyor belt was calculated by considering the friction co-efficient f, length and height of the conveyor ($l,\ H$), acceleration due to gravity (g), inclination angle δ, and the three loading effects. The conveyor belt tension was calculated using equation

$(6-3)$.

$$T_b = 1.37 \times f \times l \times g \times (2 \times L_i + 2 \times L_b + L_c) \times cos\ \delta + (H \times g \times L_c) \quad (6\text{-}3)$$

Two different powers were required during the movement of materials on the conveyor belt. The power that drove the pulley and the minimum power required to drive the electric motor. Equation (6-4) and equation (6-5) were developed for the design calculation of the power required to drive the conveyor belt mechanism. p_p represented the power required to drive the pulley and was calculated using equation (6-4) and the minimum power required to drive the electric motor was obtained using Equation (6-5).

$$p_p = \frac{T_b \times v}{1000}\ (kw) \quad (6\text{-}4)$$

$$p_m = \frac{p_p}{D_f} \quad (6\text{-}5)$$

Consequently, the conveyor belt acceleration was obtained using equation (6-6).

$$A = \frac{(B_{ts} - \boldsymbol{T_b})}{[L \times (2 \times L_i + 2 \times L_b + L_c]} \quad (6\text{-}6)$$

Furthermore, the operating time can be calculated using

$$T_t = 60A \quad (6\text{-}7)$$

The speed of rotation of pulley was calculated using equation 8.

$$V = \frac{\pi DN}{60} \quad (6\text{-}8)$$

Total motor horse power H_p was obtained with the addition of equation (6-4) and (6-5).

A speed reduction of 5% was considered to take care of losses.

$$H_p = (p_p + p_m) \times 1.05 \quad (6\text{-}9)$$

The motor current can be calculated by considering the total horse power to the ratio of voltage required, efficiency, and the power factor as stated in equation$(6-10)$.

$$Motor\ current = \frac{H_p \times 746}{voltage \times 1.73 \times efficiency \times power\ factor} \quad (6\text{-}10)$$

The tensile stress experienced when the conveyor belt is in the steady state can be obtained using equation (6-11).

$$T_p = \boldsymbol{T_b} \times \boldsymbol{s_k} \qquad (6\text{-}11)$$

Consequently, the conveyor belt acceleration can be obtained using equation $(6 - 12)$

$$A = \frac{(T_p - \boldsymbol{T_b})}{[L \times (2 \times L_i + 2 \times L_b + L_c]} \qquad (6\text{-}12)$$

Selected notations for the design

$T_b = belt\ tension$

$T_p = tension\ in\ pulley$

$f_x = friction\ co - efficient$

$f_y = run\ factor\ of\ conveyor$

$l = lenght\ of\ the\ conveyor\ (mm)$

$L_i = idler\ load\ (kg/m)$

$L_b = load\ \ effect\ of\ the\ belt\ (kg/m)$

$L_c = load\ of\ conveyed\ material\ (kg/m)$

$H = conveyor\ height\ (m)$

$p_p = power\ required\ to\ drive\ pulley$ (kw)

$p_m = power\ required\ to\ drive\ the\ electric\ motor$

$v = speed\ of conveyor\ belt\ (m/s)$

$A = conveyor\ belt\ acceleration\ (m/secs)^2$

$B_f = belt\ fracture\ strenght$

$I = spacing\ between\ idler$

$D = diameter\ of\ driving\ pulley$

T = Ambient temperature

$N = number\ of\ revolution\ per\ minute$

$g = acceleration\ due\ to\ gravity\ 9.8m/secs$

$\delta = angle\ of\ inclination\ of\ the\ conveyor\ (degrees)$

$T_t = Operating\ time$

$s_k = start - up\ co - efficient$

$c_c = capacity\ of\ conveyor$

$c_r = \ factor\ responsible\ for\ friction\ to\ occur$

$m_i = mass\ of\ idler$

Using the set of derived equations above, values were assumed for some of the design parameters,

and solved using the engineering equation solver (EES). Results obtained are given in Table 6-1:

TABLE 6-1: Design parameters for the conveyor belt

L_b	$\mathbf{17kg}$
c_c	$400kg/secs$
f_x	0.02
f_y	0.014
v	$2.4m/Sec$
T_t	$12secs,$
D	0.62
N	$75\ rev/min$
H	$20mm$
l	$240mm$
L_i	$18{,}5kg$
I	$1.4mm$
δ	$6°$
sk	1.5
D_f	1.0

c_r	14
c_v	0.80
m_i	20kg
G	9.81
Current (I)	700Amps

6.2 Results and discussion

The graph of figure 6-2 showed the relationship between the operating speed of an electric motor and the operating time of the conveyor belt drive. There was a reduction in the time spent during operation as the driving speed increases. Also, Figure 6-3 showed the relationship between the power consumption and time of operation, the operating conditions were suitable and efficient in an advanced manufacturing environment. MATLAB software was adopted to build Simulink mathematical models and solved using the engineering equation solver (EES). Results obtained were simulated to obtain the best results that gave us optimal design parameters that predicted optimal design conditions.

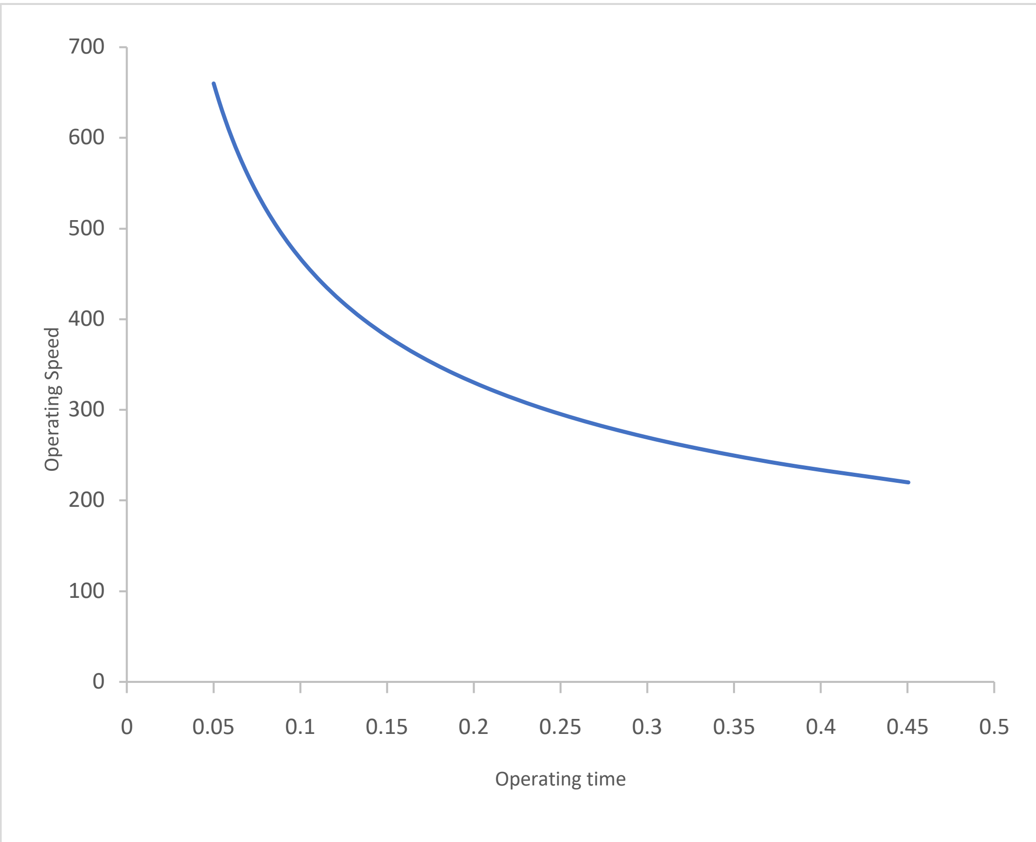

Figure 6-2: Operating speed against time

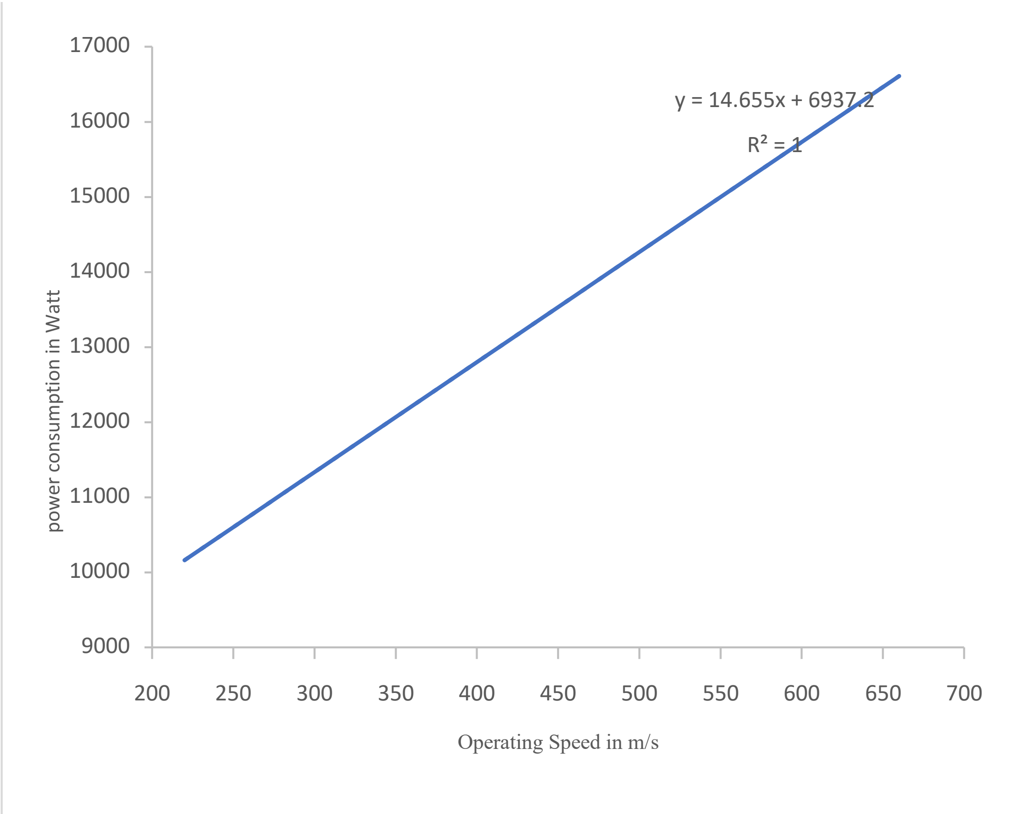

Figure 6 - 3. Power consumption vs. operating speed

6.3 Conclusion

A model-based approach was implemented with initial parameters assumed to research the effect of varying the loads below and above the rated speed of the electric motor on the conveyor belt system. The design conditions were studied to determine the effects of the selected design parameters on the throughput rate during the packaging stage in the manufacturing setup. The developed mathematical models were analyzed and the outcome gave a suitable operational strategy used on the conveyor that yielded optimal throughput during the manufacturing process. The simulation results showed that the design parameters used, led to an optimal operating speed at a reduced time of operation.

For the selected design, at 390m/sec, the optimal operating time was 0.4secs with a power consumption of 12700W. The outcome showed that the selected design parameters were suitable to be used when designing a conveyor system. The output obtained produced optimal productivity.

6.4 Summary

. The design parameters of a conveyor system were examined to select the best operating speed that gave optimal throughput during a pick and place task. Mathematical models were developed to study the effect of varying the loads below and above the rated speed of the electric motor. Standard equations were developed and analyzed using some notations to represent operating parameters of a conveyor belt manufacturing system. MATLAB software was adopted to build simulic mathematical equations and solved using the engineering equation solver (EES). Results obtained were simulated to obtain and select suitable results that gave optimal throughput at operating speed of 390m/sec, operating time at 0.4secs, and at a power consumption of 12700W. This modeled design parameters can be adopted when an efficient operating speed of a conveyor system is required for optimal throughput.

CHAPTER SEVEN

7.1 Research Discussion

The research presented a study on the impact of disruptive technologies on product process, and productivity in an advanced manufacturing environment. The rise in the potential for technological advancement in an advanced manufacturing environment led to the development of disruptive technologies. Industry 4.0 focused on the adequate application of emerging technologies in an advance-manufacturing environment in order to create an efficient manufacturing system. The use of automation tools such as robots at various stages of the manufacturing process has reshaped the manufacturing environment. Disruptive technologies, through significant innovations have emerged and have significantly contributed to the growth and success of the manufacturing environment.

The fourth industrial revolution has led to the transformation of the complex traditional manufacturing system into a flexible autonomous system. The fast growth in the technological advancement also led to the replacement of human labor with high-speed automation tools and machinery. Robots as one of the of the widely used automation tools in the manufacturing environment has become a key equipment in an advanced manufacturing environment. The Fanuc M-10i robot was used in the advanced manufacturing setup used in the research. The Fanuc M-10i robot has 6 axes of rotation and it is capable of rotating at various degrees. Its unique design enabled it to be efficient in performing some difficult tasks within the shortest period. The Fanuc M-10i robot used in the research was developed with suitable software that was programmed to coordinate pick and place task of many parts within a short period. A vision camera integrated along with its operating system sensed arriving parts and promptly sent a signal to the robot for immediate detection to pick up parts as programmed.

The M-10i-A Fanuc robot used for the manufacturing task was designed with six degrees of freedom and was capable of moving in various directions. The maximum load capacity was 10kg, its arm's reach was 1422mm, and its weight was 130kg, with a repeatability of $\pm$ 0.03°. Owing to its high degree of rotation and repeatability, the throughput rate was high when implemented to perform tasks in an advanced manufacturing environment. The robot was designed with a mechanical structure, which was controlled to perform dedicated tasks. The robot motion control involved three different phases; the perception phase, processing phase, and the action phase.

During the pick and place task, three different types of grasps were used in holding the parts: the pre-grasp, the grasp, and the post grasp. In the pre-grasp, the end-effector was positioned away from the part. The pre-grasp allowed for the trajectory motion planning in order to avoid a collision in during operations. The grasp was when the end-effector with its fingers was positioned and ready to grip the object for the pick-up task, and the post-grasp was when the end-effector moved away from the position where the part was grasped. The grasp process was controlled by computing the desired action for the end-effector to perform and the placing of the part at the desired location. The implementation of the robot and its end effector in automating the manufacturing task effectively reduced the costs of production, increased throughput, controlled waiting times, and reduced the lead time in an advanced manufacturing environment.

Disruptive technology has led to the use of various innovations such as the use of mathematical models, simulation tools, and mathematical theories in describing and analyzing manufacturing scenario. Mathematical modeling was used in translating manufacturing problems into numerical analysis which provided useful solutions to traditional manufacturing problems. Mathematical modeling and simulation were used during the decision-making stage of the manufacturing process to predict the long-term prospect of the manufacturing system. Mathematical modeling was and simulation was employed to determine best process and parameters that were implemented to yield optimal productivity in an advanced manufacturing environment.

Industrial robot was used as disruptive technology and implemented to offer solutions to manufacturing problems. The research presented and studied the impact of industrial robots on the throughput rate in an advanced manufacturing environment. The initial working parameters of the conveyor system used in the pick and place task were determine in order to determine the best set of design parameters suitable when an optimal throughput was required. Industrial robots were used to perform a pick and place the task in a virtual manufacturing environment to determine its effects on the throughput rate of the manufacturing process.

Classical mathematical models were used to describe the manufacturing scenario. The mathematical models were analyzed using the engineering equation solver and the results generated from EES were used determine optimal conditions using MATLAB.

A queue is a common phenomenon in an advanced manufacturing environment. The effect on productivity was studied and further optimized. The effect of varying the robotic operation during service was studied to determine its effect on the throughput rate. The solutions derived from the research provided the operating angle of the manipulator that yielded optimal productivity.

The manufacturing system required a cost-effective conveyor system that can operate at a higher speed in order to obtain optimal production output. Adequate selection of the design parameters was an important factor used to determine the throughput rate of the conveyor system. The design parameters of the conveyor belt system were determined and used to improve the efficiency and the throughput rate during a pick and place task. Classical mathematical models were used to describe the operation of the conveyor system during a pick and place task. A virtual manufacturing setup was used in the determining the design parameters which represented the working parameters of the conveyor system. Robots as a disruptive technology were implemented to carry out the pick and place task

The research used a conveyor system that was operated under varying load conditions with a speed reduction loss of about 5 %. The types of loads required to be conveyed, the belt tension, length and height of the conveyor system, the acceleration due to gravity, angle of inclination, operating time, electric motor current, the power required to drive the pulley, tensile strength, belt fracture strength, spacing between idler, number of revolutions per unit time, start-up coefficient, the mass of idler, the capacity of conveyor, and the power required to drive the conveyor were considered in modeling the conveyor system. All these parameters were studied and described using mathematical models. The design parameters were determined by considering a conveyor system that can accommodate a load of 400kg/sec at a conveyor speed of 2.4m/sec. The effects of varying load below and above the rated speed were studied to determine the effects of the computed design parameters on the throughput rate. The developed models were analyzed numerically using the engineering equation solver (EES). The results obtained were evaluated using MATLAB simulation software. The simulation process yielded optimal values that were implemented in the manufacturing setup. The operating parameters that yielded optimal throughput were obtained at an increased speed of 390m/sec. There was an increase in the driving speed and led to a reduction in the operating time.

Waiting time also known as a queue was one of the factors that affected the cost of production in the advanced manufacturing environment. The non-productive time during manufacturing was found to reduce the throughput rate and the efficiency of a manufacturing system. Waiting time has significant on the impact of manufacturing processes and the overall output. Waiting time occurred when the arriving parts were more than the available server. The parts were in queue until the service of the server becomes available. The longer the waiting time, the higher the lead time, and the higher the cost of production. Also, the waiting time resulted in idle time, and the utilization of manufacturing processes decreases. Long wait for services led to a decrease in the overall productivity in the advanced manufacturing environment. The waiting time was reduced in the advanced manufacturing environment by redesigning the manufacturing process. The redesigned process ensured there was an even production flow of parts. Adequate control of the waiting time provided a more productive manufacturing process that yielded an optimal throughput.

The queuing theory has a wide range of applications in an advanced manufacturing environment. Queue exists in the banking hall, hospitals, offices, traffic system, canteens, traffic system, and manufacturing environments. The study of the queue involves quantifying the phenomenon, developing models for waiting in line systems and analyzing the waiting line model. Quantities such as the average queue length, average waiting time, average service utilization, and the average number of parts arriving at the service station were critical in analyzing the impact of queue on the manufacturing system. The research optimized the waiting time using queuing theory to evaluate the performance of the manufacturing system, and to evaluate the effect of the server (robots) on overall productivity. The performance optimization on waiting time using queuing theory in an advanced manufacturing environment was studied. Mathematical models were used in describing the waiting line models and the manufacturing conditions causing the queuing the problem. The research used a virtual manufacturing environment whereby industrial robots were employed to perform a pick and place task. Heavy traffic was experienced due to multiple products arriving at the same packaging point. The trade-off point was set between the number of machines employed for production and productivity level. Server rate and queue time were two parameters used in determining the trade-off point in the manufacturing system. To adequately control the waiting time in the packaging stage of the manufacturing process, an alternative solution was proposed to reduce the waiting time of the packages in the waiting line model. Performance optimization during the manufacturing process was an essential tool that was used to support the manufacturer in achieving a cost-effective manufacturing system.

The performance optimization processes involved adequate monitoring and modification of critical operating conditions that enhanced productivity in the advanced manufacturing environment. The effective implementation of optimization tools during the selected manufacturing process enhanced the performance of the manufacturing process in a competitive environment.

The research optimized the waiting time to determine the effect on the efficiency of production. The virtual manufacturing scenario was considered using mathematical models to describe and study the scenarios. Industrial robots with programmable software were described along with it to coordinate their operations. The camera incorporated with it immediately senses the parts arriving and sends the signal to the robot (server) for immediate pick-up. The servers (robots) were assumed to perform at the same rate based on first in first out (FIFO). The system performance was modeled into a Poisson distribution function where the service times were exponentially distributed. The queuing theory was used in analyzing the waiting line models. While the Newton-Raphson iteration formula was used as a numerical tool and simulation tool. Some parameters were assumed with some operating values to represent the manufacturing system. The queuing mathematical modeling theory was used for the development of suitable mathematical models to represent and analyze the scenarios. The assumed values were computed into the models and solved numerically using the Newton-Raphson iteration method. The results obtained were varied against each other to obtain the best operating conditions and parameters that were used to obtain the required solution.

The models best describe the behavior of the products during the arriving stage and the packaging stage of the virtual manufacturing scenario. The description of the process gave the structure of the service facility required for the arrival stage modeling. Queuing is a complicated phenomenon that has a great impact on the throughput rate in an advanced manufacturing environment. Adequate control measures of the waiting time are required by employing a practical tool that can adequately control and analyze a waiting line model. The queuing theory is an effective analytical tool that can be used to solve a waiting line model. The M/M/S queue model is described in this present work; M/M/s model has its servers arranged in a parallel form where the service time at each station is identified following the same exponential law.

Classical models were used to describe a virtual manufacturing scenario where robots as a disruptive technology was used as servers in the packaging stage.

Various equations were used to describe the manufacturing scenario in which the average queuing time was presented. The average queuing time was further differentiated to optimize the performance of each robot with its corresponding queue. The outcome gave a general equation that was further analyzed using the Newton-Raphson iteration method. The outcome gave an output free of queuing. This outcome was presented in a graphical manner which shows a minimum waiting time when the waiting time was optimized. The results confirmed that the suggested model can be suitable for use when the queuing time needs to be controlled during the packaging stage in a real-life manufacturing scenario.

Considering the competitive manufacturing environment, the need to increase throughput to reduce the cost of production is of the highest interest among modern manufacturers. The throughput rate of a robotic manufacturing system was studied by using classical mathematical models to represent pick and place scenarios. The research addressed the problem faced by manufacturers trying to obtain optimal throughput when a robot is available to perform a difficult task. Classical models with assumed parameters were used to describe a scenario of a pick and place the task in a virtual manufacturing environment. The system model considers a single server queue where parts arrive via conveyor belt from multiple stations to a buffer station. The arriving parts join another conveyor where parts were transported to be picked up and placed by a robot in a virtual manufacturing environment.

The arrival behavior is randomly following a Poisson process with varying with mean arrival rate λ, which is a case of inter-arrival time (the difference between two consecutive arrivals). The arrival of the parts from the buffer station takes the form of a negative exponential distribution which follows the manner of impatient behavior of customers in the M/G/I queuing system. The repeatability motion of the robotic arm makes the system to experience a deterministic feeding time μ (mean service time). Parts that were not picked up decides to leave and return for service in the next cycle. This behavior in queuing theory is also referred to as the reneging behavior of customers.

Consequently, the total cycle time tc required for the robot to complete a cycle was calculated using the total duration that was associated with the pick and place operation. In this model, it was assumed that the conveyor was neither starved nor saturated. Following the inter-arrival behavior, the total cycle time tc was obtained by summing together the time involved in the manufacturing scenario that was studied

Given that tm is the time at which parts move pass the conveyor, $tvis$ represent the camera vision time, tp as the pick and place time, tt is the time taken to change tool, and tr equals the time taken by the unpicked parts to re-circulate and join the next queue.

The Engineering equation solver (EES) was used to solve the equations numerically and the results of the analysis were simulated using MATLAB software to achieve the best set of parameters for the system. With the set of equations and parameters assumed, optimal throughput was derived for a pick and place task. Various equations were derived and an equation for optimal throughput was developed. The equations were tested to determine the efficiency of the equations. With the set of assumed parameters, the engineering equation solver (EES) was used for the numerical analysis, and MATLAB was used to simulate the parameters against each other to obtain optimal outputs. From the classical models formulated, it can be concluded that the equation for optimal throughput was effective. The graphical illustration compares the mean arrival rate and the cost of production. Outcomes showed that the slower the arrival rate of parts, the higher the cost of production. Also, the graph of throughput against the arrival of the part showed that in this study, an optimal throughput can be achieved at 1.6 parts/mm^2. This model can be useful among manufacturers when optimal throughput is required to be obtained in an advanced manufacturing environment.

CHAPTER EIGHT

8.0 Conclusions and Recommendations

8.1 Conclusion

The research presented and studied the impacts of robots as a disruptive technology on product, process, and productivity in an advanced manufacturing environment. With the introduction of automation technology, a unique manufacturing process of replacing human labor with industrial robots has begun to have an improved trend in an advanced manufacturing environment. Industrial robots as a disruptive technology have great impact on the process of manufacturing, and productivity in an advanced manufacturing environment. Industrial robots are highly valued in the manufacturing environment due to its unique attributes: reliability, high precision, predictability, repeatability. It can also reduce the manufacturing process variability, increases throughput, and productivity. Industrial robot has extensively increased the scope for replacing human labor by reducing the need for human intervention in automated applications in an advanced manufacturing environment.

Typical applications for industrial robots in an advanced manufacturing environment include assembling of parts, handling processes such as the pick and place task, dispensing, welding, and lot more. In this study, the impact of industrial robots as a disruptive technology in an advanced manufacturing environment has been studied. The effects on product quality, the production process, and how productivity can be used to achieve higher throughput rate was examined. Industrial robots have been successful used in manufacturing environment to create efficiencies from the early stage of manufacturing through the final stage. Industrial robots can easily be programmed to operate continuously in lights-out situation. Industrial robots are valuable automation tool an advanced manufacturing environment for a number of attributes: precision, reliability, repeatability, predictability, and resistance to hazardous environments.

The new surge of industrial robots is in applications that requires advanced intelligence.

Industrial robots are associated with a wide range of complementary technologies – vision camera, sensing ability, speech recognition, and advanced mechanics. This special characteristic results in some exclusive new levels of functionality for some assumed difficult jobs in an advanced manufacturing environment. The quality and quantity of output achieved by industrial robots is highly efficient remarkable and has great impact on productivity.

By increasing throughput, and decreasing downtime, the robotic automation application is an excellent way of improving efficiency in an advanced manufacturing environment. Following are some of the benefits of robotics in terms of productivity:

1) Industrial robots are capable of manufacturing high-quality and precise work.
2) They can efficiently produce parts in larger quantities within short period of time.
3) An industrial robot improves the safety conditions in manufacturing environment.
4) Industrial robots have the potential to perform in harsh manufacturing environments.
5) They can easily be reprogrammed for producing varying products and designs.

Modeling, simulation, and optimization have been effective in decision-making in an advanced manufacturing environment. Proper measuring through modeling and simulation gives manufacturers a prior picture of how their system will behave in a real-life manufacturing scenario and allows for further improvement. The modeling and simulation process provided an efficient and valuable solution to some of the complex manufacturing stages. The modeled manufacturing stages can be optimized to find the best solution among the various alternatives provided. The process of optimizing a manufacturing process gives adequate measurement reliability, higher efficiency, and increases the overall productivity in the manufacturing environment.

Robots were used to perform the pick and place task in a virtual manufacturing environment. Classical mathematical models were used in describing the manufacturing processes and making decisions at various stages involved. The study considered the design parameters of a conveyor system where robots were implemented to pick up arriving parts from a moving conveyor. The design parameters of a conveyor system were examined to select the best operating speed that gave optimal throughput during a pick and place task. Mathematical models were developed to study the effect of varying the loads below and above the rated speed of the electric motor. Standard equations were developed and analyzed using some notations to represent operating parameters of a conveyor belt manufacturing system. MATLAB software was adopted to build simulic mathematical equations and solved using the engineering equation solver (EES). Results obtained were simulated to obtain and select suitable results that gave optimal throughput at operating speed of 390m/sec, operating time at 0.4secs, and at a power consumption of 12700W. This modeled design parameters can be adopted when an efficient operating speed of a conveyor system is required for optimal throughput.

The mathematical model was effectively used in the decision-making stage of a virtual manufacturing process. Industrial robots were implemented at the packaging stage of a virtual manufacturing scenario in which mathematical models were used to describe each stages of the manufacturing process. Some suitable parameters and operating conditions were assumed, and the Newton-Raphson iteration formula was implemented for numerical analysis of the models. Simulation was carried out to achieve optimal values that yielded efficient productivity. The optimization process gave an outcome that adequately showed how queuing can be managed in the packaging stage in an advanced manufacturing environment.

The throughput rate of an automated manufacturing process was modeled and the condition for optimal throughput in an advanced manufacturing environment was determined. Classical models with assumed parameters were used to describe a scenario of a pick and place task in a virtual manufacturing environment. The models were studied and analyzed using Queuing theory and the renewal reward theorem. Various expressions were developed, and the engineering equation solver (EES) was used for the numerical computation. The numerical results were simulated using MATLAB to achieve the desired results. An equation that can be used to calculate optimal throughput was also derived. In the study, an optimal throughput was obtained with an arrival rate of 1.63 parts/mm^2.The outcome of study suggested a model that can be effective when solution to optimal throughput is required during the pick and place task of a robotic line manufacturing system. The operational variation of a manipulator (robot) was implemented and the effects of the variation on productivity during a pick and place task was determined. The pick and place task were carried whereby the manipulator motion was modified within a selected operational range. Various mathematical equations were developed and analyzed to obtain the best set of parameters that provided optimal throughput. The outcome was compared and simulated using MATLAB to obtain optimal results. With the set of operating parameters used. The research presented some effective operating parameters for the manipulator as a smart disruptive technology, which can adequately be implemented to improve the throughput rate during a pick and place task in an advanced manufacturing environment. The optimal manipulator position angle was at 88 degrees. The angle yielded optimal throughput at an operating speed of 96 m/s

8.2 Recommendation

It is recommended that further research is still required in the area of robotic motion. It will enable further findings on how to control the operation of the robots to obtain optimal productivity in an advanced manufacturing environment.

Appendices

Appendix 1: Acceptance letters for Conferences and Journals

Appendix 2: MATLAB Reference Data.

The tables of values generated from the use of MATLAB simulation software is presented in the form of the tables below.

Table A1: Simulation Results for Throughput and Pick-up Rate under Varying Pick-up Time.

PPR	Tr	Tpick/sec
0.047619	0.000144	3.0
0.045455	7.3E-05	3.5
0.043478	3.69E-05	4.0
0.041667	1.81E-05	4.5
0.040000	8.2E-06	5.0
0.038462	3.19E-06	5.5
0.037037	8.7E-07	6.0
0.035714	6.19E-08	6.5
0.034483	9.43E-08	7.0
0.033333	5.83E-07	7.5
0.032258	1.3E-06	8.0
0.031250	2.13E-06	8.5
0.030303	2.97E-06	9.0
0.029412	3.79E-06	9.5
0.028571	4.57E-06	10
0.027778	5.3E-06	10.5

Table A2: Simulation Results for Rate of Arrival and Throughput under Varying Angle of Placement.

Rate of Arrival RB	Tr	Pb
0.009021667	0.001619	0.000995
0.011478899	0.002058	0.001344
0.000444099	8.01E-05	0.001475
0.001210995	0.000218	0.001478
0.094615298	0.016236	0.001129
0.005117652	0.000921	0.000902
0.00603819	0.001086	0.000925
0.535498806	0.074892	0.001191
0.000701484	0.000126	0.001392
0.000607746	0.00011	0.001359
0.100550105	0.017202	0.001199
0.006522951	0.001172	0.000922
0.004933255	0.000888	0.000879
0.048058959	0.008449	0.001065
0.001512475	0.000273	0.001316
0.000416417	7.51E-05	0.001146

Table A3: Simulation Results for PPR and PX under Varying Pick-up time.

PPR	PX1 (mm//sec)	PX2 (mm//sec)
20.8	1.45	100.0587
21.8	1.7	77.655
22.8	1.95	55.2513
23.8	2.2	32.8476
24.8	2.45	10.4439
25.8	2.7	-11.9598
26.8	2.95	-34.3634
27.8	3.2	-56.7671
28.8	3.45	-79.1708
29.8	3.7	-101.575
30.8	3.95	-123.978
31.8	4.2	-146.382
32.8	4.45	-168.786
33.8	4.7	-191.189

Table A4: Simulation Results for Tr and Arrival Rate under Varying Angles

Rb (parts/minutes)	Tr (parts/minutes)	α (degrees)
0.009	0.0016	81
0.0115	0.0021	82
4.44E-04	8.01E-05	83
0.0012	2.18E-04	84
0.0946	0.0162	85
0.0051	9.21E-04	86
0.006	0.0011	87
0.5355	0.0749	88
7.01E-04	1.26E-04	89
6.08E-04	1.10E-04	90
0.1006	0.0172	91
0.0065	0.0012	92
0.0049	8.88E-04	93
0.0481	0.0084	94
0.0015	2.73E-04	95
4.16E-04	7.51E-05	96

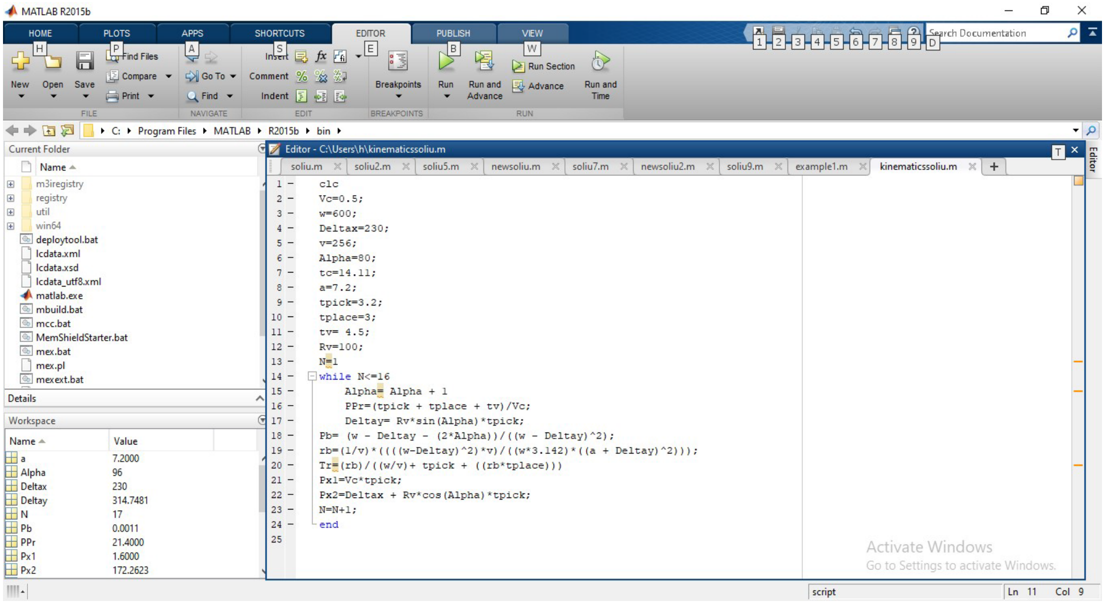

Figure A4: MATLAB Program for the Simulation Process.

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