



FACULTY OF ENGINEERING
DEPARTMENT OF MECHANICAL AND PRODUCTION
ENGINEERING

MASTER OF SCIENCE IN ADVANCED MANUFACTURING SYSTEMS
ENGINEERING DISSERTATION

DEVELOPMENT OF A MATHEMATICAL MODEL FOR INTEGRATION OF
ROBOTS IN A STEEL MANUFACTURING PLANT

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A Dissertation Submitted to Kyambogo University Graduate School in Partial Fulfillment for the
Award of Master of Science in Advanced Manufacturing Systems Engineering Degree of
Kyambogo University

July 2021

DECLARATION

I, Ongom Christopher Adoko, candidate for the Masters of Science in Advanced Manufacturing Engineering Degree of Kyambogo University declare that this research thesis is my original work and has never been presented for a degree in any other university and no part of this dissertation is plagiarized work.

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Sign. Date.

APPROVAL

This Master of Science Dissertation entitled “DEVELOPMENT OF A MATHEMATICAL MODEL FOR INTEGRATION OF ROBOTS IN A STEEL MANUFACTURING PLANT”. Prepared and submitted by Ongom Christopher Adoko in partial fulfillment of the requirements for the Masters of Science in Advanced Manufacturing Systems Engineering Degree of Kyambogo University conducted under my supervision is now ready for examination.

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ACKNOWLEDGMENT

I thank God for the strength and wisdom he has given me to do this research. I wish to express my sincere appreciation to my supervisors Dr. Kizito Paul Mubiru and Mr. Kangwagye Samuel for professional guidance rendered to me during the process of undertaking this research. I extend my gratitude to all the staff at the Department of Mechanical and Production Engineering, Kyambogo University, for the support and encouragement given to me.

It is with great pleasure that I recognize and thank the management and staffs of Roofing's Rolling Mills Uganda limited and Steel & Tube Industries Limited, Uganda for allowing me conduct this research at their organization. I thank the management and staff for the guidance, support, and for all the data and information provided that made this research successful.

Finally, I extend my sincere gratitude to my wife and son for the encouragement and prayers offered to me during my research. I thank my mother for all the support rendered to me throughout my entire life and during this research.

DEDICATION

I dedicate this hard work to my son Isaiah Eyul Ongom, my wife Brenda Andruda Ongom, my mother Sylvia Adoko Ongom and to my Late Father Milton Adoko Ongom.

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NORMENCLUTURE

ACRD:	Advisory Council of Research and Development
AMTs:	Advanced Manufacturing Technology
BF:	Blast Furnace
BOF:	Basic Oxygen Furnaces
DRI:	Direct Reduced Iron
EAF:	Electric Arc Furnace
HRI:	Human-Robot Interaction
IFR:	International Federation of Robotics
ILO:	International Labour Organization
ISO:	International Organization for Standardization
MHI:	Material Handling Institute
OHF:	Open Hearth Furnace
PWC:	Price Water Coopers
RFID:	Radio Frequency Identification
RIM:	Robotic Integration Model
RPA:	Robotic Process Automation
SLAM:	Simultaneous Localization and Mapping
SMEs:	Small Medium Enterprises

ABSTRACT

The use of computer-controlled robots is increasingly picking up in today's manufacturing industries. Industrial robot application in manufacturing industries allows for improved flexibility and configurability required for providing product variability. However, in technologically low developed countries, steel manufacturing tasks in steel industries are mainly executed manually. Due to the demand for improved product quality, productivity, safety, and reduction in manufacturing costs, there is a need for these plants to integrate robots into the operations. Two automated steel manufacturing Plants A and B, consisting of three manufacturing cells were considered during the research. The aim was to study the material handling systems used in each manufacturing cell, the material storage systems, steel manufacturing processes, the adaptability of each manufacturing cell to new technologies, and the current steel manufacturing technologies to identify manufacturing tasks suitable for robot integration. A systematic robotic integration process in steel manufacturing industries by utilizing a Markov decision model was developed. A finite-state Markov decision process model for robot automation decision was formulated while considering specific tasks to be accomplished by a robot in a given manufacturing cell. The Markov chain formulated represented states of robot performance under automation policies. The material handling cost matrices represented the long-run measures of each manufacturing cell performance for the Markov decision process problem formulated. The aim was to determine an optimal robotic automation decision for each manufacturing cell to minimize the long-run material handling costs for the given state of performance. Computational efforts using the Markov decision process approach provided promising results for material handling cost minimization for both steel plants and the replacement of humans with robots at the zinc pot reduced the average waiting time and increased the line utilization rate. The overall steel processing time correspondingly decreased by about 63% compared to the existing manufacturing cell. Robot integration in both steel plants presented solutions for reducing labour costs, material-handling damage, improving the productivity of automated steel manufacturing systems, and overall safety of the steelworkers. However, it is desirable to extend the research to analyse the impact on the non-stationary performance of a robot on the decisions taken. There is a need to expand the model to consider automation options for minimum material handling costs in the context of Continuous-Time Markov Chains (CTMC). The assumptions made during the simulation study did not consider worker fatigue and machine breakdowns. The justification of the proposed model by considering worker fatigue and machine breakdowns is an area of further research in this field of study.

CHAPTER ONE

INTRODUCTION

This chapter provides an overview of the background of the research, applications of robots in steel manufacturing industries today, manufacturing problems in steel industries, and the objective of the study.

1.1 Background of the study

The manufacturing processes have evolved over the past years from a manual set of mechanical tasks to a set of complicated computer-aided manufacturing technological processes that have resulted in the modernization of the overall manufacturing processes Nyori (2015). In today's manufacturing industries, the use of computer-controlled robots to complete manual tasks is increasingly picking up more than ever before Riben (2015). Industrial robots' use in metal industries replaces workers in the monotonous, repetitive, heavy, hot, and inhospitable working environment to reduce cost, increase productivity, improve product quality and eliminate harmful tasks Wallén (2008). Industrial robots with artificial intelligence embedded with machine learning technologies are used in steel manufacturing industries to inspect bulky items for errors. The machine learning capability powers cognitive competence to automate the transportation of work in progress and avoid safety risks while using predictive intelligence. Industrial robotic technology applications in manufacturing industries are expanding far beyond robot functionality of heavy lifting of materials to handling complex tasks difficult for humans to handle (Qin, 2016 and Legun 2021).

1.1.1 Application of industrial robots in steel manufacturing industries

The manufacturing tasks assigned to industrial robots today range from assembly, machining, material handling, packaging, welding, and material transport among others Dauth (2017), Athawale (2012). In particular, the applications of robots in metalworking industries are in material handling, machine servicing, manufacturing operations, installation works, and product control jobs. Karabegovic (2011) stressed that industrial robot applications in metal industries worldwide are most abundant in motor vehicle and automobile manufacturing while robot application in metal processing industries is drastically decreasing Ermolov (2020). Industrial robot application decrease in the metal processing industries is due to the automation and modernization of the manufacturing processes (Karabegovic, 2012 and Hagele, 2016). However, Phuyal (2020) points out that the main challenge of integrating smart manufacturing systems like industrial robots is the integration of new technology equipment with the existing ones. The machine-to-machine system

communication and interconnectivity of the overall manufacturing system requires a better communication system for the integration to work perfectly.

Most manufacturing industries today are constantly looking to identify manufacturing processes that can be automated using robotic process automation to optimize time-centric and repetitive routine processes, maximize productivity, reduce manufacturing costs by minimizing human error and increase the agility of manufacturing processes. Rüßmann (2015) and Leshob et al. (2018). Computer-controlled industrial robotics technology appears to represent perfect interactions between technological potential and manufacturing challenges in the steel-making industries. Using advanced manufacturing technologies permits the integration of the full spectrum of all production functions and manufacturing processes. Kotha et al. (2000). With the outstanding advantages of high accuracy, high work efficiency, ability to work in a highly hazardous environment, and the ability to bear greater working strength, industrial robots create better conditions for the improvement of productivity, safety, and quality in steel manufacturing industries Li Guangjun (2019). Industrial robot application in manufacturing allows for improved flexibility and configurability required for product variability. With industrial robot use, manufacturing industries can keep up with consumer demands and product innovations thereby increasing their market share while maintaining customer satisfaction Bader (2018)

1.1.2 Problems in Ugandan steel manufacturing industries

Most steel processing and manufacturing industries in technologically low developed countries are involved in small-scale steel production with a few factories in large-scale steel making processes. Mini mills involved in steel rolling processes use semi-finished cast products from integrated mills as material inputs from their manufacturing processes. The recycled scrap used to make semi-finished steel products by integrated mills are raw materials inputs for mini-mills. Steel manufacturing processes in both mills use obsolete technology and lacks appropriate technology transfer initiatives holding back productivity, quality, capacity utilization, and product diversification in the iron and steel industry. Senfuka (2011). In research conducted by Mohamed et al. (2009), they found a technology adoption strategy for manufacturing firms as a way to enhance productivity, quality, and competitive advantage while failure to develop and integrate new technologies into the manufacturing system contributes to the firm's decline in productivity, quality, and competitiveness. Tsarouchi (2016) explained that human-robot interactions streamline steel manufacturing processes thereby increasing production output and improving workplace safety where robots take over undesirable tasks that require humans to work under physical strain.

New robotic automation technological developments in the steel-making process allow for improvements in the safety and prediction of product quality via sensors. Murad (2011) argued that as manufacturing industries focus on new technical developments, the adjustments needed in the organizations to accommodate these technologies are not considered. It is necessary to look into the internal and external factors within the manufacturing industries that may influence new advanced technology adoption decisions by a manufacturing firm Brownell (1990).

1.1.3 Motivation

While there has been an increase in research on manufacturing firm's innovations in other developed and developing countries all over the world, empirical data on advanced manufacturing technological innovations in Ugandan manufacturing sectors remains insufficient. In research conducted by Julius Ecuru et al. (2014), formal Ugandan manufacturing firms involved in sub-sectors of foods and beverages are actively engaging in incremental and adaptive innovations relating to the product quality, manufacturing processes, and packaging improvements mostly accomplished in-house. Advanced manufacturing technological innovations in steel manufacturing industries are at a very low scale with most industries relying on traditional steel manufacturing techniques in most steel manufacturing processes. The transformation of Ugandan steel manufacturing industries from the current level of manufacturing technologies to use industrial robotic technologies in its manufacturing systems call for critical examination of the iron and steel value chain and the technological factors that could facilitate their proper and effective adoption and use.

1.1.4 Statement of the Problem

In technologically developing countries like Uganda, the use of advanced manufacturing technologies such as robots are still at a very low scale. Uganda's steel manufacturing processes are characterized by; traditional steel manufacturing techniques, heavy loads and hot material handling, lack of appropriate technology transfer, and obsolete technology. These have held back Productivity, Quality of steel products, steel product diversification, and steel manufacturing industries' Capacity utilization below 50% Obwona (2015). While working under high temperatures exposes workers to excessive heat stress leading to changes in seminal parameters among men Reinhold (2019), and increase infertility rates among women Hamerezaee et al. (2017), frequent heavy materials handling causes musculoskeletal diseases and poses latent risks of safety accidents among steel workers Yu et al. (2015). While the introduction of modern technologies is crucial for the survival of steel manufacturing industries, there is a need to

investigate the potential for integrating robotics technologies with the current steel manufacturing processes in Ugandan steel manufacturing industries.

1.2 Research Objectives

1.2.1 Main objective

To develop a mathematical model for systematic robot integration processes and provide optimal robot automation solutions for steel manufacturing industries in Uganda.

1.2.2 Specific objectives

The specific objectives of the study are to:

- i. Examine the plant layout designs and material handling systems in steel manufacturing industries.
- ii. Determine candidate tasks for robotic integration processes in steel manufacturing industries.
- iii. Develop a mathematical model for robotic integration processes in steel manufacturing industries.
- iv. Validate the developed mathematical model by utilizing a simulated factory environment.

1.3 Research Questions

- i. How will robotic technologies integrate with the existing plant layout designs and material handling systems?
- ii. What manufacturing tasks require robot automation and non-automation?
- iii. What are the criteria for integrating robotic automation technologies in steel manufacturing industries?
- iv. What simulation factory environment validates the developed mathematical model?

1.4 Justification

In technologically developing countries like Uganda, the use of advanced manufacturing technologies such as robots are still at a very low scale with most steel manufacturing industries relying on traditional steel manufacturing techniques carried out in an inhospitable and unsafe working environment. Besides, steel-manufacturing processes dominated by obsolete technology lacks appropriate technology transfer initiatives that have held back productivity, quality, capacity utilization, and product diversification.

As industrial robot adoption and use become pivotal for manufacturing firms in developed countries, the same cannot be said of their adoption by manufacturing firms in developing

countries. As most researchers widely assumed that industrial robots are not economically feasible in developing countries (Elizondo-Noriega, 2019, Visawan, 2004 and Murad, 2011), empirical evidence to support such assumptions is scarce. However, no specific initiatives to cause a step-change in industrial robotic automation in steel manufacturing industries in Uganda are in place. To address the technological factors affecting industrial robot adoption and use in steel manufacturing industries, it is necessary to understand the root cause affecting industrial robot integration processes into manufacturing firms in developing countries.

1.5 Significance of the study

The research intends to address the inferior working conditions in steel manufacturing industries using advanced manufacturing technologies like industrial robots to perform operations that pose high safety risks to workers, and convert the existing traditional steel manufacturing production processes into a flexible manufacturing system to utilize machines to their extents to obtain maximum output from the overall steel manufacturing system. The developed model can be adopted in any steel plant that aims to advance to high-tech production processes by introducing robot utilization in their manufacturing tasks.

1.6 Conceptual Framework

The research focused on manufacturing automation and robotics technology; an independent variable controlled during the study. The dependent variables considered during the study were assessed to determine their effects on the independent variable. The moderating variables (plant layout designs, material handling systems, and manufacturing task automation requirements) selected, evaluated, and controlled helped to establish whether it changes the relationship of the independent variable presented in *figure 1.1* below.

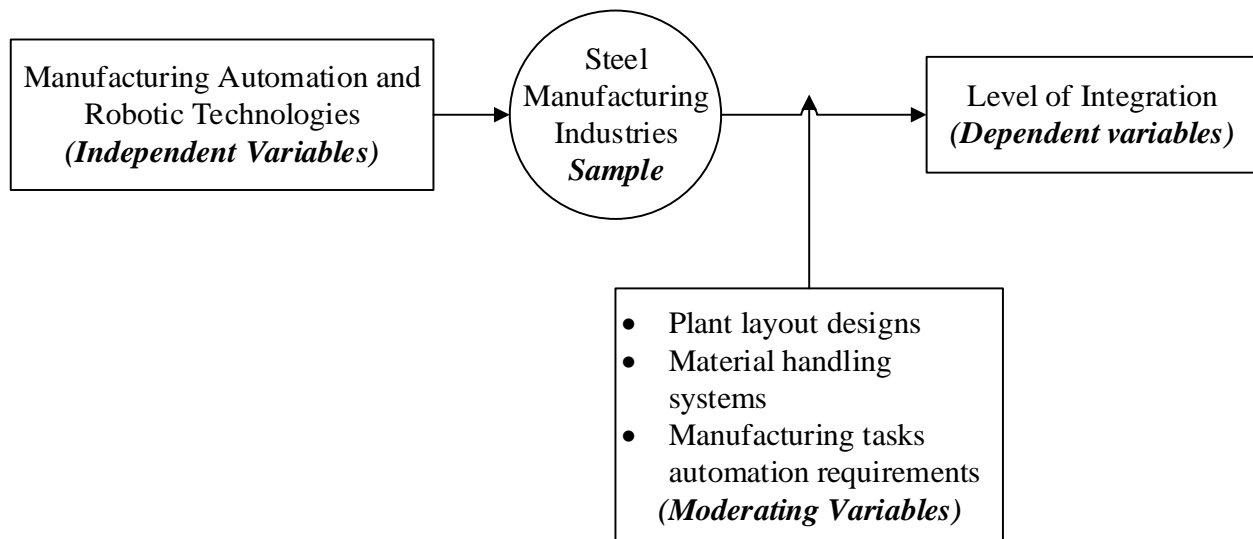


Figure 1.1: Conceptual Framework

1.7 Scope of the study

The research focused on industrially advanced robotics technology integration within Ugandan steel manufacturing industries. The study examined the different plant layout designs, material-handling systems, and machine automation requirements needed for the integration of robotic automation technologies in the steel manufacturing industries in Uganda. Two steel manufacturing plants in Uganda considered were Roofing's Rolling Mills Uganda limited and Steel and Tube industries Uganda.

1.8 Organization of the Dissertation

The dissertation is organized into five chapters. Chapter one presents the introduction and the background of the research study, chapter two reviewed the various related academic research from most scholars concerning industrial robot automation in steel manufacturing industries. The research methodology is explained in chapter three of the dissertation while the findings of the study is presented, analyzed and discussed in chapter four. Conclusions and recommendations drawn from the research findings are presented in Chapter Five.

CHAPTER TWO

LITERATURE REVIEW

This chapter reviews the relevant academic and industry literature related to industrial automation, advanced manufacturing technologies, and robotics technologies used in steel manufacturing processes. It further looks at relevant literature regarding new technology adoption in steel manufacturing industries and factors affecting advanced manufacturing technology adoption.

2.0 Industrial Robots adoption in Manufacturing

ISO 8373 (2012) defined an industrial robot as a reprogrammable multipurpose manipulator programmable automatically in three or more axes fixed and controlled in one place or mobile for use in industrial automation. On the other hand, Stauffer (1979) stressed that industrial robots are mechatronic devices that automatically manipulate or transports parts within a manufacturing process. Industrial robots pose a high degree of flexibility and variability in their motion and activities, making them capable of performing multiple manufacturing operations to increase manufacturing efficiency, productivity, and effectiveness.

The adoption of industrial robots has been on a growing trajectory since the installation of the first industrial robot at a GM facility in the 1960s Engelberge (1980). Since then, the industrial robot adoption rate by manufacturing firms has accelerated over the last 50 years due to the advancement in electronic technologies necessitated by increasing demands for higher quality manufactured products Elizondo-Noriega (2019). While the adoption and use of industrial robots in manufacturing firms are concentrated in automotive industries, electronic industries, and metal forming and making industries, industrial robot adoption and use are mainly in the automotive industrial sectors (Gorlach, 2008, Bader, 2018, Isak, 2011, and Karabegovic, 2012). Despite the commercial success of industrial robots in developed countries, big and medium-sized manufacturing firms have benefited fully from using industrial robots in their manufacturing processes Elizondo-Noriega (2019). The adoption and use of industrial robots in developing countries are influenced by problems of high equipment acquisition costs, high electricity costs, and lack of trained personnel with the ability to operate and maintain sophisticated equipment like industrial robots. These problems always make industrial robot adoption and integration economically and practically unviable Sabattini (2013).

The interest in process automation evolved from minimizing human interference with the systems to avoid health hazards and increase productivity. The use of integrated network systems in a manufacturing system for sharing information between manufacturing to end-user presents a major challenge. The main challenge of the integration of a smart manufacturing system like industrial robots is the integration of new technology equipment with the existing ones. The manufacturing systems configuration of the existing processes might be outdated and new industrial robotic technologies may require new systems configurations. Also, the machine-to-machine system communication and interconnectivity of the overall manufacturing system requires a better communication system for the integration to work perfectly Phuyal (2020). Tzafestas (2014) explained that while the adoption of robots in the manufacturing environment is key to addressing the demand for flexible material handling, the need for rapid reconfiguration of the working environment and the desire for robots to operate on large manufacturing structures need to be critically assessed for all robot operations. Besides, MHI (2014) argues that industrial robots with artificial, motion, and gesture sensitive technologies and new capabilities for automation control are key in facilitating a manufacturing system where humans. Machines and computers interact freely and effectively during human-robot collaborations.

The installation, adoption, and operation of robots in a manufacturing setup is relatively expensive and requires a significant level of expertise. It is crucial to ensure that robot applications in manufacturing processes are appropriate. In their technology road map, Sabbatini et al. (2013) described costs and lack of flexibility of the current manufacturing systems as some of the barriers to greater adoption of robotic technologies in manufacturing industries. The high costs involved in new technology adoption make it difficult to achieve the desired efficiency to make robotic technology introduction cost-effective while lack of manufacturing system flexibility makes changeovers expensive, time-consuming, and unsafe. The use of mobile robots as assistance technologies in industrial applications requires the determination of mobile robots' capabilities and a clear description of the tasks performed by the robot Angerer et al. (2012). The manufacturing tasks that require manual handling of loads greater than 5 kilograms, operations that need the movement of parts between the workspaces, manufacturing processes with frequent work interaction with people, and tasks that occur in a frequently changing environment requires the use of robotic technologies as shown in table 1.2 below

Table 1.2: Required capabilities for a mobile robot in manufacturing

	Industrial requirements for assistive robotics
Navigation	Free to navigate in an unstructured environment
Gripping technology	used for many part geometries
Hardware components	compliance with manufacturing standards
Workload	ergonomically undesirable tasks over 20 kg
Workspace	floor space of around 1.8 M ²
Availability	Availability of over 98%
Energy supply	Constant supply for 24 hours
Safety	Well demarcated for man to machine interaction

To enhance robot adoption in manufacturing, (Schneier, 2015 and Angerer 2012) suggested areas of improvement within the manufacturing processes. They proposed that to improve safety, the use of sensors to detect and track workers as well as changes in the robot behaviors in response to people’s behaviors is an important factor in robot adoption in a manufacturing environment. While it is key to make it easier and faster for the robot to react to changes in the manufacturing processes and tasks, substantial information about the robot environment should be clearly defined from prior knowledge and sensor inputs. With a model of tasks and the use of sensors to help robots understand the degree of completion of manufacturing tasks, the collaborations between humans and robots should feel natural and intuitive.

2.1 Human-Robot Interaction in manufacturing

Providing human-robot communication for robots and people awareness of what is expected around the working environment is crucial in human-robot interactions as humans and robots share the same workplace in a manufacturing environment. Manufacturing tasks divided between humans and robots through human-robot interactions presents unique advantages by both the robot and humans in a manufacturing setup as robots execute tedious and strength-based tasks while humans focus on tasks that require brainwork Krüger (2009). Léger (2016), argues that the costs of collaborative robots programmed through offline coding devices and controlled by well-trained experts are quite expensive and require significant time and effort. According to Tsarouchi et al. (2016), as modern smart manufacturing experiences faster product upgrades, more product customization with reduced lifecycles is required to meet the ever-changing customer demands. The association between a human’s flexibility, perception, and intelligence combined with robot repeatability and precision offers advantages to collaborative frameworks. The main inspiration

for human-robot interaction is in the improvements in efficiency, flexibility, and productivity while reducing human ergonomic stress and workload.

(Krüger, 2009, and Tsarouchi et al. 2016) further argue that a safe and flexible example of cooperation between robots and humans is in form of a hybrid cell, which provides promising ways of achieving better productivity, as opposed to the manual cells. The coexistence of a human and a robot composes the hybrid cells classified into shared tasks and workspace, similar tasks and workspace, and similar tasks and separate workspace. In the case of shared tasks and workspace, the relation between humans and robots is discrete as shown in *Figure 2.2 below*.

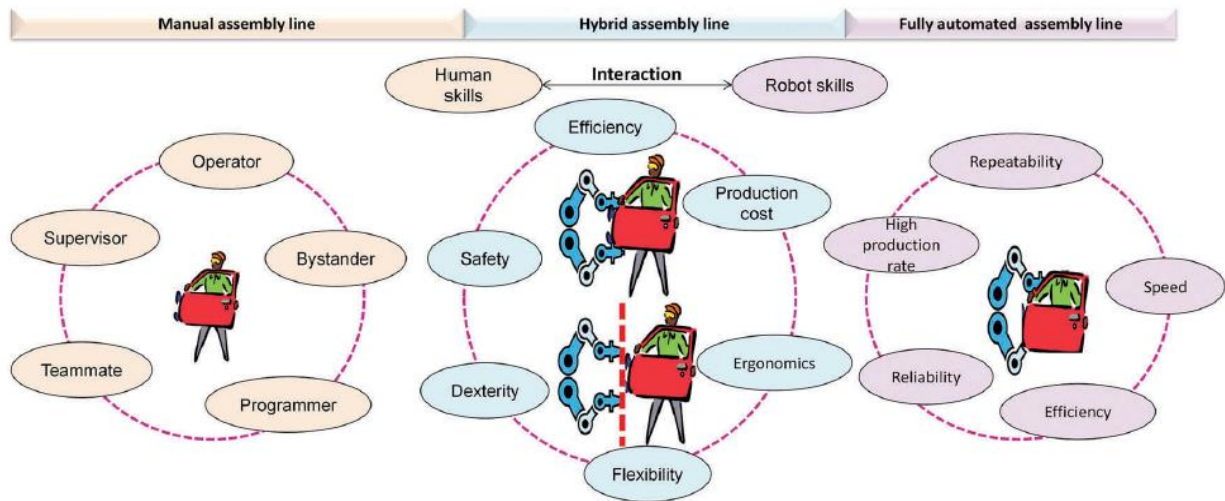


Figure 2.2: Assembly lines and HRI. Tsarouchi et al (2016)

According to Bannat (2009), HRI is associated with cognitive capabilities such as perception, flexibility, adaptability, and the ability to solve a problem in an unstructured environment characterizes the factory of the future. Although HRI use is increasing in several applications such as service, rescue, space exploration, and entertainment, it is ironic that the traditional, industrial robots use in the automotive industries are not autonomous enough to allow close interaction with humans Tsarouchi et al. (2016)

2.2 Robot Navigation and localization

It is crucial to know the location and orientation of industrial robots operating in a sizeable facility to coordinate robot localization and navigation operations. The most common methods for robot localization and navigation employed in most manufacturing industries include radio-frequency identification (RFID) systems, cameras, odometry, and two-dimensional bar codes. In today's manufacturing industries, the use of more advanced technologies that make use of algorithms to accomplish the localization and navigation tasks simultaneously using SLAM algorithms for

Simultaneous Localization and Mapping employed in most manufacturing processes require robot technologies Schneier (2015). In a manufacturing environment, the robot positions itself on the contributed map using SLAM by identifying landmarks around it in the real world and navigating each location step by step Luo et al. (2010). Guilherme et al. (2002), points out that while map-based navigation system recognizes objects found in the manufacturing environment to generate movements basing on visual observations, map-based navigation system for industrial robots mainly relies on the generated geometric models of the manufacturing environment. Map building-based robot navigation system on the other hand uses sensor-aided technology to construct their topological models of the environment. The generated models help the robot to navigate, locate and identify its position and orientation in a predetermined path. According to Conduraru (2014), mobile robots using magnetic compasses, inertial navigation, and odometry directly without any external marks, maps, or devices are simple and easy to use when installing and setting up external devices.

2.3 Robot Planning and coordination

In his research, Raja (2012) noted that during navigation, the robot develops and builds the perception of its working environment, develops its motion control, and a plan of what paths it will follow using the map of the environment built. When the robot perceives its environment, it develops an understanding of all sensory data for locating its position in the surrounding environment. Planning the robot path for each manufacturing task before accomplishing the preferred trajectory using cognitive decision is crucial when controlling robot motion. It is necessary to determine a collision-free path for mobile robots during path planning to optimize robot coordination and performance in terms of time, energy, and distance covered. Global path planning is required where moving obstacles, the trajectory of stationary objects, and information about the work environment are not available in advance. The robot gets information through the use of sensors when complete details of the environment are not available as the robot moves. Marvel et al. (2014) suggest that there are many aspects of the operation of mobile robots planned and coordinated for the robot to navigate within its working environment. It is crucial to ensure there is limited congestion in traffic during navigation, robot navigation paths are free and do not meet, there is timely delivery of materials, and the robot throughput speed is compatible with the work cadence. In scenarios where there is a need for faster changeovers for robot tasks especially where human-robot interactions are involved, offline robot planning and coordination are not applicable. Acuña et al. (2012) noted that it is necessary to use methods that enable robots to

modify their trajectory to coordinate their movements to maintain productivity. A path planning method that allows the robot to navigate safely in a dynamic manufacturing environment referred to as a dynamic artificial potential field enables robots to avoid obstacles moving at higher velocities. Mobile robots can repel static objects using artificial potential field algorithms.

2.4 Robotic Process Automation

According to Wilson (2014), automation is the process of controlling operations, processes, or systems automatically using electronic or mechanical devices to perform tasks carried out manually. Automation is the replacement of man by machine for the performance of tasks, and it can provide movement, data gathering, and decision-making. Mahbub (2008) further defined automation as a self-regulation process performed using programmable machines to carry out a series of tasks. ISO 11065 (1992) precisely defined automation in an industrial context suitable for this research as “the implementation of processes by automatic means.” In this context, industrial automation comprises; platforms (usually machines, tools, devices, installations, and systems), autonomy (defined through an organization, process control, automatic control, intelligence, and collaboration), processes (actions, operations, functions), and power sources

Leshob (2018) refers to Robotic Process Automation (RPA) as the applicability of advanced technologies to configure software-industrial robots that interpret and capture existing applications for manipulating data, processing, and communicating with other related software systems. RPA uses software-based robots to perform repetitive tasks that require manual labour. Aalst, et al. (2018) explained that automating processes addresses the most frequent case types with less frequent cases not considered due to high costs which increases when different systems are integrated. Besides, RPA provides a link between traditional process automation and work done by humans through having agents that interact with different systems as shown in figure 3.2 below.

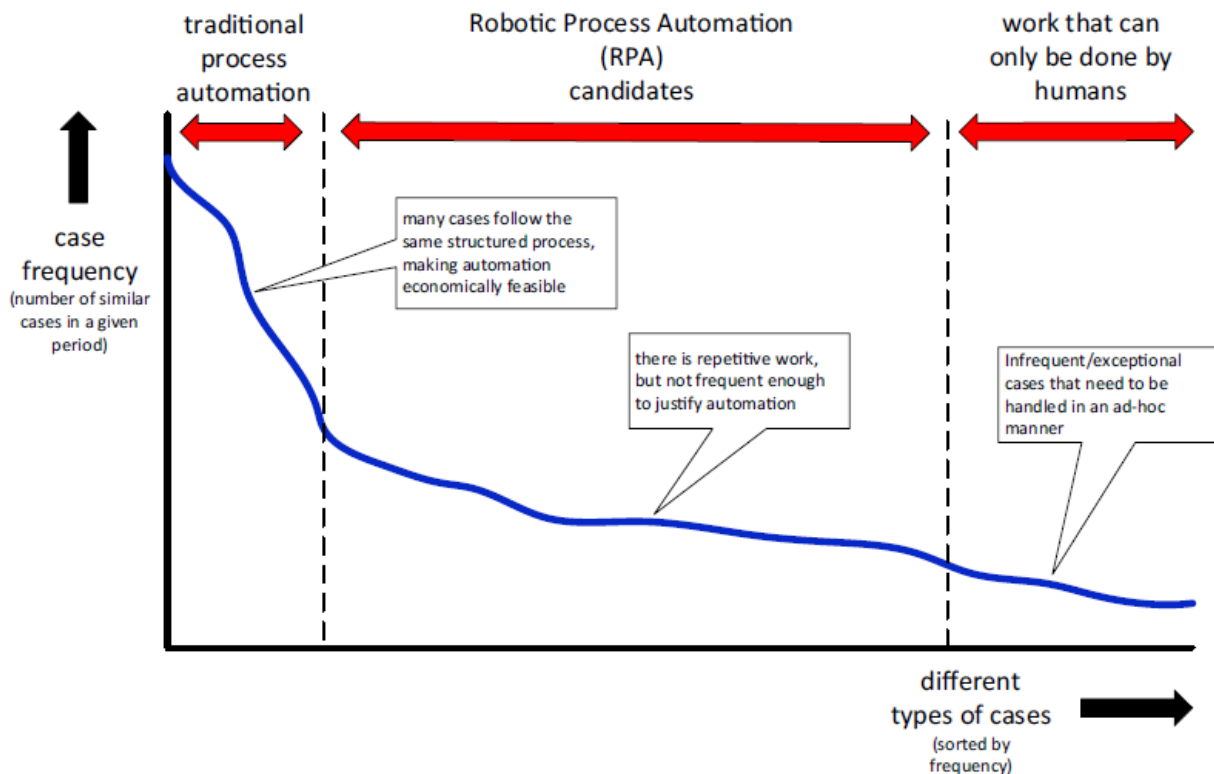


Figure 3.2: Robot Process Automation tasks classification

RPA aims to replace people in manufacturing tasks with automation carried out in an ‘outside-in manner to improve the information system and enable different agents to interact with different information systems Aalst et al. (2018). Leshob (2018) explained that manufacturing organizations today are constantly looking to identify processes for automation using RPA to achieve maximum results

2.5 Application of industrial robotic technologies in manufacturing industries

Automotive industries today are the biggest benefactors of robotic automation technologies. Most industrial robot applications in automotive industries are in repetitive tasks such as cutting, stamping, welding, and assembly as well as the end of line processes such as spray-painting and coating. Similarly, the electrical and electronic industries have adopted industrial robots for cutting, assembly of parts and products like computers and other precision equipment Bader (2018).

Industrial robotic technology applications in manufacturing industries are expanding far beyond robot functionality of heavy lifting of materials to handling complex tasks difficult for humans to handle (Legun, 2021 and Quin, 2016). The manufacturing tasks assigned to industrial robots today range from assembly, machining, material handling, packaging, welding, and material transport

among others Pwc (2020). The applications of robots in metalworking industries are in material handling, machine servicing, manufacturing operations, installation works, and product control jobs World Robotics (2010). Isak et al. (2011) further stressed that industrial robot applications in metal industries worldwide are most abundant in motor vehicle and automobile manufacturing while robot application in metal processing industries is drastically decreasing. Karabegovic et al. (2012) argues that the decrease in industrial robot application in steel manufacturing industries is associated with the modernization and automation of steel manufacturing processes. As mobile industrial robots strive to address the need for faster reconfiguration of manufacturing processes, it is necessary to look into customer demands for flexible material handling for robots operating on large steel structures. According to MHI (2014), for collaborative human-robot interactions in systematic and different ways, industrial robots with artificial intelligence, new capabilities in autonomous control embedded with motion and gesture sensitive technologies facilitates faster human-robot interactions in a manufacturing environment.

Industrial robot application decrease in the metal processing industries is due to the automation and modernization of the manufacturing processes. Mobile robots address the demand for flexible material handling desire for robots to operate on large structures and the need for rapid reconfiguration of manufacturing areas. For material handling, the MHI (2014) expects new capabilities in autonomous control and artificial intelligence along with motion and gesture sensitive technologies that could lead to manufacturing systems where workers and robots interact freely and efficiently in new ways. The main robotic technologies, common tasks, and typical industrial applications summarized in Table 2.2 explained the wider applications of industrial robots in manufacturing industries today.

Main Categories	Common Tasks	Typical Domain	Established Industry Adopters	New and Future industry Adopters
Fixed and caged industrial robots <i>Designed to operate within physical barriers (includes Articulated arm, SCARA, Cylindrical, and Cartesian)</i>	Assembly Welding/Riveting Drilling/Fastening Die casting Picking/packaging/sorting Painting/coating	Industrial manufacturing plants and factories	Industrial products manufacturing Retail and consumer Food and beverage Electronics Pharmaceutical	Oil and Gas, pipeline distribution Construction All industries adopting robotic additive (3D printing) manufacturing
Collaborative robots <i>Designed to work side-by-side with humans</i>	Materials handling In-plant transportation Product and asset inspection Assembly Robotic 3D printing Picking/packing/sorting Point-of-sale assembly Automated palletizing Product/shelf scanning (in a warehouse and retail environments) Brick-laying	Industrial manufacturing plants/factories Warehouses Distribution centers Pipe networks Drilling operations Construction sites	Industrial products manufacturing Retail (warehouses) Medicine (assisted surgery) Semi-conductor Electronics Oil and gas industry Healthcare Law enforcement Agriculture Online retailers Retail and consumer	Service industries (e.g., hotels, hospitals, restaurants, retailers) Retail (product scanning and assembly) All industries adopting robotic additive (3D printing) manufacturing Construction
Collaborative stationary robots <i>Quickly programmable to augment/supplant manual tasks with humans at a stationary site</i>				
Collaborative Autonomous Mobile Robots (AMRs) <i>(designed to work closely with humans) and automated guided vehicles (AGVs)</i>				
Robotic Exoskeletons <i>Wearable robotics systems designed to augment human physical performance</i>	Assists manual human labor (e.g., lifting, gripping, carrying)	Manufacturing assembly lines Warehouses	Industrial manufacturing (especially the auto sector) Retail & Consumer (in warehousing operations)	All other industries requiring heavy manual labor, especially in the handling of materials)

Table 2.2: Robot Technologies and their Application PwC (2020)

2.6 Markov's Chain Decision Analysis

Stewart (1994) defined a stochastic process as a family of random variables $\{X_{(t)}, t \in T\}$ indexed by 't' which is usually a time parameter. The random variable $X_{(t)}$ denotes an observation of the system at time instant 't'. A stochastic process with discrete-time indices, for example, $T = \{0, 1, 2, \dots\}$, is called a discrete-time parameter stochastic process if time is continuous. For example $T = \{0 \leq t \leq +\infty\}$, is a continuous-time parameter stochastic process. The values that random variable $X_{(t)}$ can take are called states, and the set of all possible values constitutes the state space of the process. If the values assumed by the variable $X_{(t)}$ are discrete, it forms a discrete state space

A Markov process is a stochastic process that satisfies the Markov property. It is a sequence of random variables $X_1, X_2, X_3, \dots, X_n$ with the Markov property, namely that, given the present state, the future and past state is independent. Formally,

$$P_r \left(X_{n+r} = \frac{x}{X_1}, = x_1, X_2 = x_2, \dots, X_n = x_n \right) = P_r \left(X_{n+r} = \frac{x}{X_n}, = x_n \right) \quad (1)$$

if both conditional probabilities are defined, i.e. if $P_r(X_1 = x_1, \dots, X_n = x_n) > 0$ the possible values of X_n form a countable set S called the state space of the Chain Chiagunye et al. (2015)

Markov Chains often described by a sequence of directed graphs, where the edges of the graph n labeled by the probabilities of going from one state at time n to another state at time (n + 1),

$$P_r \left(X_{n+r} = \frac{x}{X_n}, = x_n \right) \quad (2)$$

However, Markov Chains assumes time-homogenous scenarios, in which case the graph and matrix are independent of n and not presented as sequences Chiagunye et al. (2015). Markov's analysis represented diagrammatically in figure 4.2 and through transition matrices represents state transitions. The figure shows a Markov chain model of a process with two stages A1 and A2, where the probability of making a transition from stage *i* to stage *j* is q_{ij} Leigh et al. (2017).

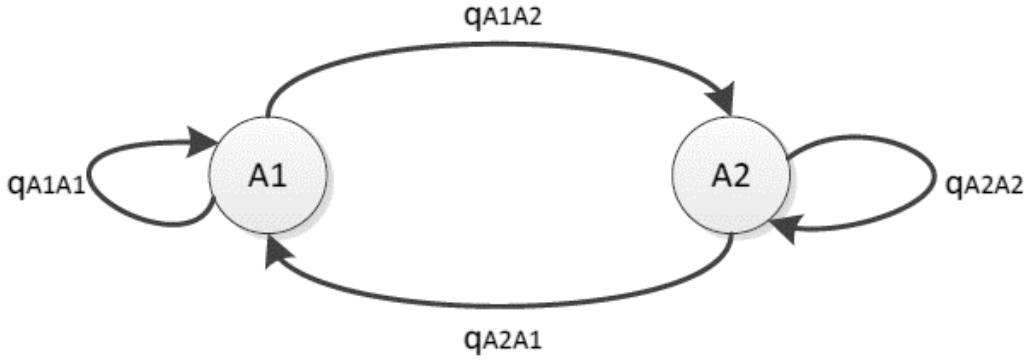


Figure 4.2: Markov Chain Diagram

$$\begin{pmatrix} q_{A1A1} & q_{A1A2} \\ q_{A2A1} & q_{A2A2} \end{pmatrix} \quad (3)$$

The transition matrix shows the probability of transitioning between the rows stages to the column stage. To form a Markov chain model, the transition probabilities are required. These are calculated using equation 4 which determines the probability of making a transition from stage i to stage j , which is represented by P_{ij} . Where m is the total number of transitions and n_{ij} is the number of transitions from i to j .

$$p_{ij} = \frac{n_{ij}}{\sum_{k=1}^m n_{i,k}} \quad (4)$$

2.6.1 Markov Chain Model States

The Markov chain model is a sequential process that consists of many steps. For those steps considered as Markov Chain states, they should respect all the following three conditions:

- i. "State i communicates itself"
- ii. "If state i communicates with state j , then j communicates with state i ."
- iii. "If state i communicates with state j , and j communicates with state k , then i communicates with state k ."

According to Chiagunye et al. (2015), the probability of going from state i to state j in n time steps is given by: $P_{ij}^{(n)} = P_r \left(X_n = \frac{j}{X_0}, = i \right)$ and the single step transition is $P_{ij} = P_r \left(X_1 = \frac{j}{X_0}, = i \right)$

For a time-homogenous Markov Chain, the probability is: $P_{ij}^{(n)} = P_r \left(X_{n+k} = \frac{j}{X_k}, = i \right)$ and $P_{ij} = P_r \left(X_{k+1} = \frac{j}{X_k}, = i \right)$. A Markov Chain of order m , where m is finite, is a process satisfying

$$\begin{aligned}
P_r \left(X_n = \frac{x_n}{X_{n-1}}, = x_{n-1}, X_{n+2} = x_{n-2}, \dots X_1 = x_1 \right) \\
= P_r \left(X_n = \frac{x_n}{X_{n-1}}, = x_{n-1}, X_{n+2} = x_{n-2}, \dots X_{n-m} = x_{n-m} \right) \text{ for } n > m
\end{aligned} \quad (5)$$

In other words, the future state depends on the past m states. It is possible to construct a Chain Y_n from X_n which has the ‘classical’ Markov property by taking as state-space the ordered m tuples of x values, i.e. $Y_n = (X_n, X_{n-1}, \dots, X_{n-m+1})$ Chiagunye et al. (2015)

2.7: Summary of Literatures Reviewed

Table 3.2 presents a summary of related literatures from different researchers and their findings

Table 3.2: Summary of literature

Researcher	Research area	Findings
Julius Ecuru, Peter O. Lating & Lena Trojer (2014)	<i>Innovation characteristics of formal manufacturing firms in Uganda</i>	<ul style="list-style-type: none"> Formal Ugandan manufacturing firms involved in sub-sectors of foods and beverages are actively engaging in incremental and adaptive innovations relating to the product quality, manufacturing processes, and packaging improvements mostly accomplished in-house. Advanced manufacturing technological innovations in steel manufacturing industries are at a very low scale with most industries relying on traditional steel manufacturing techniques.
Aalst, Wil & Bichler, Martin & Heinzl, Armin. (2018)	<i>Robotic Process Automation. Business & Information Systems Engineering.</i>	<ul style="list-style-type: none"> RPA provides a link between traditional process automation and work done by humans through having agents that interact with different systems
Athawale, V. M., Chatterjee, P., & Chakraborty, S. (2012).	<i>Selection of industrial robots using compromise-ranking method</i>	<ul style="list-style-type: none"> The manufacturing tasks assigned to industrial robots today range from assembly, machining, material handling, packaging, welding, and material transport
Karabegovic, I., & Hadzalic, E. 2012.	<i>Industrial Robot Application Trend in the World’s Metal Industry.</i>	<ul style="list-style-type: none"> The applications of robots in metalworking industries are in material handling, machine servicing, manufacturing operations, installation works, and product control jobs
PwC. (2020).	<i>Robot-ready: Adopting a new generation of industrial robots</i>	<ul style="list-style-type: none"> Robotic Exoskeletons (<i>Wearable robotics systems designed to augment human physical performance</i>) are suitable for material handling tasks in steel manufacturing industries.

CHAPTER THREE

RESEARCH METHODOLOGY

This chapter describes how the research addressed the objectives of the study. It examined the methods used to collect and analyze data regarding the possibility of integrating industrial robotics automation technologies in Ugandan steel manufacturing firms.

3.0 Research design

The research accomplished the objective using mixed research design approaches consisting of both qualitative and quantitative research methods. Qualitative research methods used analyzed different manufacturing tasks automation requirements and examined how robots can integrate with the current manufacturing processes. Quantitative methods used determined and quantified the influence of industrial robot integration on the overall steel manufacturing process.

3.1 Sampling techniques

The research employed purposive sampling techniques for choosing steel manufacturing industries in Uganda with a considerable level of automation for most steelmaking processes. Two steel manufacturing industries with three different steel manufacturing processes categorized under manufacturing cell one, two, and three provided solutions for robot integration processes.

3.2 Data coding

For not disclosing steel manufacturing industries investigated in the study, two steel manufacturing industries sampled were assigned identifier codes. Different steel manufacturing processes and manufacturing cells coded in Table 4.3 formed the basis for research data coding and collection.

Table 4.3: Research Data Coding

Codes	Description
Plant A and B	Steel manufacturing industry A and B
C_n	Steel manufacturing cells in plant A and B
M_i	Manufacturing processes in manufacturing cell C_n
T_i	Manufacturing Tasks/Activities in manufacturing Processes M
$R_{pot}(T)$	Robot integration potential for manufacturing task T
$R_{rel}(T)$	Robot relevance for manufacturing task T
T_A, T_B, T_C, T_D	Manufacturing tasks classification suitability for robot integration
MC_n-T_i	Manufacturing process M_i for manufacturing cell C_n with task T_i
$PQ_1, PQ_2,$	Robot integration potential Questions
$EQ_1 EQ_2$	Manufacturing tasks eligibility question

3.3 Methodological research process

To address the research objectives, the research roadmap presented in figure 5.3 guided the research study during data collection.

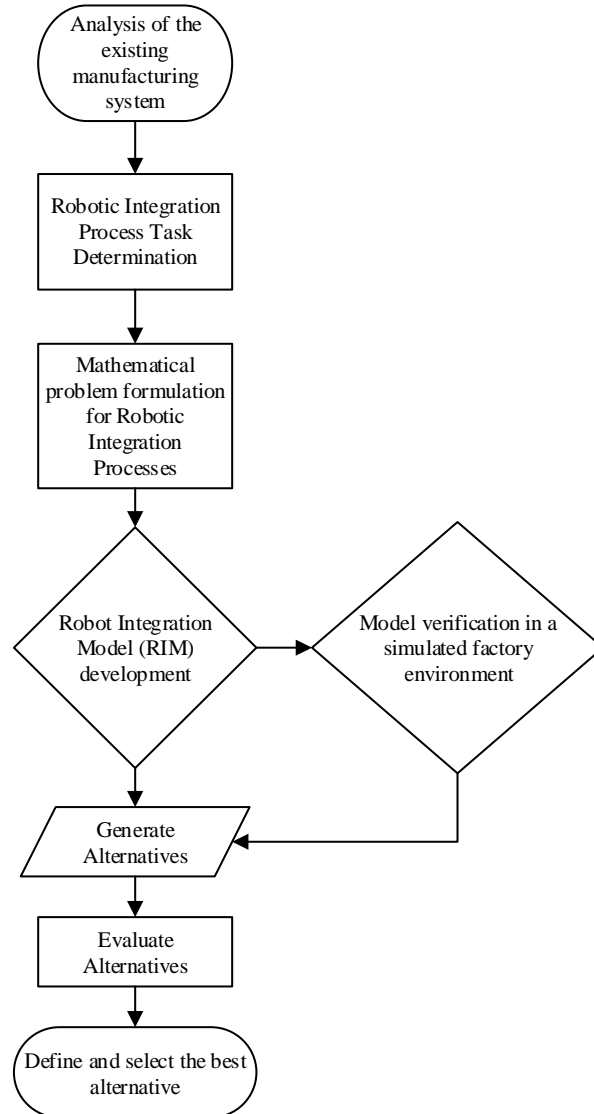


Figure 5.3: Methodological Research Process

3.3.1 Plant layout design and steel material handling system

Participatory observations of the steel manufacturing processes in each steel manufacturing cell conducted in collaborations with personnel on the production line and the quality assurance team provided the necessary data required for robot automation decisions made at each manufacturing cell. The focus was on manufacturing processes that require robot interventions. Physical layout designs, material handling equipment, steel manufacturing machines, and steel manufacturing operations are the main parameters considered during the study for robot process automation.

Visual inspection and document analysis used during the study determined manufacturing tasks automation requirements and identified potential candidate tasks for robot automation processes. The study aimed to determine the necessary adjustments necessary to accommodate robots in the current manufacturing tasks to enable robot mapping, robot localization, robot motion planning, and coordination of robot activities within a manufacturing cell.

3.3.2 Determination of candidate tasks for the robotic integration process

Manual analysis of the degree of automation of the current steel manufacturing g processes was done through the identification of manual processes, automated processes, and processes supported by an information-based system. The decision to automate or not to automate a manufacturing task in a manufacturing cell using robots relied on the level of degree of automation of the existing manufacturing process as shown in figure 6.3 below.

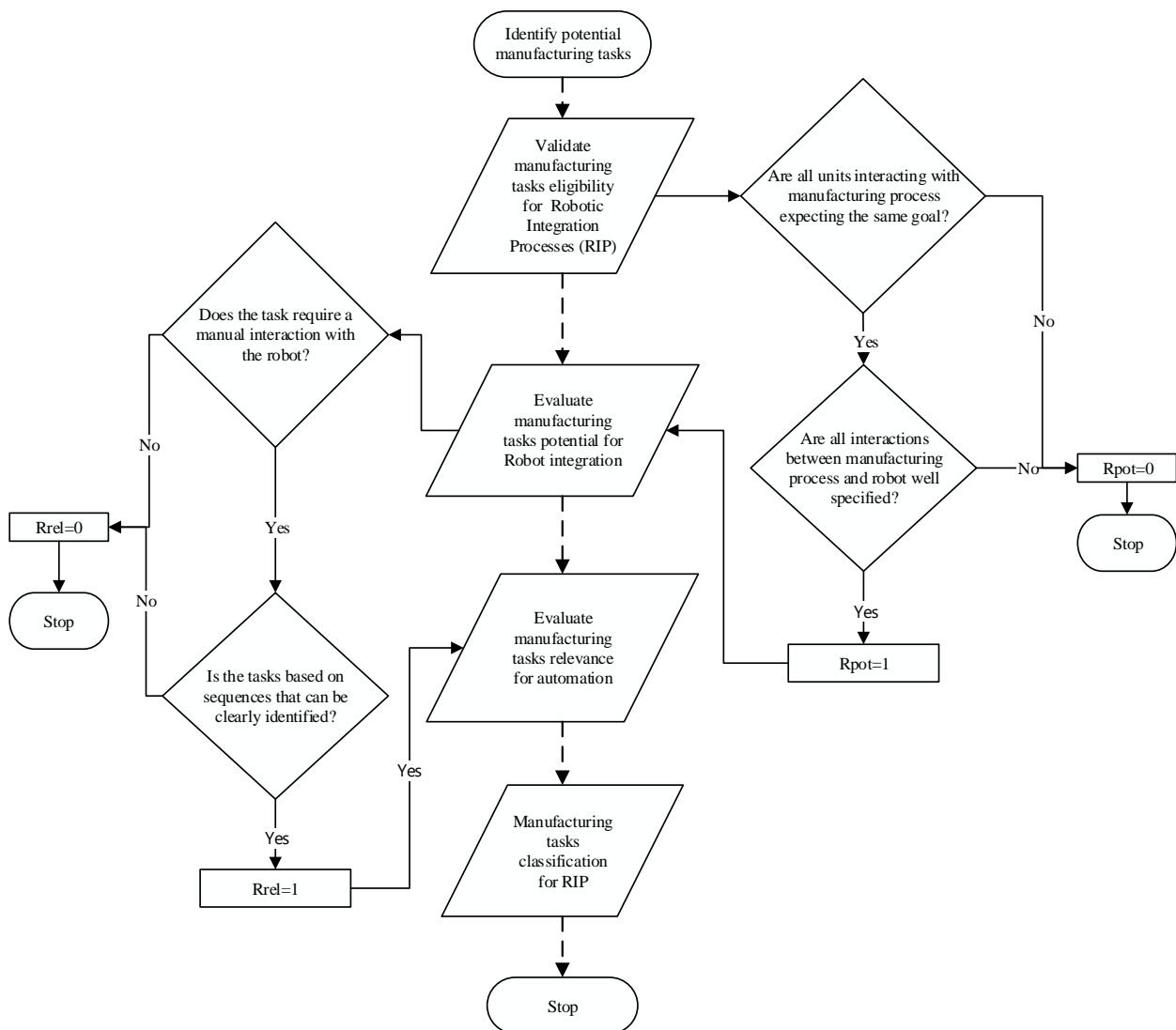


Figure 6.3: Process for analyzing and classifying a manufacturing task for robot integration

3.3.3 Mathematical model formulation for robot integration processes

In situations where the outcomes of robot automation variables are partly random and partly under the control of a decision-maker, a Markov decision process problem formulated provided optimal automation decision using mathematical models. The mathematical model formulation developed using Markov's decision process and Generic algorithm determined the optimal robot automation decision and material handling costs for a given steel manufacturing cell. The key variables used in the model formulations defined in Table 5.3 and Table 6.3 provided the basis for optimal automation decisions made at each manufacturing cell.

Table 5.3: Variables Used in the Markov model

$i, j \in E(f, u)$	Stated speed of the Robot
$R = (1, 2, \dots, n)$	Robots in steel manufacturing cells
$t = 1, 2, 3, \dots, t$	Tasks to be accomplished
s_i	Robot speed transition
M_i	Material handling cost
$K = 1 \text{ or } 0$	Automation options
ff, fu, uf, uu	Robot state transition
e_i	Expected material handling cost
a	Accumulated material handling cost
n/N	Stages/Periods
$g_n(i, R)$	Finite period dynamic programming model to determine expected accumulated material handling cost
$g_{n+1}(i, k)$	A recursive equation relating the cost from stage to stage
$s_i^k(R)$	Transition matrix, considering the number of tasks to be accomplished
$e_i^k(R)$	Expected material handling cost
$a_i^k(R)$	Accumulated material handling cost
$(k^*), e_i^{k^*}(R)$	The optimal option for automation and expected material handling cost
$(k^*), a_i^{k^*}(R)$	The optimal option for automation and accumulated material handling costs

Table 6.3: Variables used in Generic Algorithm Model

P/D	Robot Pick up/Drop off stations in a manufacturing cell
P_i/D_j	Distances between pick up stations to drop off stations
N	Number of robots in a manufacturing cell
n	Number of pick up/drop off stations in a manufacturing cell
T_{ij}	The time required to move from P_i to D_j
M_{ij}	Number of materials the robot moves from P_i to D_j
T_{avg}^m	Average time required by the robot to move materials from P_i to D_j
T_p/T_d	Pickup time/drop off time
T_m	The average generation time of materials in all pickup/drop off stations

3.4 Mathematical model verification in a simulated factory environment

The mathematical model was verification in a simulated factory environment using *Rockwell Automation Arena Version 14* Simulation Software provided models for reengineering the manufacturing processes. The input/output analyzer in arena simulation software helped to view and analyze the simulation results to verify and validate the data collected during the study. The raw data tested using the mathematical model determined the optimal material handling costs and

automation decision for robot integration alternative for both steel manufacturing industries and visualized in a simulated factory environment as shown in figure 7.3 below.

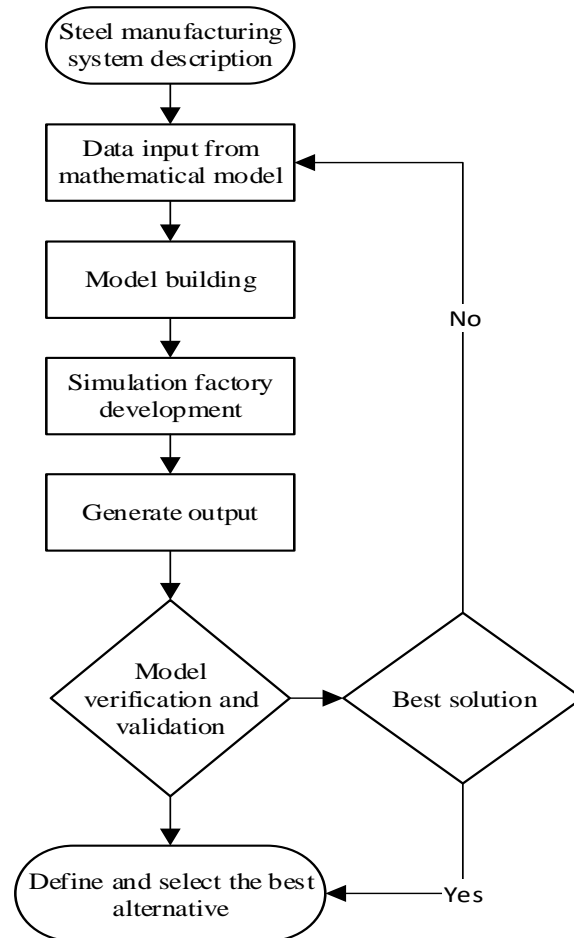


Figure 7.3: Simulated factory development steps

3.5 Summary of Methodology

The research employed various methods to collect, analyze and present data collected during the study. Data was collected through observations, interviews and document analysis of the existing records. The data was then analyzed using Microsoft Excel applications and arena simulations software while presentations were made using graphs, tables and charts where necessary. However, the simulation software used had limitations due to its inability to consider parameters like worker fatigue and machine breakdowns. To overcome this limitations, assumptions were made not to consider worker fatigue and machine breakdowns since the frequencies could not be exactly determined. Never the less, the methods used during the research provided positive results in the development and validation of a mathematical model for integration of robots within the steel manufacturing processes for the steel manufacturing plants considered.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS, AND DISCUSSIONS

This chapter presents the data collected during the study, data analysis and discussions of the findings

4.0 Introduction

Two automated steel manufacturing Plants A and B, consisting of manufacturing cells one, two, and three considered during the study showed the potential for robotic integration within the steel manufacturing processes. The aim was to study the material handling systems used in each manufacturing cell, the material storage systems, steel manufacturing processes, the adaptability of each manufacturing cell to new technologies, and the current steel manufacturing technologies used in the steelmaking processes. The decision to integrate or not to integrate an industrial robotic technology in a given manufacturing cell determined based on the analysis of labor distribution within a manufacturing cell, economic analysis of integrating an industrial robot automation technology, and steel manufacturing task classifications in terms of manual, semi-automatic, and fully automatic processes provided the optimal robotic automation decision. A Markov's decision analysis model for industrial robot integration in a given manufacturing cell determined using dynamic programming over a while found the optimal decision for automation and material handling costs under the stochastic robot performance. A simulated factory environment using arena simulation software used to visualize, test, and validate the model determined the optimal robotic performance within each manufacturing cell.

4.1 Description of existing Manufacturing systems

The study describes the current steel manufacturing situations concerning the plant layout design, material handling systems, and steel manufacturing systems in two steel manufacturing plants in Uganda. The manufacturing system parameters for robotic integration studied in the two plants included manufacturing process routes, machine layouts, and material handling systems used in each manufacturing cell. The aim was to determine the necessary adjustments required on the existing process layouts and material handling systems for robot mapping, localization, planning, and coordination of robot activities within a given steel manufacturing cell for the successful integration of robotic automation technologies.

4.1.1 Steel manufacturing cell One-Galvanized wireline

Hot rolled wires of different dimensions used in steel manufacturing cell one as raw material inputs for the wire drawing processes are manually delivered using overhead cranes to the uncoiling

machine before drawing. The cold wire drawing processes in both steel plants uses sets of die chambers and heating furnaces operating at reducing temperature ranges for annealing processes. The quenched wire is cleaned using hydrochloric acid, rinsed, fluxed with zinc ammonia chloride, and galvanized in a zinc bath. The manufacturing process routes and steel product flow for a galvanized wire production line at steel Plant A and Plant B is presented in figure 8.4.

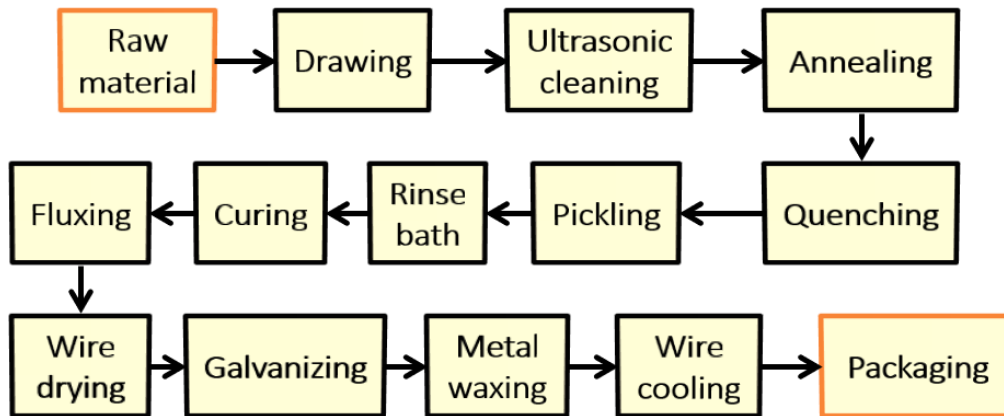


Figure 8.4: Steel manufacturing process routes in manufacturing cell one

Overhead cranes, manually driven trolleys, and manual material handling are predominantly used material handling systems in manufacturing cell one for both steel plants. Steel manufacturing cell has mechanically assisted manufacturing technologies, semi-automated processes, physically aided assisted machines, and steel manufacturing systems that are hard to reconfigure for other manufacturing processes and new industrial robotic automation technologies. In steel manufacturing cell one, zinc ingots are loaded manually onto manually driven trolleys and taken for charging into the zinc pot for wire galvanizing processes.

4.1.2 Steel Manufacturing Cell Two-Continuous Galvanizing Line

In steel manufacturing cell two, hot-rolled sheets of materials used as raw material inputs for sheet galvanizing processes in steel manufacturing plant A undergoes cleaning through pickling processes and cold rolling to attain the required specifications. The cold-rolled sheets undergo heat treatments in heating furnaces before charging in the zinc pot for galvanizing at a temperature of 650°C. The galvanized sheets are treated and coated with chromium, dried, and coiled for use as raw material inputs in the profiling and colour coating processes. The manufacturing process routes used in steel manufacturing cell two are presented in figure 9.4.

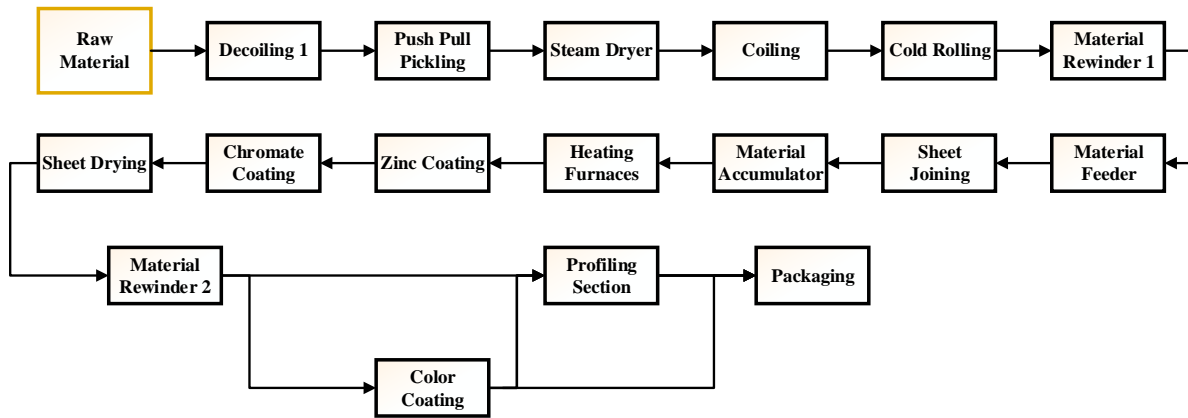


Figure 9.4: Steel manufacturing process routes in manufacturing cell two

Automated guided vehicles and overhead cranes are the most dominant material handling systems used in steel manufacturing cell two. Mechanical and manual transport systems used in processes where overhead cranes and automated guided vehicles cannot reach have limitations in operations around the zinc pot. Mechanically assisted manufacturing technologies, semi and fully automated manufacturing processes, and sensor-aided assisted machines are the major characteristics of the manufacturing systems in steel manufacturing cell two for manufacturing plant B. Steel manufacturing cell two is a self-adapting manufacturing cell for reconfiguring other manufacturing processes and new automation industrial robotic technologies. The material handling types used in steel manufacturing cell two for moving finished and unfinished steel products presented in figure 10.4 provided an optimal solution for robot-machine interaction during robot integration processes.

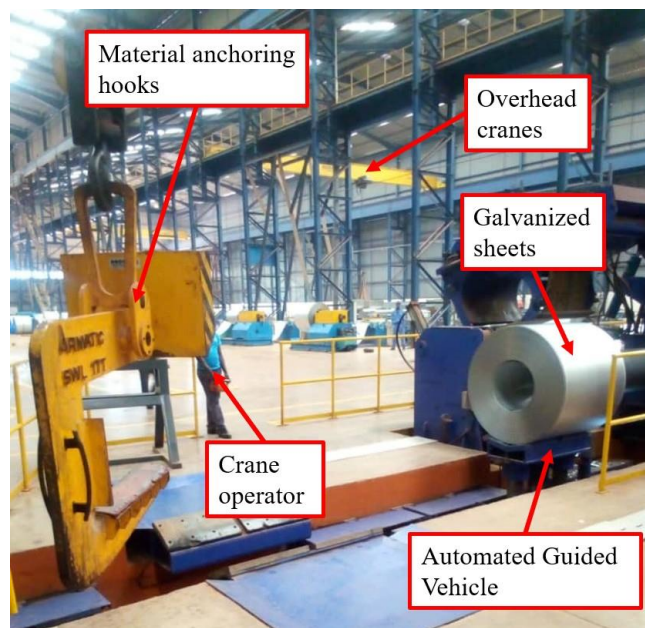


Figure 10.4: Automated material handling equipment types at steel manufacturing cell two

To ensure damage-free and accident-free material handling processes for the robot, sensor-aided technologies need to be integrated with the existing material handling systems to ensure optimal robot performance in manufacturing cell two.

4.1.3 Steel Manufacturing Cell Three-Hot Steel Rolling Line

The hot steel rolling manufacturing processes in manufacturing cell three uses scrap and billets as raw material inputs. The molten steel from scrap materials cast into ingots/billets for use in the hot rolling processes is ruff-rolled for initial elongation processes before final rolling using straight rolling mills. The metal ‘Rebars’ cooled in a cooling bed are cut into different sizes for packaging. While the hot steel rolling processes for steel manufacturing plant B are continuous, the hot steel rolling processes for steel manufacturing plant A are not a continuous process. The cast ingots from steel plant B are stored in a cooling bed before taken into a reheating furnace for continuous casting processes. Although both steel manufacturing processes are characterized by manual material sorting of steel scrap during metal screening processes, manual handling of hot steel products during hot steel rolling processes occurs at steel inspection stations. Hot steel manufacturing process routes for steel manufacturing plant A and steel manufacturing plant B presented in figure 11.4 provide an overview of steel manufacturing process routes in manufacturing cell three.

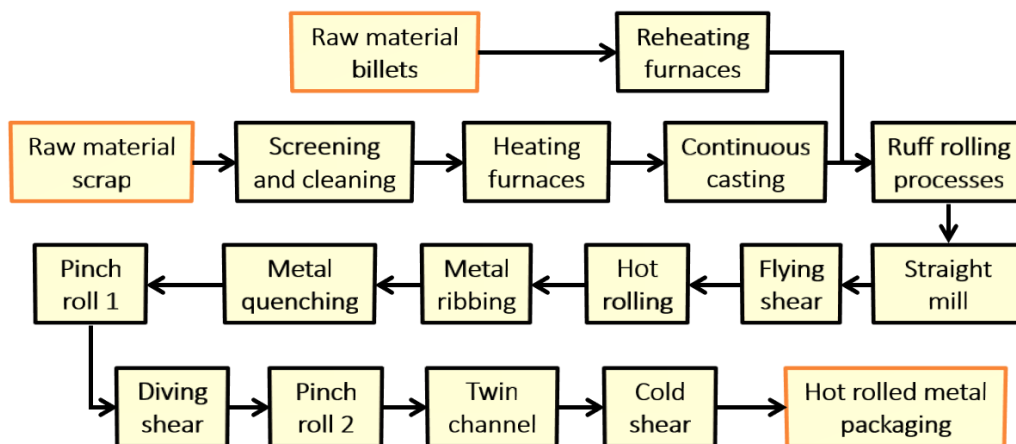


Figure 11.4: Steel manufacturing process routes in manufacturing cell three

Overhead cranes, conveyors, mechanical, and manual material handling of steel are the most common material handling system used in steel manufacturing cell three. Mechanically assisted technologies, physical and sensor-aided machines, and fully automated processes dominate most operations in steel manufacturing plant B. Steel manufacturing cell two can be automatically reconfigured for other manufacturing processes. Figure 12.4 presents an overview of steel manufacturing processes at steel plant A.

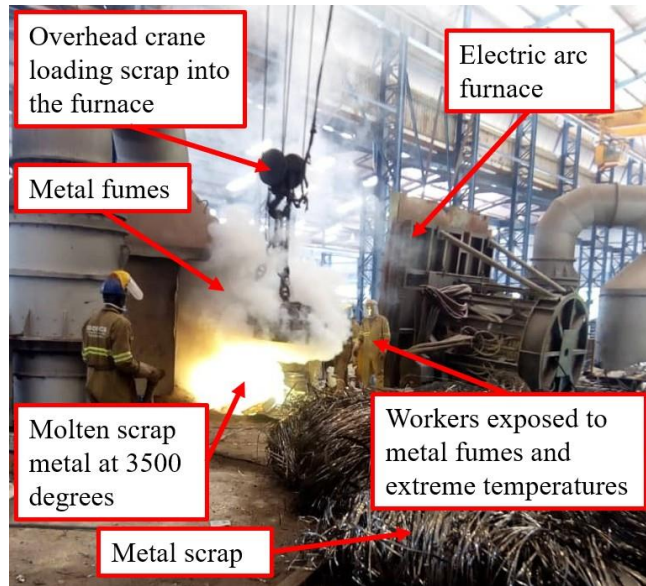


Figure 12.4: Steel manufacturing tasks at steel plant A

4.1.4 Automated Material handling systems

During automated material handling of finished steel products in each manufacturing cell, overhead cranes and automated guided vehicles in both plants require accurate distance to finished goods information to hold precisely the grip of the steel products. The material handling equipment operators identify the presence of steel materials and guarantee proper alignment of the overhead cranes and placement of materials in the logistic areas. Damage-free automated material handling of steel plates, sheets, rods, and strips in both steel manufacturing plants is a crucial task in attaining quality steel products and safety. The automated material handling equipment used in both steel manufacturing plants lack metal detection sensors for steel materials used in each manufacturing cell. The protection of steelworkers from automated transport material handling equipment is an important safety issue in all types of production and material handling processes in a steel manufacturing plant. Automated safety detection systems that detect obstacles in the automated guided vehicle pathways to prevent collision with physical assets and steelworkers crossing paths with the machine are lacking in both steel manufacturing plants. Figure 13.4 illustrates the material handling equipment used in both steel manufacturing plants.

An industrial robot installed in a given manufacturing cell must work directly with people within the manufacturing cell without causing any harm to people. The existence of a suitable and sufficiently dimensioned safety system for human-robot interaction in a given manufacturing cell is required. Human-robot integration is necessary for steel manufacturing cell 1, 2, and 3 around

manufacturing task that exposes humans to high safety risks and non-ergonomic working positions. The human-robot interactions streamline steel manufacturing processes increasing production output and improving workplace safety where robots take over undesirable tasks that require humans to work under physical strain. New robotic automation technological developments in the steelmaking process allow for improvements in the safety and prediction of product quality via sensors. The implementation of industrial robots in steel manufacturing cells two and three greatly improved the manufacturing processes at the heating furnaces and zinc pot increasing the production rates and worker safety. Industrial robots use in steel manufacturing cell three replaced workers used to inspect the conditions of molten steel manually during continuous casting processes at the heating furnaces using hand-held tools.

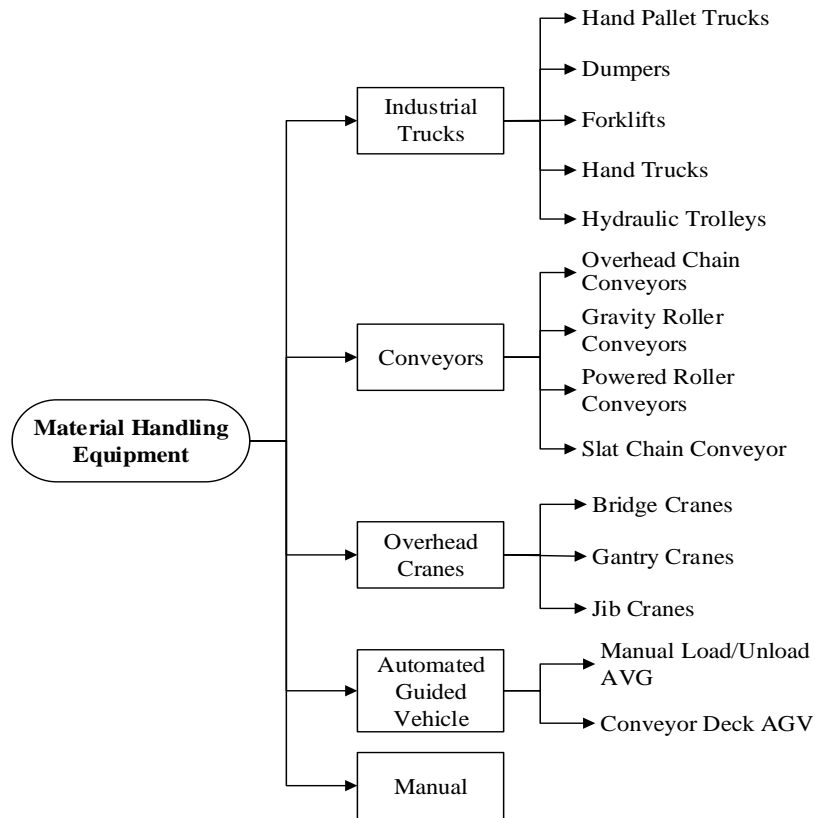


Figure 13.4: Material Handling Equipment Types at steel Plant A and Plant B

4.2 Determination of candidate tasks for robotic integration processes

The manufacturing tasks in manufacturing cells C_1 , C_2 , and C_3 evaluated the eligibility for robot process integration to determine the robot integration potential and robot relevance for each manufacturing task. Selected manufacturing processes in each cell showed significant eligibility for robot integration in different manufacturing tasks. For a given manufacturing process (M_i) comprising of steel manufacturing task (T_i) with (n) sub-tasks in a given steel manufacturing cell (C), the robot integration potential (R_{pot}) for each manufacturing process is determined by

$$R_{pot}(M_i) = \frac{\sum_{i=1}^n R_{pot}(TM_i)}{n} \quad (6)$$

Similarly, robot relevance (R_{rel}) for the same manufacturing process is given by,

$$R_{rel}(M_i) = \frac{\sum_{i=1}^n R_{rel}(TM_i)}{n} \quad (7)$$

Manufacturing tasks eligibility for robot integration determined using the robot integration potential and robot relevance based on two main questions

EQ1: Are all units interacting with the manufacturing processes and the robot expecting the same goal?

EQ2: Are all interactions between the robot and manufacturing processes well specified?

Each manufacturing task should address these questions to be eligible for validation for robot integration processes. A manufacturing task that answers “NO” to any one of the questions is not eligible for robot integration processes.

The robot integration potential weight for a manufacturing process is a value between zero ‘0’ and one ‘1’. If the manufacturing process or manufacturing tasks requires robot integration, the robot integration potential value is given as ‘1’ i.e. ($R_{pot} = 1$). For a manufacturing task that does not require a robot, the robot integration potential value is ‘0’ ($R_{pot} = 0$). The potential for a manufacturing task/process to use robotic automation technologies based on two main questions determined candidate tasks for robotic integration processes.

PQ1: will the manufacturing tasks/process require manual interaction with the robot?

PQ2: is the manufacturing process/tasks based on clearly identified sequences?

A manufacturing task should answer “YES” to all questions to qualify for robotic integration processes and the robot integration potential value should be equal to ‘1’ ($R_{pot} = 1$). If a manufacturing task answers “NO” to one question, the robot integration potential value is ‘0’ ($R_{pot} = 0$) and the manufacturing task is not eligible for robot integration. The manufacturing

tasks classifications for both steel-manufacturing plants presented in table 7.4 demonstrated manufacturing cell potential for robot integration.

Table 7.4: Manufacturing tasks determination for robot potential

Task Code	Task description	EQ ₁ Y/N	EQ ₂ Y/N	PQ ₁ Y/N	PQ ₂ Y/N	R_{pot} value	R_{rel} value	R_{pot}	Task classification (T _A , T _B , T _C & T _D)
MC ₁ -T ₁₁	Wire Drawing	Y	N	Y	Y	0.75	0.25	0	Moderately suitable
MC ₁ -T ₁₂	Cleaning	N	Y	N	Y	0.4	0.25	0	Not Suitable
MC ₁ -T ₁₃	Annealing	Y	N	N	Y	0.4	0.3	0	Not Suitable
MC ₁ -T ₁₄	Galvanizing	Y	Y	Y	Y	1.0	1.0	1	Highly Suitable
MC ₁ -T ₁₅	Wire Coiling	Y	N	Y	N	0.55	0.4	0	Moderately suitable
MC ₂ -T ₂₁	Sheet De-coiling	N	N	Y	N	0.25	0.45	0	Not Suitable
MC ₂ -T ₂₂	Picking	Y	N	N	Y	0.4	0.25	0	Not Suitable
MC ₂ -T ₂₃	Sheet Coiling	N	N	Y	N	0.3	0.4	0	Not Suitable
MC ₂ -T ₂₄	Sheet Joining	Y	N	Y	N	0.6	0.3	0	Moderately suitable
MC ₂ -T ₂₅	Zinc Coating	Y	Y	Y	Y	1.0	1.0	1	Highly Suitable
MC ₂ -T ₂₆	Color Coating	N	N	Y	N	0.4	0.75	0	Less Suitable
MC ₂ -T ₂₇	Profiling	N	N	Y	N	0.3	0.75	0	Less Suitable
MC ₃ -T ₃₁	Metal Sorting	Y	N	Y	N	0.7	0.4	0	Moderately suitable
MC ₃ -T ₃₂	Casting	Y	Y	Y	Y	1.0	1.0	1	Highly Suitable
MC ₃ -T ₃₃	Heating	Y	Y	Y	Y	1.0	1.0	1	Highly Suitable
MC ₃ -T ₃₄	Ruff Rolling	Y	N	N	Y	0.3	0.25	0	Not Suitable
MC ₃ -T ₃₅	Hot Rolling	Y	N	N	Y	0.4	0.6	0	Less Suitable

$MC_{i}-T_{j}$ are task codes where M , C , and T represent manufacturing process, cell, and task, respectively. For example, $MC_{3}-T_{35}$ is a manufacturing process in cell three with task five.

Manufacturing tasks classification for each steel manufacturing process in manufacturing cell C₁, C₂ and C₃ coded as “T_A”-Not suitable for robot integration, “T_B”-less suitable for robot integration, “T_C”-moderately suitable for robot integration, and “T_D”-highly suitable for robot integration placed each task in the right quadrant. The classification quadrant in figure 14.4 determined the task based on low-to-high for robot automation processes. Manufacturing tasks suitable for the robot integration process has a robot potential equivalent value of 1 ($R_{pot} = 1$) and manufacturing tasks not suitable for robot integration process has a robot potential equivalent value of 0 ($R_{pot} =$

0). Although a task has a robot potential of '0' ($R_{pot} = 0$), it was further classified to determine its level of suitability for robot integration processes and the robot relevance value determined. The moderately suitable task for robot integration processes needed streamlining the manufacturing processes to accommodate robotic automation technologies.

Rrel	High [1.0]	B Less suitable tasks for robot integration	D Highly suitable tasks for robot integration
	[0.5]	A Tasks Not suitable for robot integration	C Moderately suitable tasks for robot integration
		[0.0] Low	[0.5] [1.0] High Rpot

Figure 14.4: Manufacturing tasks classification quadrant

From table 7.1 above, manufacturing tasks MC₁-T₁₄, MC₂-T₂₅, MC₃-T₃₂, and MC₃-T₃₃ with a robot integration potential value of 1 ($R_{pot} = 1$) in manufacturing cells C₁, C₂, and C₃ are highly suitable for robotic integration processes. These manufacturing tasks provide the required conditions for the integration of robotics technologies in steel manufacturing plants A and B. Mathematical problem formulation for integrating robotic technologies in steel manufacturing cells C₁, C₂, and C₃ based on manufacturing tasks MC₁-T₁₄, MC₂-T₂₅, MC₃-T₃₂, and MC₃-T₃₃ provided promising results for robot integration processes.

Manufacturing tasks with high robot integration potential ($R_{pot}(T) > 0.5$) and high robot relevance in manufacturing processes ($R_{rel}(T) > 0.5$) are highly suitable for robot integration processes. Manufacturing tasks with high robot integration potential ($R_{pot}(T) > 0.5$) and low robot relevance in manufacturing processes ($R_{rel}(T) < 0.5$) are moderately suitable for robot integration processes. Manufacturing tasks with low robot integration potential ($R_{pot}(T) < 0.5$) but has a high robot relevance in manufacturing processes ($R_{rel}(T) > 0.5$) are less suitable for robot integration processes. Finally, for manufacturing tasks with low robot integration potential ($R_{pot}(T) < 0.5$) and low robot relevance in manufacturing processes ($R_{rel}(T) < 0.5$) are not suitable for robot integration processes.

For example, for manufacturing task MC_1-T_{11} with a robot potential value of 0.75 ($R_{pot} = 0.75$) and robot relevance value of 0.25 ($R_{rel} = 0.25$) implies that 75% of the overall manufacturing processes can be integrated using robotic automation technologies while only 25% of the tasks require manual intervention with robotic technologies. Although task MC_1-T_{11} has a high robot integration potential of 75%, only 25% of the activities require the use of robots in its manufacturing processes. The robot relevance in the manufacturing process is very low and it is not economically viable to integrate robotic technologies in manufacturing task MC_1-T_{11} . Steel manufacturing tasks MC_2-T_{25} with a high robot potential value of 1.0 ($R_{pot} = 1.0$) and a high robot relevance value of 1.0 ($R_{rel} = 1.0$) is highly suitable for robot integration processes. Integrating robots for manufacturing tasks MC_2-T_{25} replaced workers in unsafe working conditions, reduced material handling costs, improved the quality of zinc-coated steel products, and reduced the overall manufacturing costs for steel manufacturing cell two as shown in figure 15.4

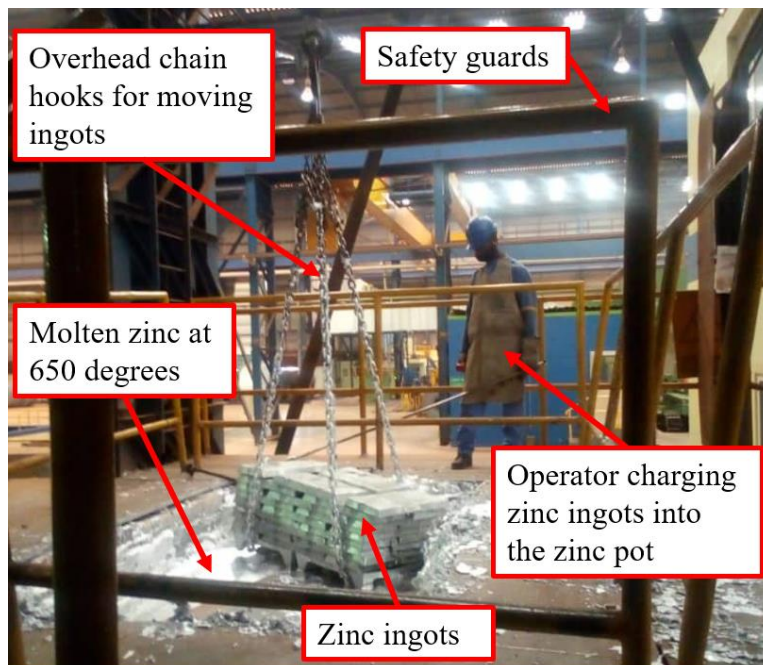


Figure 15.4: Overview of steel manufacturing tasks MC_2-T_{25}

Manufacturing tasks MC_2-T_{26} , MC_2-T_{27} , and MC_3-T_{35} has a robot potential value of less than 0.5 ($R_{pot} < 0.5$) and a robot relevance value greater than 0.5 ($R_{rel} > 0.5$). Although this manufacturing task relevant to robot use is high ($R_{rel} > 0.5$), the robot integration potential for these manufacturing tasks is very low ($R_{pot} < 0.5$). The robot integration processes are hard to achieve and not economically viable hence classifying these tasks as less suitable for robot

integration processes. Manufacturing tasks MC_1-T_{12} , MC_2-T_{22} , MC_2-T_{23} , and MC_3-T_{34} , with robot potential value of less than 0.5 ($R_{pot} < 0.5$) and robot relevance value of less than 0.5 ($R_{rel} < 0.5$) are not suitable for robot integration processes. The manufacturing tasks' potential and relevance for integrating robot technologies explained in figure 16.4 provided optimal robot automation solutions for each manufacturing cell.

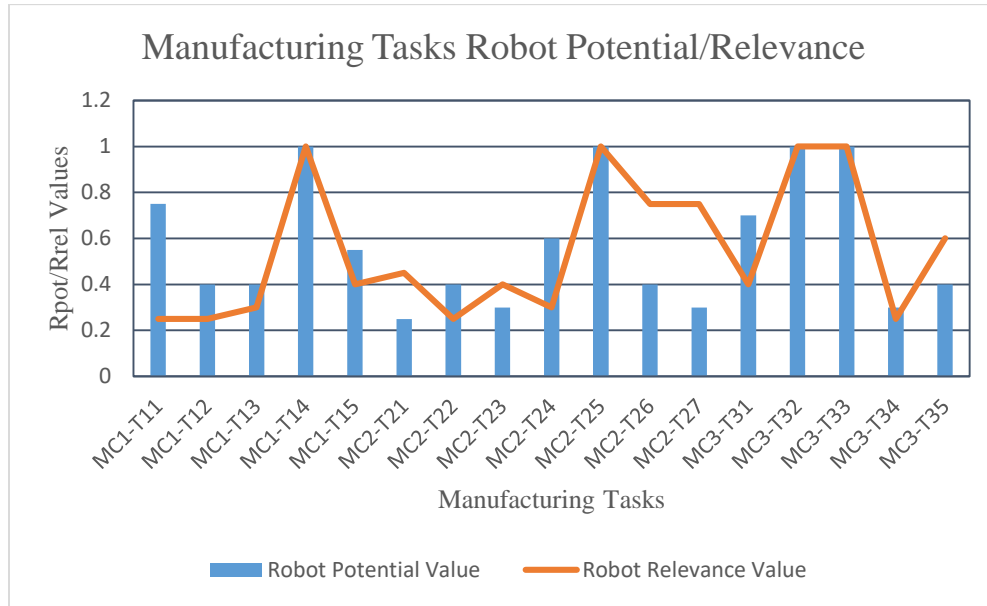


Figure 16.4: Manufacturing Tasks Potential/Relevance for robot integration

4.3 A Markov Decision Analysis Model for Robot Automation

Two automated steel manufacturing plants consisting of three manufacturing cells considered during the study for robotic automation presented promising results for robot integration. Associated with robot performance in a given manufacturing cell is stochastic stationary performance. While considering specific tasks accomplished in a given manufacturing cell, a finite-state Markov decision process model formulated where states of a Markov chain represented possible states of performance under automation policies. The material handling cost matrix determined at each manufacturing cell represented the long-run measure of performance for the Markov decision process problem. The aim was to determine an optimal robotic automation decision for each manufacturing cell to minimize the long-run material handling costs for the given state of performance. The decision for Automation or Non-automation made at a given manufacturing cell using dynamic programming over a finite period planning horizon provided an optimal automation decision for each manufacturing cell. The model tested using the data collected

during the study demonstrated the existence of an optimal state-dependent industrialization decision and material handling cost for the manufacturing cells considered in this study.

4.3.1 The finite-period dynamic programming model for optimal robotic automation options and material handling costs.

In building the mathematical model for optimal robotic automation options and material handling costs using Markov Decision Analysis, key notations used in model development are defined below;

- i. i, j set of states of performance
 - ii. C Set of manufacturing cells
 - iii. K Set of options for automation
 - iv. T Task Matrix
 - v. P Performance matrix
 - vi. M Material handling cost matrix
 - vii. P_{ij}^k The probability that performance of manufacturing cells changes from state i to state j given automation policy K
 - viii. \mathbf{e} Expected material handling cost
 - ix. α Accumulated material handling cost
 - x. n, N Stages
 - xi. F Favourable performance
 - xii. U Unfavourable performance
- $i, j \in \{F, U\}$ $K \in \{0,1\}$

Noting that the performance of manufacturing cells can be either in-state F or state U , the problem of finding optimal robotic automation options is expressed as a finite-period dynamic programming model. Assuming $\mathcal{G}_n(i, k)$ denotes the optimal expected material handling cost accumulated at the end of periods $n, n + 1, n + 2, \dots \dots N$ given that the state of the system at the beginning of period n is $i \in \{F, U\}$, the recursive equation relating \mathcal{G}_n and \mathcal{G}_{n+1} Mubiru (2010)

$$\mathcal{G}_n(i, k) = \text{Min} \begin{bmatrix} P_{iF}^k(C)M_{iF}^k(C) + \mathcal{G}_{n+1}(F, K) \\ P_{iU}^k(C)M_{iU}^k(C) + \mathcal{G}_{n+1}(U, K) \end{bmatrix} \quad (8)$$

$$i, U \in \{F, U\} \quad K = \{1,2,3\} \quad n = 1,2,3, \dots \dots N$$

Together with the conditions $\mathcal{G}_{N+1}(F, K) = \mathcal{G}_{N+1}(U, K) = 0$

The robot transition matrices from one state to another within a given manufacturing cell with automation policy K are calculated using equation (9) below.

$$P_{ij}^k(C) = T_{ij}^k(C)[T_{iF}^k(C) + T_{iU}^k(C)] \quad (9)$$

The expected material handling costs for the robot in a given manufacturing cell are calculated using equation (10) below.

$$e_{ij}^k(C) = P^k(C)M^k(C) \quad (10)$$

For a given time, n , the accumulated material handling costs for the robots installed in the steel manufacturing industry are calculated using equation (11) below.

$$\alpha_i^k(C) = e_i^k(C) + P_{iF}^k(C)g_n(F, K) + P_{iU}^k(C)g_n(U, K) \quad (11)$$

4.3.2 Robot optimization in a steel manufacturing cell.

For Period I,

When performance is favourable (state F) the optimal options for robotic automation in a given steel manufacturing cell is

$$K = \begin{cases} 1 & \text{if } e_F^1(C) < e_F^0(C) \\ 0 & \text{if } e_F^1(C) \geq e_F^0(C) \end{cases} \quad (12)$$

When performance is unfavourable (state U) the optimal options for robotic automation in a given steel manufacturing cell is as follows

$$K = \begin{cases} 1 & \text{if } e_U^1(C) < e_U^0(C) \\ 0 & \text{if } e_U^1(C) \geq e_U^0(C) \end{cases} \quad (13)$$

The associated optimal material handling costs for robots in a given steel manufacturing cell when performance is favourable under automation policy K is given by;

$$g_1(F, C) = \begin{cases} e_F^1(C) & \text{when } K = 1 \\ e_F^0(C) & \text{when } K = 0 \end{cases} \quad (14)$$

When performance is unfavourable, the associated material handling cost for robots in a given steel manufacturing cell is as follows

$$g_1(U, C) = \begin{cases} e_U^1(C) & \text{if } K = 1 \\ e_U^0(C) & \text{if } K = 0 \end{cases} \quad (15)$$

For Period II,

When performance is favourable, (state F), the optimal robotic automation options in a given steel manufacturing cell is as follows

$$K = \begin{cases} 1 & \text{if } \alpha_F^1(C) < \alpha_F^0(C) \\ 0 & \text{if } \alpha_F^1(C) \geq \alpha_F^0(C) \end{cases} \quad (16)$$

When performance is unfavourable (state U), the optimal robotic automation options in a given steel manufacturing cell as follows

$$K = \begin{cases} 1 & \text{if } \alpha_U^1(C) < \alpha_U^0(C) \\ 0 & \text{if } \alpha_U^1(C) \geq \alpha_U^0(C) \end{cases} \quad (17)$$

When performance is favourable (state F), the optimal material handling costs for robots in a given steel manufacturing cell is as follows

$$g_2(F, C) = \begin{cases} \alpha_F^1(C) & \text{if } K = 1 \\ \alpha_F^0(C) & \text{if } K = 0 \end{cases} \quad (18)$$

When performance is unfavourable (state U), the optimal material handling costs for robots in a given steel manufacturing cell is as follows

$$g_2(U, C) = \begin{cases} \alpha_U^1(C) & \text{if } K = 1 \\ \alpha_U^0(C) & \text{if } K = 0 \end{cases} \quad (19)$$

4.3.3 Generic Algorithm for Robot path planning under automation decision K_1

Consider a two-dimensional grid layout of a steel manufacturing cell in figure 17.4 below.

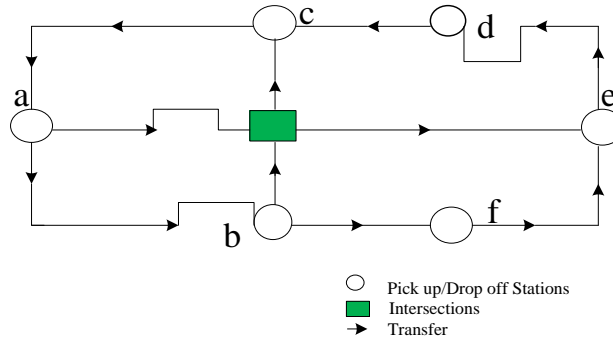


Figure 17.4: Grid layout for Robot paths in a steel manufacturing cell

When automation decision $K=1$ is taken under favourable robot performance (F) in a given steel manufacturing cell, the robot localization and navigation guide paths are determined. While considering a manipulation robotic system, the assumptions for the robot navigation on a given path considered in the model include.

- i. The robot path is a two-dimensional guide path. The robot can change direction depending on the path traversing
- ii. The velocity of the robot is constant. The travel time of the robot is proportional to the travel distance
- iii. Traffic interference between robots is not taken into consideration
- iv. All pickup requests from all stations are served by one robot
- v. It is assumed that the robot can serve all request assigned to it
- vi. Pickup time, drop-off time and transport time between pick-up stations and drop-off stations are well known.

Using a Genetic Algorithm (GA) for determining the guide path for a robot in a layout for a given steel manufacturing cell, the defined key notations for the model are as follows.

- i. P/D *Pick up/Drop off stations in a manufacturing cell*
- ii. $P/D_i/P/D_j$ *Distances between pick up stations to drop off stations*
- iii. N *Number of robots in a manufacturing cell*
- iv. n *Number of pick up/drop off stations in a manufacturing cell*
- v. V *Velocity of the robot*
- vi. T_{ij} *Time required to move from P/D_i to P/D_j*
- vii. M_{ij} *Number of materials the robot moves from P/D_i to P/D_j*
- viii. T_{avg}^m *Average time required by the robot to move materials from P/D_i to P/D_j*
- ix. T_p/T_d *Pickup time/drop off time*
- x. T_1 *The average generation time of materials in all pick-up/drop off stations*

When ‘N’ robots are randomly located in n number of pickup/drop-off stations, the matching time of materials of ‘N’ robots existing in ‘N’ pick up/drop off stations is theoretically zero. In consideration of this theory, when there are ‘N’ robots in a given manufacturing cell ‘X’ and ‘Y’ containing ‘0’ and ‘1’ elements, the robot dwell points are

$$X_i = \begin{cases} 0 & P/D_i \text{ if a robot is located in dwell point } x_i \\ 1 & \text{Otherwise} \end{cases} \quad (20)$$

Where $X_i = (x_1, \dots, x_j, \dots, x_n)$ for $\sum_{i=1}^n X_i < N$

$$Y_j = \begin{cases} 1 & P/D_j \text{ if a robot is located in dwell point } y_i \\ 0 & \text{Othewis} \end{cases} \quad (21)$$

Where $Y_i = (y_1, \dots, y_j, \dots, y_n)$ for $\sum_{j=1}^n Y_j < N$ *Morikawa et al, (2020)*

Considering the number of robots in a given manufacturing cell, the average time T_{avg} of the transport between pickup station and drop off stations are expressed as

$$T_{avg} = \frac{\sum T_{ij}}{n(n-1)} \quad (22)$$

In a manufacturing cell where one robot exists in a pick-up/drop-off station (a), a case may arise in which a material moved to station (b) by the robot was in station (c). The robot first travels from station (a) to station (c), loads the material, and travels from station (c) to final station (b) and the robot tasks are completed. The total time T_T taken by the robot to complete the tasks is,

$$T_T = T_{ac} + T_p + T_{cb} + T_d \quad (23)$$

Given that T_{ac} and T_{cb} are the times required by the robot to move from stations (a) to (c) and station (c) to (b) respectively. The assumption made is that a robot does not know its next destination unless it is loaded with steel materials. T_{ac}, T_p, T_{cb}, T_d Depends on robot performance. Theoretically, the manufacturing cell will function if there is no request for the transfer of the next transfer within the total time of the tasks T_T hence

$$T_T = T_{ac} + T_p + T_{cb} + T_d \leq T_1 \quad (24)$$

In a typical manufacturing cell, the average travel time between pickup stations varies from station to station depending on the number of materials between pickup and drop-off stations. Considering the robot operation time, the average time for moving materials between pickup and drop off stations is,

$$T_{avg}^m = \frac{\sum(T_{ij}M_{ij})}{\sum M_{ij}} \quad (25)$$

Substituting the average value of time required by the robot to move between pick up and drop off station in consideration of transfer consideration of equation (25) into T_{ac} and T_{cb} of equation (24) results in the following equation.

$$2T_{avg}^m + T_p + T_d \leq T_1 \quad (26)$$

This is a constraint condition for a manufacturing cell with one robot. Assuming that the manufacturing cell with 'N' robots has 'N' times the transfer processing capacity of the entire system, equation (26) is re-written as

$$N > \frac{2T_{avg}^m}{T_1} \quad (27)$$

For ($T_p = T_d = 0$) assuming pick time and drop off time = 0

4.3.4 Case study about the choice of robotic integration in Plant A and Plant B

The study selected steel manufacturing Plant A and Plant B in Uganda to test and demonstrate the use of the mathematical model formulated using the data collected during the study. Decision support sought in terms of an optimal option for robot automation at each steel manufacturing cell minimized the material handling cost of steel products during the manufacturing cycles while maximizing the robot performance over a while. The manufacturing task potential and relevance for robot integration processes together with the respective robot performance states for a given steel manufacturing cell is presented in *Table 8.4*

Table 8.4: Manufacturing task robot potential/relevance versus robot performance states

Cell	Manufacturing Tasks	Robot Tasks Potential	Robot Performance States	Robot Tasks Relevance	Robot Performance States
C ₁	MC ₁ -T ₁₁	75	F	25	U
	MC ₁ -T ₁₂	40	U	25	U
	MC ₁ -T ₁₃	40	U	30	U
	MC ₁ -T ₁₄	100	F	100	F
	MC ₁ -T ₁₅	55	F	40	U
C ₂	MC ₂ -T ₂₁	25	U	45	U
	MC ₂ -T ₂₂	40	U	25	U
	MC ₂ -T ₂₃	30	U	40	U
	MC ₂ -T ₂₄	60	F	30	U
	MC ₂ -T ₂₅	100	F	100	F
	MC ₂ -T ₂₆	40	U	75	F
	MC ₂ -T ₂₇	30	F	75	U
C ₃	MC ₃ -T ₃₁	70	F	40	U
	MC ₃ -T ₃₂	100	F	100	F
	MC ₃ -T ₃₃	100	F	100	F
	MC ₃ -T ₃₄	30	U	25	U
	MC ₃ -T ₃₅	40	U	60	F

Samples of material handling tasks with their respective material handling costs (in USD) for each steel manufacturing cell for both steel plants collected are presented in Table 9.4 and table 10.4. The state transition of robotic performance at each steel manufacturing cell examined for a while provided optimal robot performance for each manufacturing task.

Table 9.4: Manufacturing tasks versus robot state transition at manufacturing cell

cell (C)	States F/U	Automation Policy K=1		Automation Policy K=0	
		F	U	F	U
1	F	100	75	100	25
	U	55	40	40	30
2	F	100	60	100	30
	U	40	25	75	45
3	F	100	100	100	100
	U	70	30	40	25

Table 10.4: Material handling costs versus robot state transition at manufacturing cells

cell (C)	States F/U	Automation Policy K=1		Automation Policy K=0	
		F	U	F	U
1	F	33	15	30	8
	U	24	5	12	16
2	F	45	35	48	28
	U	22	33	37	18
3	F	55	65	60	55
	U	78	18	46	50

4.3.5 Computation of Model Parameters

During period I

Using equation (9), the performance transition matrices calculated at the respective manufacturing cells under the automation decision (K=1) provided robot probability transition matrices under favourable and unfavourable robot performance.

$$\begin{array}{l}
 \text{Manufacturing cell 1} \quad P_1^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.5714 & 0.4286 \\ 0.5789 & 0.4211 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 2} \quad P_2^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.6250 & 0.3750 \\ 0.6154 & 0.3846 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 3} \quad P_3^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.5000 & 0.5000 \\ 0.7000 & 0.3000 \end{bmatrix} \\ U \end{array}
 \end{array}$$

when the decision for non-automation is taken, (K=0) the robotic performance matrices at each respective manufacturing cell is given by;

$$\begin{array}{l}
 \text{Manufacturing cell 1} \quad P_1^0 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.8000 & 0.2000 \\ 0.5714 & 0.4286 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 2} \quad P_2^0 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.7692 & 0.2308 \\ 0.6250 & 0.3750 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 3} \quad P_3^0 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 0.5000 & 0.5000 \\ 0.6154 & 0.3846 \end{bmatrix} \\ U \end{array}
 \end{array}$$

The material handling costs (in USD) for the decision of robotic automation (K=1) for each manufacturing cell is given by;

$$\begin{array}{l}
 \text{Manufacturing cell 1} \quad M_1^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 33 & 15 \\ 24 & 5 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 2} \quad M_2^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 45 & 35 \\ 22 & 33 \end{bmatrix} \\ U \end{array} \\
 \\
 \text{Manufacturing cell 3} \quad M_3^1 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 55 & 65 \\ 78 & 18 \end{bmatrix} \\ U \end{array}
 \end{array}$$

Similarly, the material handling costs for the decision of non-automation (K=0) in a given steel manufacturing cell is given by;

$$\text{Manufacturing cell 1} \quad M_1^0 = \begin{array}{c} F \quad U \\ F \begin{bmatrix} 30 & 8 \\ 12 & 16 \end{bmatrix} \\ U \end{array}$$

$$\begin{array}{l} \text{Manufacturing cell 2} \\ \text{Manufacturing cell 3} \end{array} \quad M_2^0 = \begin{array}{c} F \\ U \end{array} \begin{bmatrix} 48 & 28 \\ 37 & 18 \end{bmatrix} \quad M_3^0 = \begin{array}{c} F \\ U \end{array} \begin{bmatrix} 60 & 55 \\ 46 & 50 \end{bmatrix}$$

When the decision to integrate a robot in a manufacturing cell is taken (K=1), the probability matrices P_1^1, P_2^1, P_3^1 and the material handling cost matrices M_1^1, M_2^1, M_3^1 yield the expected material handling costs for the three manufacturing cells. Under favourable robot performance in a manufacturing cell (state F), the expected material handling cost is calculated using *Equation (10)* as follows.

$$\begin{array}{l} \text{Manufacturing cell 1} \\ \text{Manufacturing cell 2} \\ \text{Manufacturing cell 3} \end{array} \quad \begin{array}{l} e_F^1(1) = (0.5714)(33) + (0.4286)(15) \\ e_F^1(1) = 25.59 \\ e_F^1(2) = (0.6250)(45) + (0.3750)(35) \\ e_F^1(2) = 41.25 \\ e_F^1(3) = (0.5000)(55) + (0.5000)(65) \\ e_F^1(3) = 60.00 \end{array}$$

When the automation decision (K=1) is taken under unfavourable robot performance (state U) in a given manufacturing cell, the material handling costs for each manufacturing cell is given by

$$\begin{array}{l} \text{Manufacturing cell 1} \\ \text{Manufacturing cell 2} \\ \text{Manufacturing cell 3} \end{array} \quad \begin{array}{l} e_U^1(1) = (0.5789)(24) + (0.4211)(5) \\ e_U^1(1) = 16.00 \\ e_U^1(2) = (0.6154)(22) + (0.3846)(33) \\ e_U^1(2) = 26.23 \\ e_U^1(3) = (0.7000)(78) + (0.3000)(18) \\ e_U^1(3) = 60.00 \end{array}$$

When a decision for non-automation (K=0) is taken, the probability matrices P_1^0, P_2^0, P_3^0 and the material handling costs matrices M_1^0, M_2^0, M_3^0 yield the expected material handling costs for manufacturing tasks in each manufacturing cell. When the robot performance is favourable (state F) under non-automation decision (K=0), the expected material handling costs calculated using *equation (10)* are given by.

$$\begin{array}{l} \text{Manufacturing cell 1} \\ \text{Manufacturing cell 2} \end{array} \quad \begin{array}{l} e_F^0(1) = (0.8000)(30) + (0.2000)(8) \\ e_F^0(1) = 25.60 \\ e_F^0(2) = (0.7692)(48) + (0.2308)(28) \end{array}$$

$$\begin{aligned}
& e_F^0(2) = 43.38 \\
\text{Manufacturing cell 3} \quad & e_F^0(3) = (0.5000)(60) + (0.5000)(55) \\
& e_F^0(3) = 57.50
\end{aligned}$$

Similarly, when the robot performance is unfavourable (state U) under non-automation decision ($K=0$), the expected material handling costs for each manufacturing task in a given manufacturing cell are given by.

$$\begin{aligned}
\text{Manufacturing cell 1} \quad & e_U^0(1) = (0.5714)(12) + (0.4286)(16) \\
& e_U^0(1) = 13.71 \\
\text{Manufacturing cell 2} \quad & e_U^0(2) = (0.6250)(37) + (0.375)(18) \\
& e_U^0(2) = 29.88 \\
\text{Manufacturing cell 3} \quad & e_U^0(3) = (0.6154)(46) + (0.3846)(50) \\
& e_U^0(3) = 47.57
\end{aligned}$$

The expected material handling costs calculated when robot performance is favourable and unfavourable given automation decision $K \in \{0,1\}$ for period one is given in table 11.4.

Table 11.4: Expected material handling costs versus robot state transition at manufacturing cells

Manufacturing cell (C)	States	Expected material handling costs	
		(K=1)	(K=0)
C1	F	25.59	25.6
	U	16	13.71
C2	F	41.25	43.38
	U	26.23	29.88
C3	F	60	57.5
	U	60	47.57

During period II

The accumulated material handling costs under favourable robot performance (state F) when automation decision ($K=1$) is taken to integrate a robot in a particular manufacturing cell is calculated using *equation (11)* as follows

$$\begin{aligned}
\text{Manufacturing cell 1} \quad & \alpha_F^1(1) = 25.29 + (0.5714)(25.6) + (0.4286)(13.70) \\
& \alpha_F^1(1) = 46.40 \\
\text{Manufacturing cell 2} \quad & \alpha_F^1(2) = 41.25 + (0.6250)(43.38) + (0.3750)(29.88) \\
& \alpha_F^1(2) = 79.57 \\
\text{Manufacturing cell 3} \quad & \alpha_F^1(3) = 60.00 + (0.5000)(57.5) + (0.5000)(47.54) \\
& \alpha_F^1(3) = 112.52
\end{aligned}$$

When the robot performance in a manufacturing cell is unfavourable (state U) under automation decision ($K=1$), the accumulated material handling costs is given by,

$$\begin{aligned} \text{Manufacturing cell 1} \quad & \alpha_{U}^1(1) = 16.00 + (0.5789)(25.6) + (0.4211)(13.71) \\ & \alpha_{U}^1(1) = 36.59 \\ \text{Manufacturing cell 2} \quad & \alpha_{U}^1(2) = 26.23 + (0.6150)(43.38) + (0.3846)(29.88) \\ & \alpha_{U}^1(2) = 64.40 \\ \text{Manufacturing cell 3} \quad & \alpha_{U}^1(3) = 60.00 + (0.7000)(57.50) + (0.3000)(47.54) \\ & \alpha_{U}^1(3) = 114.51 \end{aligned}$$

When a decision for non-automation ($K=0$) is taken for a given manufacturing cell under favourable robot performance (state F), the following material handling costs are obtained

$$\begin{aligned} \text{Manufacturing cell 1} \quad & \alpha_{F}^0(1) = 25.60 + (0.8000)(25.60) + (0.2000)(13.71) \\ & \alpha_{F}^0(1) = 48.82 \\ \text{Manufacturing cell 2} \quad & \alpha_{F}^0(2) = 43.38 + (0.7092)(43.38) + (0.2308)(29.88) \\ & \alpha_{F}^0(2) = 81.04 \\ \text{Manufacturing cell 3} \quad & \alpha_{F}^0(3) = 57.5 + (0.5000)(57.50) + (0.5000)(47.54) \\ & \alpha_{F}^0(3) = 110.02 \end{aligned}$$

Similarly, when a non-automation decision ($K=0$) is taken under unfavourable robot performance (state U) in a manufacturing cell, the accumulated material handling costs are calculated as follows.

$$\begin{aligned} \text{Manufacturing cell 1} \quad & \alpha_{U}^0(1) = 13.71 + (0.5714)(25.60) + (0.4286)(13.71) \\ & \alpha_{U}^0(1) = 34.20 \\ \text{Manufacturing cell 2} \quad & \alpha_{U}^0(2) = 29.88 + (0.6250)(43.38) + (0.3750)(29.88) \\ & \alpha_{U}^0(2) = 68.20 \\ \text{Manufacturing cell 3} \quad & \alpha_{U}^0(3) = 47.54 + (0.6154)(57.5) + (0.3846)(47.54) \\ & \alpha_{U}^0(3) = 101.21 \end{aligned}$$

The accumulated material handling costs calculated when robot performance is favourable and unfavourable given automation decision $K \in \{0,1\}$ for period two is given in table 12.4.

Table 12.4: Accumulated material handling costs versus robot state transition at manufacturing cells

Manufacturing cell (C)	States F/U	Accumulated material handling costs	
		(K=1)	(K=0)
C1	F	46.4	48.82
	U	36.59	34.2
C2	F	79.57	81.04
	U	64.4	68.2
C3	F	112.52	110.02
	U	114.51	101.21

4.3.6 The Optimal Robot Automation Decision and Material Handling Cost

4.3.6.1 During Period I

The optimal automation decision and material handling costs for a robot in a given manufacturing cell under favourable and unfavourable robot performance were determined using *equations (12-15)*. The expected material handling costs versus robot state transition for each manufacturing cell under automation policy $K \in \{0,1\}$ is presented in figure 18.4.

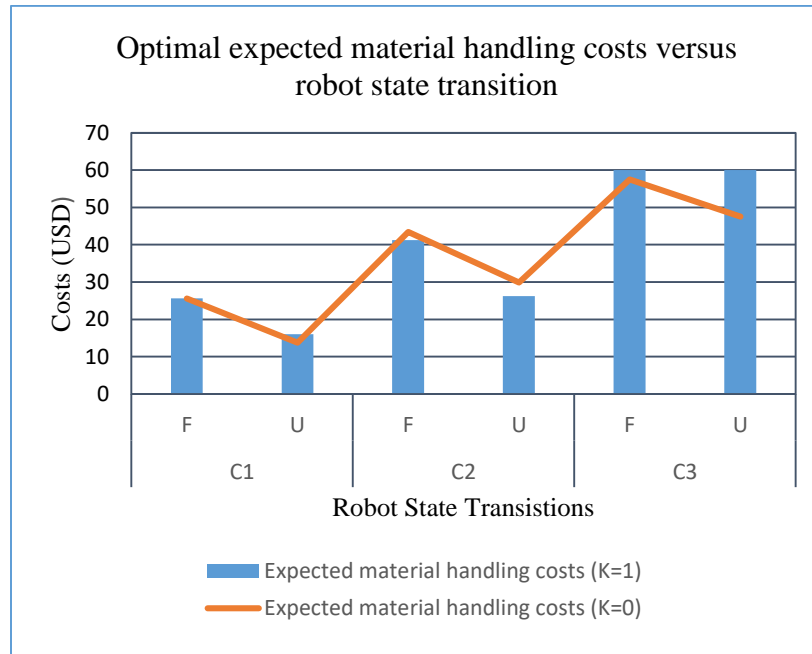


Figure 18.4: Optimal expected material handling costs during period I

For steel manufacturing cell 1, since $25.29 < 25.60$, it follows that $K = 1$ is an optimal automation decision with associated material handling costs of 25.29 USD when robot performance is favourable. Since $13.71 < 16.0$, it follows that $K = 0$ is an optimal automation decision with associated material handling costs of 13.71 USD under unfavourable robot performance. Automating manufacturing task MC_1-T_{14} only yields optimal automation decision and material handling costs when the robot performance is favorable.

For steel manufacturing cell 2, since $41.25 < 43.38$, it follows that $K = 1$ is an optimal automation decision with associated material handling costs of 41.25 USD when robot performance is favourable. Similarly, since $26.23 < 29.88$, it follows that $K = 1$ is an optimal automation decision with associated material handling costs of 26.23 USD under unfavourable robot performance. Integrating a robot for manufacturing task MC_2-T_{25} provides an optimal solution for automation decision and material handling costs when robot performance is both favorable and unfavorable.

For steel manufacturing cell 3, since $56.50 < 60.00$, it follows that $K = 0$ is an optimal automation decision for robot integration with associated material handling costs of 56.50 USD under favourable robot performance. Since $47.54 < 60.00$, it follows that $K = 0$ is an optimal automation decision with associated material handling costs of 47.54 USD when robot performance is unfavourable. The decision for non-automation for manufacturing tasks MC_3-T_{32} and MC_3-T_{33} in steel manufacturing cell 3 provides optimal material handling costs under favourable and unfavourable robot performance.

4.3.6.2 During Period II

The optimal robot automation decision and the accumulated material handling costs for each manufacturing cell determined over a while using *Equations (16-19)* provided the optimal robot integration decision. The accumulated material handling costs versus robot state transition for each manufacturing cell under automation policy $K \in \{0,1\}$ is presented in figure 19.4.

At manufacturing cell 1, since $46.40 < 48.82$, it follows that $K = 1$ is an optimal decision for automation with associated accumulated material handling costs of 46.40 USD when performance is favourable. Manufacturing tasks MC_1-T_{14} in cell 1 are suitable for robot integration under favorable robot performance with optimal material handling costs. Since $34.20 < 36.59$, it follows that $K = 0$ is an optimal decision for automation with associated accumulated material handling cost of 34.20 USD when performance is unfavourable. Although the integration of a robot in manufacturing cell 1 provides optimal material handling costs under favourable robot performance, it does not yield optimal solutions for manufacturing cell 1 under unfavourable robot performance. The use of robots for manufacturing tasks MC_1-T_{14} increases the material handling costs and overall steel manufacturing costs for manufacturing cell 1. It is therefore not economically viable to integrate a robot in manufacturing cell 1 under favorable robot performance only.

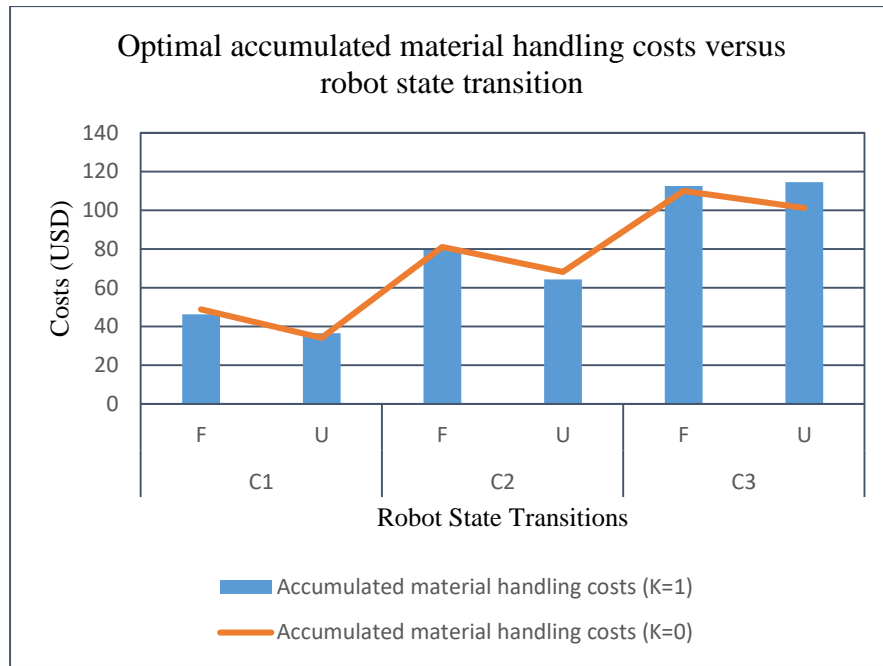


Figure 19.4: Optimal accumulated material handling costs during period II

At manufacturing cell 2, since $79.54 < 81.04$, it follows that $K = 1$ is an optimal decision for automation with associated accumulated material handling costs of 79.54 USD when robot performance is favourable. The integration of a robot in manufacturing cell 2 yields optimal material handling costs for manufacturing task MC_2-T_{25} under favorable robot performance. Since $64.40 < 68.20$, it follows that $K = 1$ is an optimal decision for automation with associated accumulated material handling costs of 64.40 USD when robot performance is unfavourable. Similarly, industrial robot' use in manufacturing cell 2 yields an optimal automation decision and material handling costs for manufacturing task MC_2-T_{25} under unfavorable robot performance. The integration of industrial robots in manufacturing cell 2 provides solutions for automation under favorable and unfavorable robot performance demonstrating robot potential through yielding optimal automation decision and material handling costs. Industrial robot' use in manufacturing cell 2 provides solutions for minimizing material handling costs, increasing productivity, replacing people working in an unsafe working environment, and reducing the overall steel manufacturing costs.

At manufacturing cell 3, since $110.02 < 112.52$, it follows that $K = 0$ is an optimal decision for automation with associated accumulated material handling costs of 110.02 USD when performance is favourable. The decision for non-automation of manufacturing tasks MC_3-T_{32} and MC_3-T_{33} in manufacturing cell 3 under favorable robot performance yields the optimal material handling costs. Since $101.21 < 114.51$, it follows that $K = 0$ is an optimal decision for

automation with associated accumulated material handling costs of 101.21 USD when performance is unfavourable. Similarly, the decision for non-automation under unfavourable robot performance yields optimal material handling costs for steel manufacturing cell 3. Robot integration in steel manufacturing cell 3 does not provide an optimal solution for automation and material handling for manufacturing tasks MC₃-T₃₂ and MC₃-T₃₃ when robot performance is favorable and unfavorable. Although most manufacturing tasks in cell 3 have high robot integration potential and robot relevance to manufacturing processes, the use of robots in these tasks increases the material handling costs and the overall steel manufacturing costs under favorable and unfavorable robot performance. Integrating industrial robots for steel manufacturing tasks MC₃-T₃₂ and MC₃-T₃₃ in steel manufacturing cell 3 is not suitable for cell performance.

4.4 Model Verification in a Simulated Environment

Steel manufacturing cell two presented optimal automation solutions for robot integration processes under favourable and unfavourable robot performance for both automation and non-automation decisions. Manufacturing tasks MC₂-T₂₅ with a high robot potential ($R_{pot} = 1$) and a high robot relevance to the manufacturing process ($R_{rel} = 1$) presented optimal automation decision and material handling costs satisfying the conditions $K \in \{0,1\}$ using the mathematical model. A simulation of the existing continuous galvanizing line in steel manufacturing cell two performed using Arena software validated the results from the mathematical model developed. The performance of the robot installed in a simulated factory environment for manufacturing tasks MC₂-T₂₅ yielded optimal material handling costs under favourable and unfavourable robot performance. A simulation of the existing steel manufacturing process routes for the continuous galvanizing line determined before the integration of robotic technologies aided in identifying bottlenecks with the manufacturing processes.

The robot performance within the manufacturing cell determined using equations (20) and (21) provided optimal robot utilization at any given time during normal operation. While considering the robot operation zones within the manufacturing cell, the average time traveled by the robot given by equation (22) minimized robot distances within the manufacturing cell. Under automation or non-automation decision, the optimal robot performance and material handling costs derived from equations (23-27) when robot performance is favourable or unfavourable provided optimal distances moved by the robot within the manufacturing cell.

4.4.1 Modeling and Simulation of the existing steel manufacturing processes

A simulation model layout of the existing steel manufacturing processes in cell two developed using arena simulation software presented the utilization of the existing steel manufacturing systems with their respective machine usages. The key parameters set and used in the model development included the steel manufacturing processing time, material handling equipment, and various steel processing machines located at each workstation. Steel manufacturing machines at each workstation scheduled for a Seize-Delay-Release action implied that a particular machine would receive a steel product (Seizing), processes the product (delay), and releases the product for further processing at the next stage. Each steel manufacturing process was set as high, medium or low depending on whether the manufacturing process is value-adding, non-value-adding, transfer, or waiting processes. The machine processing time for each steel product used in the model development was triangular delay type. Besides the average steel processing time, the minimum and maximum steel manufacturing time for a given process considered during the simulation runs optimized manufacturing tasks performed. A simulation of the existing continuous galvanizing line in cell two presented in *figure 20.4* evaluated the overall line performance before robot integration.

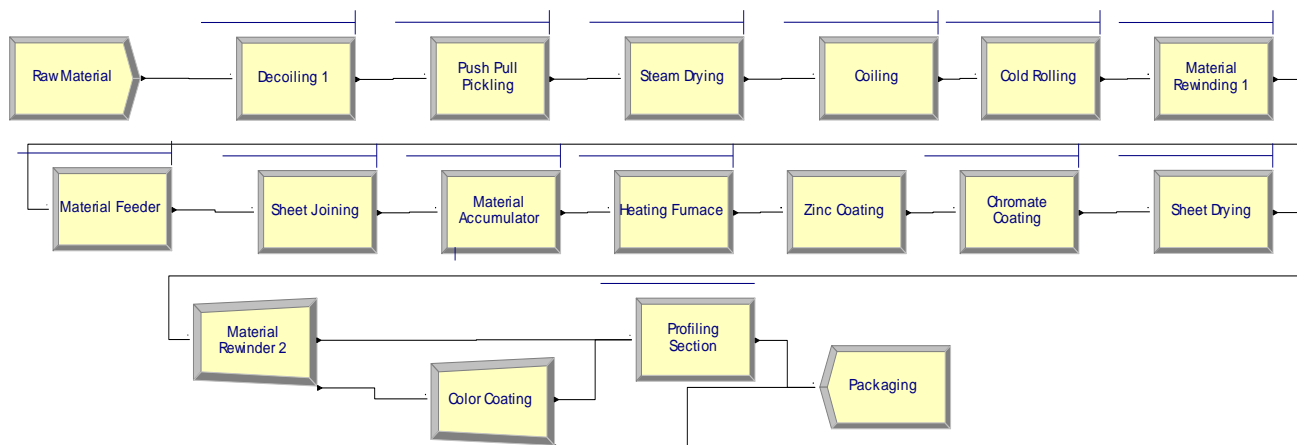


Figure 20.4: Arena model of the existing steel manufacturing processes

4.4.2 Optimization of the existing manufacturing cell two

During the model development and simulation, a detailed analysis of all steel manufacturing processes for the production of galvanized sheets yielded optimum results for the existing galvanizing processes in manufacturing cell two. The steel sheet galvanizing processes modeled using Arena software presented an overview of the overall manufacturing system after the simulation runs. Results from the simulation provided optimum scheduled machine utilization of

the existing manufacturing processes with its associated total number of steel products seized during the production runs as presented in *tables 13.4* and *table 14.4* respectively.

Table 13.4: Scheduled machine utilization of the existing line obtained from the software

Category Overview				
Steel Manufacturing Cell Two				
Replications:	30	Time Units:	Hours	
Resource				
Usage				
Scheduled Utilization	Average	Half Width	Minimum Average	Maximum Average
Accumulator	0.02305355	0.00	0.01503734	0.03110650
Chromate	0.02236451	0.00	0.01586186	0.03160778
Coiling Machine	0.02296089	0.00	0.01531357	0.03102216
Cold Rolling Machine	0.02329802	0.00	0.01559372	0.03058787
Decoiler	0.02325298	0.00	0.01581295	0.03080568
Dryers	0.02221988	0.00	0.01611838	0.03025248
Electric Furnaces	0.02306023	0.00	0.01561478	0.03136207
Feeder	0.02330713	0.00	0.01521673	0.03315207
Material Accumulation	0.00	0.00	0.00	0.00
Material Rewinder	0.02290422	0.00	0.01432428	0.03059029
MIG Sheet Welding Machine	0.02311911	0.00	0.01578387	0.03121057
Pickling Machine	0.02296232	0.00	0.01599039	0.03178651
Profiling Machine	0.04411372	0.00	0.03175395	0.05935535
Steam Dryer	0.02329053	0.00	0.01664535	0.03147709

4.4.2.1 Machine utilization of the existing line

Thirty replications carried out during a 24-hour simulation run presented the machine scheduled utilization values for each manufacturing process as shown in table 13.4. The data retrieved from the software represented graphically in figure 21.4 provides more clarity of the existing line utilization. Profiling machine has the highest utilization rate with material accumulation having the lowest scheduled utilization rates. The material accumulation rate is zero (0) implying that no buffer accumulated at the accumulator since most production machines operated normally with no bottlenecks detected during the production processes. The rest of the machines operated at an average utilization rate as steel products flow during manufacturing processes. The constant scheduled utilization rates for most machines implied a continuous and constant flow of steel products within the production line.

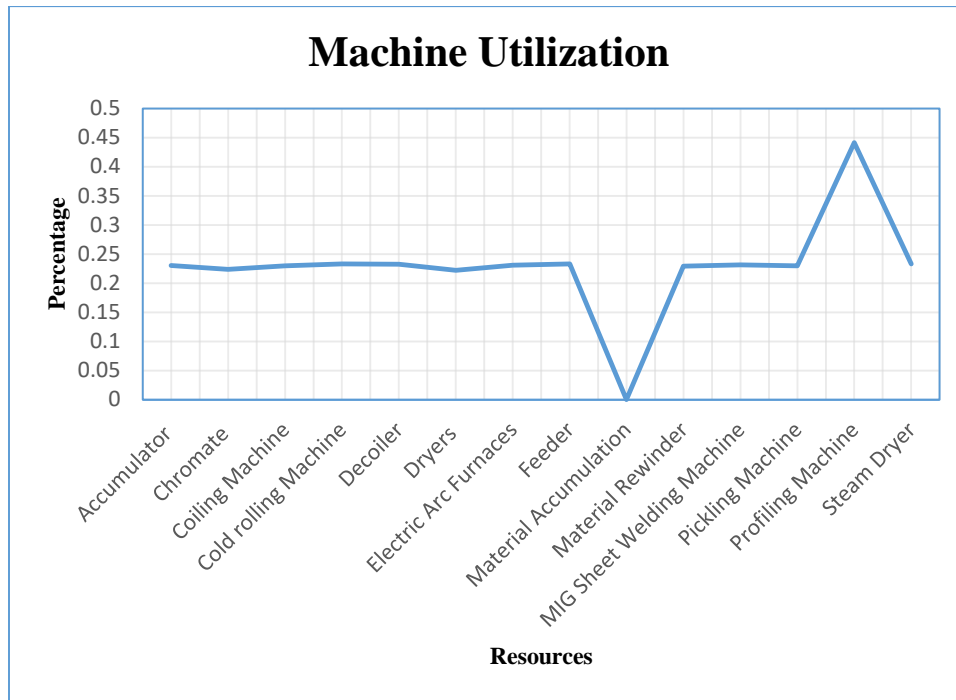


Figure 21.4: Machine utilization of the existing manufacturing cell

4.4.2.2 Machine usage rates of the existing line

Evidenced by the ‘As-Is-Analysis’ of the existing steel manufacturing system, the simulation results generated the total number of steel products seized by each steel manufacturing cell after thirty (30) replications. Table 14.4 shows the total number of steel products seized by each steel processing machine as generated from the software. The average machine usages for most steel manufacturing processes are the same indicating a reduction in the queue lengths at every workstation. At the material accumulation station, no product is kept waiting since machine utilization rates are the same with no bottleneck detected. Results from the simulation showed an increase in the queue length for the profiling machine and a drastic decrease in queue length for material accumulation. The general utilization and machine usages of the existing manufacturing cell is low as per the simulation data implying that there is a need to increase the machine utilization rate for steel manufacturing cell two to get optimum machine utilization with a maximum number of steel products produced. For the queue simulation results obtained, the waiting time reduced after increasing the machine speed and upgrading the existing technologies to increase the production rates.

Table 14.4: Total number of products seized by each machine as generated from the software

Category Overview				
Steel Manufacturing Cell Two				
Replications:	30	Time Units:	Hours	
Resource				
Usage				
Total Number Seized	Average	Half Width	Minimum Average	Maximum Average
Accumulator	33.2667	2.23	23.0000	45.0000
Chromate	32.0333	2.24	23.0000	45.0000
Coiling Machine	33.2667	2.23	23.0000	45.0000
Cold Rolling Machine	33.2667	2.23	23.0000	45.0000
Decoiler	33.3000	2.22	23.0000	45.0000
Dryers	32.0333	2.24	23.0000	45.0000
Electric Furnaces	33.2333	2.23	23.0000	45.0000
Feeder	33.2667	2.23	23.0000	45.0000
Material Accumulation	0.00	0.00	0.00	0.00
Material Rewinder	33.2667	2.23	23.0000	45.0000
MIG Sheet Welding Machine	33.2667	2.23	23.0000	45.0000
Pickling Machine	33.3000	2.22	23.0000	45.0000
Profiling Machine	63.9667	4.47	46.0000	90.0000
Steam Dryer	33.2667	2.23	23.0000	45.0000

Figure 22.4 shows individual machine usages for the existing simulated steel manufacturing cell as generated from Arena software.

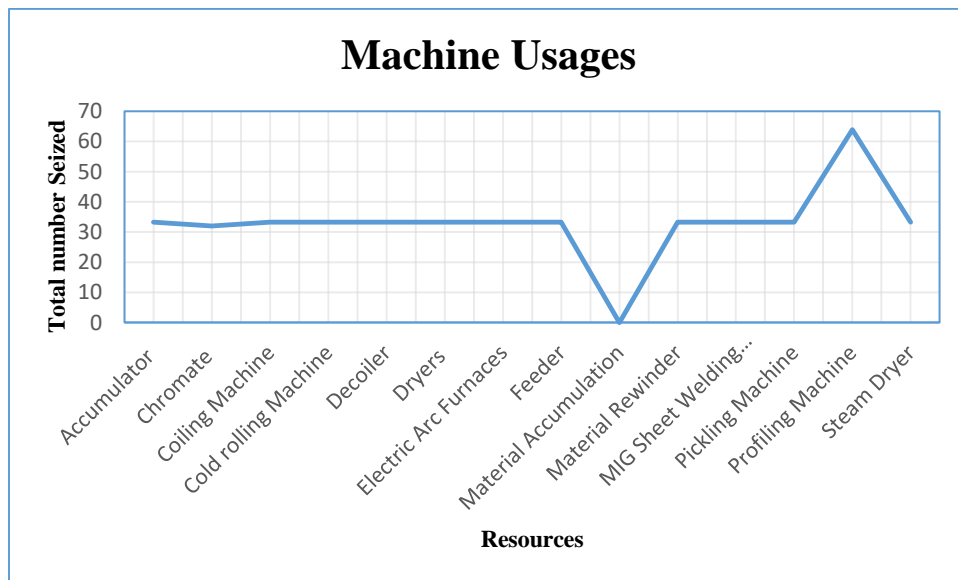


Figure 22.4: Individual machine usages of the existing steel manufacturing cell

4.4.3 Simulation model development of a designed continuous sheet galvanizing process

The existing steel manufacturing processes modeling in Arena simulation environment and robot integration for manufacturing tasks MC₂-T₂₅ during sheet galvanizing processes yielded optimum line utilization and machine usages. During the simulation processes, a transporter assigned using the ‘Assign’ module moves the raw materials to the raw material station and awaits further processing commands as in *figure 23.4*

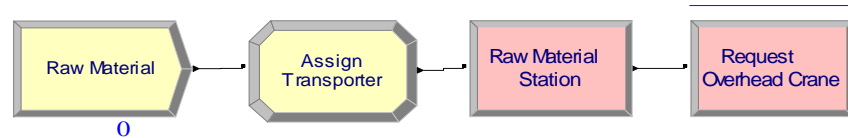


Figure 23.4: Designed continuous sheet galvanizing process sub-model I

When steel processing begins, the ‘Request Transporter’ Module requests an overhead crane to move the raw materials from the raw material station to ‘Enter Station 1’ on the production line. The raw material undergoes different manufacturing processing at ‘Enter Station 1’ beginning with sheet de-coiling up to sheet material rewinding as the final stage before a forklift moves to ‘Enter station 2’ for further processing as in *figure 24.4*.

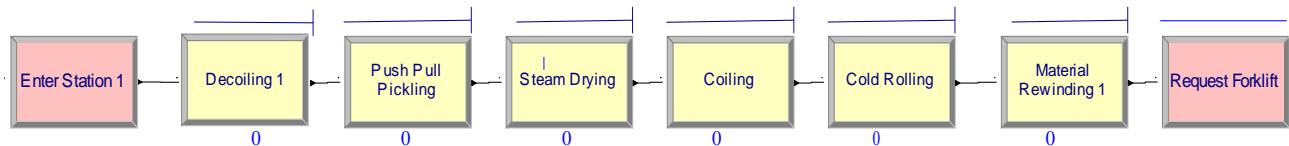


Figure 24.4: Designed continuous sheet galvanizing process sub-model II

A forklift request made using the ‘Request transporter’ module moves the sheet coil to enter station 2 of the next production stage. The material feeder receives the raw material and joins it for continuous production processes. The material buffer stored in the material accumulator offsets any material stock-outs during continuous galvanizing processes as shown in *figure 25.4*.

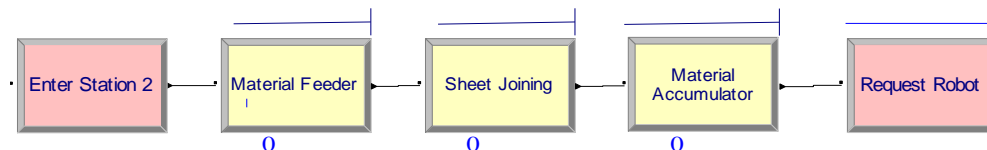


Figure 25.4: Designed continuous sheet galvanizing process sub-model III

A robot integration for manufacturing activities between sub-model III and sub-model IV focused on steel manufacturing processes at the heating furnaces and zinc pot during the simulation. A robot request made using the ‘Request Transporter’ module moves steel materials to ‘Enter station 3’ for continuous zinc galvanizing processes. Robot mapping, localization distances, and motion planning for coordination of robot activities during sheet galvanizing processes optimized robot

utilization and usage. The transport module section of Arena software helped to simulate the robot-working environment the model development for the galvanizing processes as indicated in figure 26.4.

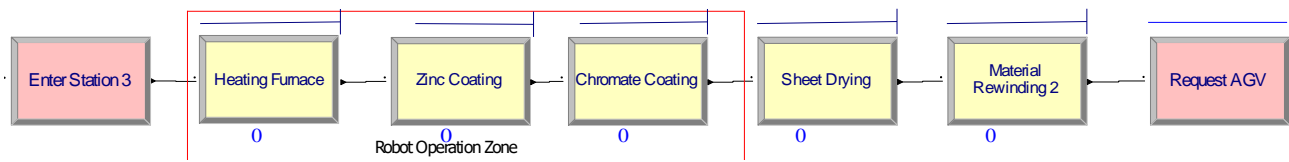


Figure 26.4: Designed continuous sheet galvanizing process sub-model IV

The final request made for the Automated Guided Vehicle moves the finished coiled galvanized sheets to the final station of the model development ‘Enter station 2’ for profiling and final packaging. Figure 27.4 represents the final stage of the simulation modeling for the continuous galvanizing line with the ‘Dispose Module’ of Arena simulation software represented by ‘Packaging.’

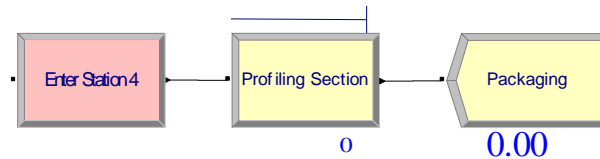


Figure 27.4: Designed continuous sheet galvanizing process sub-model V

4.4.4 Scheduled machine utilization of the designed line

The data collected during the research particularly the average time spent by steel products on specific manufacturing processes and the waiting times were the key parameters used to obtain an optimal robot automation decision during simulations. On the other hand, qualitative and quantitative analyses done through observations of the simulation runs provided data for optimizing manufacturing processes. From the quantitative results, a general increase in scheduled utilization of all steel manufacturing machines observed during simulation runs minimized bottlenecks within the processes. A simulation data comparison of the existing continuous galvanizing processes and the redesigned continuous galvanizing process model with the robot performing certain manufacturing tasks yielded improvement in all processes. From figure 29.4, electric furnaces, material re-winder, and sheet forming machines are the top three machines with the highest scheduled utilization rates. The scheduled utilization rates for other machines follow a constant trend due to the reduction in queue lengths at every steel manufacturing process. The material accumulator utilization was very low since all machines operated at their full capacities during the simulation process with no buffers detected on the production line.

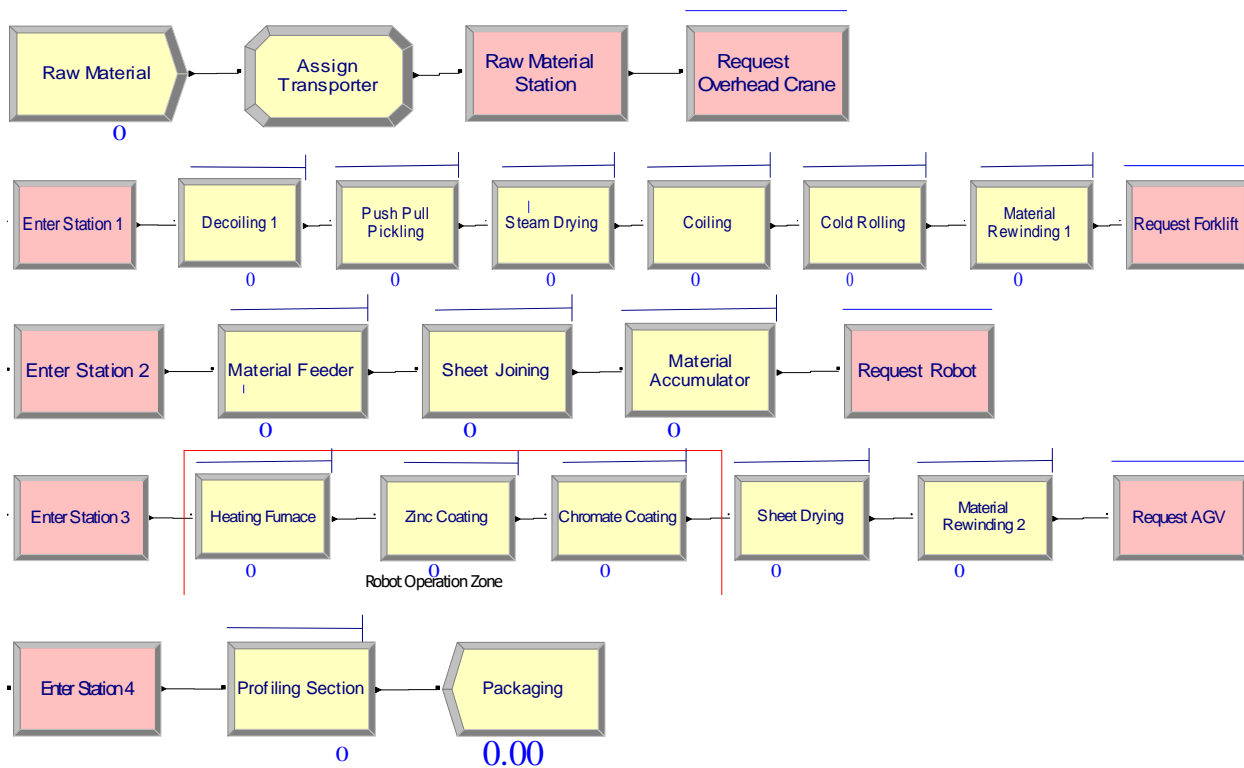


Figure 28.4: Simulation of the designed process layout in run mode extracted from Arena Software

A detailed data extracted from the simulation runs in figure 28.5 presented in table 15.4 and figure 29.4 is a representation of scheduled machine utilization of the redesigned galvanizing line.

Table 15.4: Scheduled machine utilization of the designed line obtained from the software

Category Overview				
Simulated Steel Manufacturing Cell Two				
Replications:	30	Time Units:	Hours	
Resource				
Usage				
Scheduled Utilization	Average	Half Width	Minimum Average	Maximum Average
Accumulator	0.1994	0.00	0.1756	0.2222
AGV	0.1997	0.00	0.1765	0.2223
Chromate Bath	0.1984	0.00	0.1736	0.2203
Coiling Machine	0.1996	0.00	0.1750	0.2217
Cold Rolling Machine	0.2001	0.00	0.1776	0.2240
Decoiler	0.2006	0.00	0.1751	0.2233
Electric Furnaces	0.3634	0.01	0.3141	0.4047
Heaters	0.1988	0.00	0.1763	0.2190
Material Accumulation	0.00	0.00	0.00	0.00
Material Rewinder	0.3981	0.01	0.3525	0.4384
MIG Sheet Welding Machine	0.1996	0.00	0.1770	0.2246
Pickling Machine	0.2011	0.00	0.1801	0.2252
Resource 1	0.2006	0.00	0.1751	0.2233
Sheet Forming Machine	0.3607	0.01	0.3165	0.3961
Steam Dryer	0.2009	0.00	0.1767	0.2230
Zinc Pot	0.1999	0.00	0.1785	0.2230

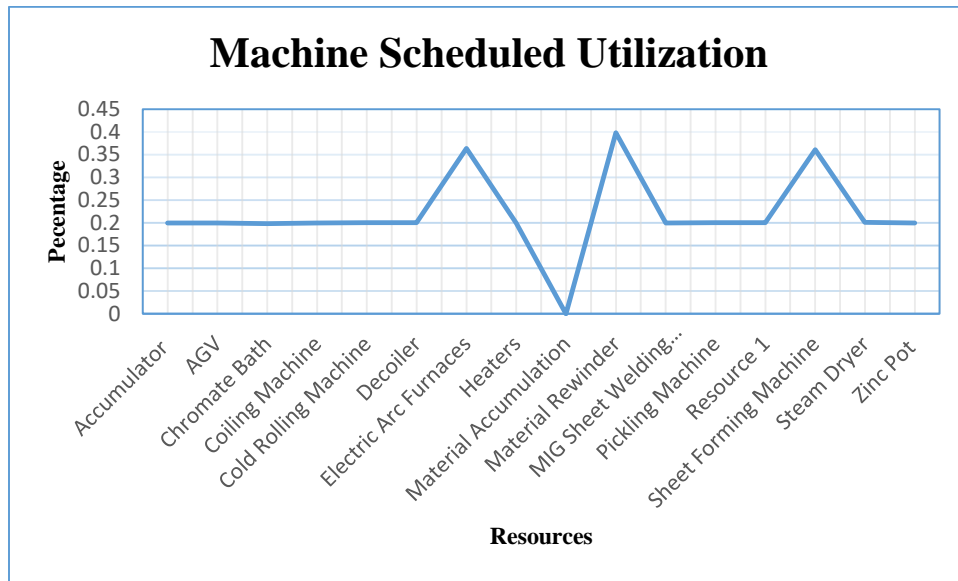


Figure 29.4: Machine utilization rates of the designed manufacturing cell

From figure 28.4, there is a general increase in the overall machine scheduled utilization rates of the designed galvanizing processes compared to the existing galvanizing process. The scheduled utilization rate for the accumulator increased from 0.0231 to 0.1994 indicating an increase in the utilization of about 88 percent. Similarly, the utilization rate for material re-winder increased from 0.0229 to 0.3981 representing a 94 percent increase in material re-winder utilization.

4.4.5 Machine usage rate for the redesigned galvanizing line

Reports from the simulation run generated machine usage rates with the total number of steel products seized during the production processes. After 30 replications run within 24 hours, there was a general increase in the number of steel products seized by each machine at every production stage. The total number of products seized by the accumulator increased from 33.2667 in the existing manufacturing cell simulation to 287.03 products seized in the designed simulated manufacturing cell as shown in table 16.4 and figure 30.4.

Table 16.4: Machine usage rates of the designed manufacturing cell generated from the software

Category Overview				
Simulated Steel Manufacturing Cell Two				
Replications:	30	Time Units:	Hours	
Resource				
Usage				
Total Number Seized	Average	Half Width	Minimum Average	Maximum Average
Accumulator	287.03	6.08	253.00	317.00
AGV	287.33	6.10	254.00	318.00
Chromate Bath	285.97	6.06	251.00	317.00
Coiling Machine	288.77	6.17	255.00	321.00
Cold Rolling Machine	288.53	6.15	255.00	321.00
Decoiler	289.70	6.22	256.00	323.00
Electric Furnaces	286.53	6.06	252.00	317.00
Heaters	285.87	6.10	250.00	317.00
Material Accumulation	0.00	0.00	0.00	0.00
Material Rewinder	573.77	12.21	505.00	635.00
MIG Sheet Welding Machine	287.20	6.06	254.00	317.00
Pickling Machine	289.37	6.18	256.00	322.00
Resource 1	289.70	6.22	256.00	323.00
Sheet Forming Machine	285.00	6.00	249.00	316.00
Steam Dryer	289.03	6.11	256.00	321.00
Zinc Pot	286.33	6.10	251.00	317.00

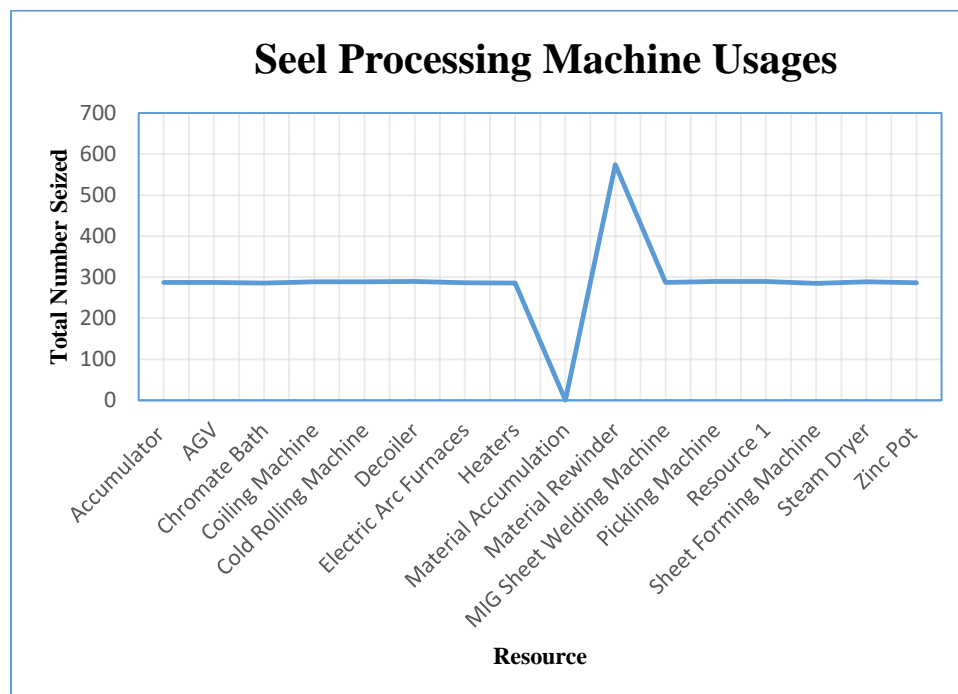


Figure 30.4: Machine usage rate of the designed manufacturing cell

The high number of products seized by the material re-winder indicates an increase in the total number of queues the absence of products seized at the material accumulation station during

normal operation processes. The graph in *figure 30.4* indicates that all resources are operating at their maximum utilization rates with a minimal number of buffers generated by each production process.

4.4.6 Modelling and simulation of transporters

The ‘Request transporter’ module in Arena simulation software aided in modeling and simulation of transporters during material handling operations. Robot integration in a simulation environment as one of the transporters for material handling operations that pose greater risks to workers minimized material handling costs during galvanizing processes. Besides the robot, other transporters used during the simulation include Automated Guided Vehicle, Forklifts, and overhead cranes. The transporter usage report with its associated utilization rates generated by the software during the simulation runs optimized robot performance within the manufacturing cell as presented in table 17.4. From figure 31.4, Automated Guided Vehicles and Forklifts are the most utilized transporters in steel manufacturing cell two followed by overhead cranes and robots being the least utilized transporter. The low utilization rate of the robot is due to restricted robot operation zone for only manufacturing tasks MC₂-T₂₅ while other transporters’ operation zones are not limited to one task.

Table 17.4: Transporter utilization rate generated by the software during simulation runs

Category Overview						
Simulated Steel Manufacturing Cell Two						
Replications:	30	Time Units:	Hours			
Transporter						
Usage						
Number Busy	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Automated Guided Vehicle	0.3955	0.01	0.3452	0.4388	0.00	1.0000
Forklift	0.3987	0.01	0.3533	0.4412	0.00	1.0000
Overhead Crane	0.2009	0.00	0.1776	0.2240	0.00	1.0000
Robot	0.1987	0.00	0.1749	0.2198	0.00	1.0000
Number Scheduled	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Automated Guided Vehicle	10.0000	0.00	10.0000	10.0000	10.0000	10.0000
Forklift	10.0000	0.00	10.0000	10.0000	10.0000	10.0000
Overhead Crane	10.0000	0.00	10.0000	10.0000	10.0000	10.0000
Robot	10.0000	0.00	10.0000	10.0000	10.0000	10.0000
Utilization	Average	Half Width	Minimum Average	Maximum Average	Minimum Value	Maximum Value
Automated Guided Vehicle	0.03954631	0.00	0.03451995	0.04387966	0.00	0.1000
Forklift	0.03987420	0.00	0.03532618	0.04411781	0.00	0.1000
Overhead Crane	0.02009029	0.00	0.01775515	0.02239583	0.00	0.1000
Robot	0.01987100	0.00	0.01749434	0.02197917	0.00	0.1000

The increase in number scheduled for each transporter improves the utilization and reduces the idle time during normal operation. As observed from the usage report in table 17.4, most transporters low utilization rates during normal operation.

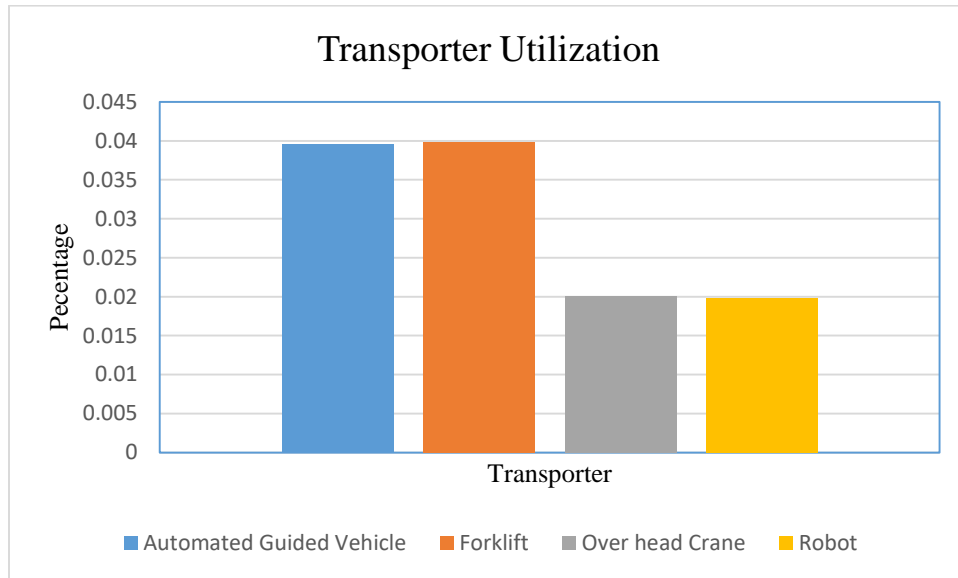


Figure 31.4: Transporter scheduled utilization rates

4.4.7 Design considerations for safe human-robot collaboration

Although the technical challenges of integrating robots within the steel manufacturing processes have been addressed, steel workers' safety is a primary factor for achieving robot acceptance in a steel plant. There is need to separate steel workers from the robot's working environment for the operators' safety to be ensured. Robots integrated in a steel plant should be embedded with crash safety, active safety, and adaptive safety mechanisms for safe human robot collaborations. Crash safety mechanisms ensures that only safe/controlled collisions may only take place among robots, humans and obstacles. The extent of power/force exerted by the robot on humans is the main objective. The collision detection functions allow the robot to avoid potential collision by slowing its speed or pausing, reversing course along its paths and or executing another safe path. Active safety mechanisms allow for timely detection of imminent collision between steelworkers and the robot while stopping robot's operations in a controlled way. Adaptive safety mechanisms are for intervening in the operations of the robot hardware systems while employing corrective actions that lead to collision avoidance without affecting robot operations. In a steel manufacturing cell where collision between the steel workers and the robot cannot be avoided, precautions should be taken to ensure no sharp, pointed, cutting edges or rough surfaces on the robot are found. The workspace where a steel worker may collide with the robot needs to be designed to provide steel workers with sufficient space to move thus avoiding clamping situations.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents conclusions derived from the results discussed and provides recommendations to the industry and areas for further research

5.1 Conclusions

Robots integration in steel manufacturing plants A and B presented solutions for material handling in both plants in reducing labour costs, material handling damage, improving the productivity of automated steel manufacturing systems, and overall safety of the steelworkers. A Markov decision model and a Genetic Algorithm for the selection criteria of robotic automation in two steel manufacturing plants presented in this study yielded optimal robot integration for manufacturing cells one, two, and three. The model determined an optimal decision for automation and material handling costs under stochastic robot performance. The decision of whether or not to automate using a robot at a specific manufacturing cell made using Genetic Algorithm and dynamic programming over a finite period planning horizon provided promising results for manufacturing cells one, two, and three. Results from the study indicated optimal decisions for automation and material handling costs for the given problem at the respective manufacturing cells. Computational efforts using the Markov decision process approach provided promising results for material handling cost minimization for the two steel manufacturing plants.

During the simulation of the existing line, bottlenecks detected at the Zinc pot during manual handling of hot zinc ingots for sheet galvanizing processes provided data used during line optimization. The replacement of humans with robots at the zinc pot reduced the average waiting time increased the line utilization rate that led to an increase in the productivity of steel manufacturing cell two. The bottleneck areas of the existing steel manufacturing cell paved the way to rectify the simulated model to increase the productivity of the cell through the application of simulations. There was a remarkable decrease in steel processing time and transportation time within the re-designed steel manufacturing cell. The overall steel processing time correspondingly decreased by about 63% compared to the existing manufacturing cell. Bottlenecks observed during the simulation study of the existing and redesigned manufacturing cell were identical thereby validating the simulation model

5.2 Recommendation to Steel Manufacturing Industries

Results from the study provided promising results for robot integration in both steel manufacturing industries considered. Robot integration for manufacturing tasks MC₂-T₂₅ (Galvanizing processes) for wire and sheets yielded optimum material handling costs for the robot with improved line utilization, productivity and quality of the galvanized steel products. Robot integration in both steel plants for the galvanizing processes presented solutions for reducing labour costs, material handling damage, improving the productivity of automated steel manufacturing systems, and overall safety of the steelworkers. the decision to automate the manufacturing processes in both steel plants should be made for steel galvanizing processes for steel galvanizing tasks at the zinc pot.

Although manufacturing tasks MC₃-T₃₂ (Hot rolling processes) for both steel plants presented high robot potential and relevance, the use of robots in the hot rolling processes especially during scrap melting and casting is not recommended. Robot integration in the hot rolling processes did not yield optimum material handling costs when the robot performance is favourable and unfavourable thereby leading to an increase in material handling costs, production costs with a reduction in the line utilization rates. It is not recommended to integrate industrial robots for other steel manufacturing processes for both plants due to high costs of robotization of these processes, high costs associated with robot maintenance, increase in the overall costs of production and increase in costs of material handling.

5.3 Recommendations for Further Study

Results from the mathematical model provided promising results for robot integration using Markov decision analysis. However, it is desirable to extend the research to analyse the impact on the non-stationary performance of a robot on the decisions taken. There is a need to expand the model to consider automation options for minimum material handling costs in the context of Continuous-Time Markov Chains (CTMC).

Despite all the simulations done on the existing and redesigned steel manufacturing cell, the assumptions made during the simulation study did not consider worker fatigue and machine breakdowns. Besides, the study did not consider practical applications of the proposed robotic integration model. The justification of the proposed model by considering worker fatigue and machine breakdowns is an area of further research in this field of study.

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APPENDIXES

APPENDIX 1: RESEARCH DATA COLLECTION GUIDELINES

KYAMBOGO UNIVERSITY GRADUATE SCHOOL
MSC IN ADVANCED MANUFACTURING SYSTEMS ENGINEERING
RESEARCH DATA COLLECTION GUIDELINES

This research data collection guideline was in support of fulfilling the Master’s Research Topic “**Development of A Mathematical Model for Integration of Robots in A Steel Manufacturing Plant.**” The main objective of the research was to investigate the potential for integration of industrial robotic technologies and provide optimal robot automation solutions for steel manufacturing industries. The data collection processes were divided into three main areas, that is, *Plant Layout Designs; Material Handling Systems, and candidate tasks for the robotic integration process.* The researcher utilized the information provided in the data collection guidelines for the development of a mathematical Robotic Integration Model and a simulated factory environment for steel manufacturing industries in Uganda. The research converted the existing traditional steel manufacturing production processes to a flexible manufacturing system aimed at utilizing machines to their extents to obtain maximum output from the system in a safe working environment. All the data collected were treated with high confidentiality and only used for academic purposes.

*For this research, the term **industrial robot** is defined as a mechatronic device designed to automatically manipulate or transport parts or tools*

Part (i) Plant Layout Designs

The aim of studying the plant layout design was to determine the necessary adjustments required on the existing layouts for industrial robot mapping, localization, planning, and coordination of robot activities within each manufacturing cell. During the study of the existing plant layout designs, the researcher was guided by the following research question “*How can industrial robotics technologies be integrated into the current plant layout designs?*”

To answer the above question, the researcher sought answers to the following during the study.

- i.* What are the existing machine layouts in each steel manufacturing cell?
- ii.* What are the current steel manufacturing process routes in each steel manufacturing cell?

- iii. How is human labour distributed in the current steel manufacturing process layout?
- iv. How can Human-Robot interaction be accommodated in the current steel manufacturing process routes?

Part (ii) Material Handling Systems

In an attempt to study the material handling systems in steel manufacturing industries, the researcher determined how robotics automation technologies could work alongside the different material handling systems in place by answering the following research question “*How can industrial robotics technologies be integrated with the current material handling systems?*”

The researcher sought answers to the following questions during the study

- i. What material handling equipment/systems are being used in steel manufacturing industries?
- ii. How are material handling systems incorporated in the current steel manufacturing process layouts?
- iii. What material handling systems can be integrated with industrial robotic technologies?
- iv. What are the material handling costs of the current material handling systems in each steel manufacturing cell?

Part (iii) Candidate tasks for the robotic integration process

By determining candidate tasks suitable for robot integration, the researcher sought answers to the following research question. “*What manufacturing tasks require robot automation and non-automation?*” During the study, the researcher determined potential candidate tasks that require robot integration. Manufacturing tasks that were Time-consuming and time-critical, Repetitive, Prone to mistakes with critical control limits, hazardous and processes with manual material handling were considered during the study.

To provide answers to the research question above, the study was guided by the following questions.

- i. What steel manufacturing processes are most suitable for the integration of industrial robotic technologies?
- ii. What candidate tasks are eligible for robot integration processes?
- iii. What is the robot integration potential for eligible candidate tasks?
- iv. How will robotic technologies work with the current steel manufacturing machines?

APPENDIX 2: RESEARCH ACCEPTANCE LETTER 1



RRM

MR. ONGOM CHRISTOPHER ADOKO,
Department of Mechanical & Production Engineering,
Kyambogo University,
Kampala, Uganda

Saturday 12th September, 2020

Dear Christopher,

RE: PERMISSION TO CONDUCT RESEARCH AT RRM PLANT

The above matter refers.

Ms. Roofings Rolling Mills Limited is in receipt of a communication from your end, requesting for an opportunity to conduct research at our plant i.e. *"Potential for Integration of Industrial Robots in Steel Manufacturing Industries"*. A copy of the recommendation letter from Kyambogo University dated Friday 21st August, 2020 is enclosed for your kind perusal and consideration.

To that end, we are pleased to inform you that RRM Management agrees to your request and has accordingly granted you permission to conduct the above mentioned research, in a period of **Two (02) Months** effective **Thursday 1st October, 2020** at no cost implication to Ms. Roofings Rolling Mills Limited.

While conducting your research, you are expected to adhere to set Policies & Procedures in addition to handling all matters with utmost confidentiality. As a researcher you shall not disclose or publish any trade secrets or confidential information pertaining to the business of the company to any person or authority during performance of your research or thereafter. The company reserves the right to take appropriate legal action in the event of breach of this undertaking.

For Ms. Roofings Rolling Mills Limited,


SHEIKH ARIF
DIRECTOR – TECHNICAL



CC: HUMAN RESOURCE MANAGER
CC: RRM PLANT MANAGERS
CC: HOD, MECHANICAL & PRODUCTION ENGINEERING, KYAMBOGO UNIVERSITY

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APPENDIX 3: RESEARCH ACCEPTANCE LETTER 2

Okayed by Mr. Patel
on 1/9/2020

KYAMBOGO UNIVERSITY



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Department of Mechanical and Production Engineering

21st August 2020

The
Plant Manager
Steel and Tube industries limited
Namanve Industrial Park

Dear Sir / Madam

RE: GRADUATE STUDENT RESEARCH PROJECT

I am obliged to write to you at this moment regarding the above referenced caption. The Department of Mechanical & Production Engineering of Kyambogo University runs a Master of Science Degree Programme in Advanced Manufacturing Systems Engineering. One of the requirements for an Award of the Degree is for the student to conduct an Industrial Project which has a contribution to knowledge and Industry / the Company.

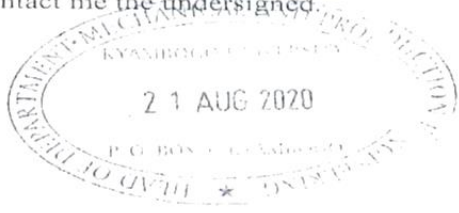
Sir / Madam, the bearer of this note (**Mr. Ongom Christopher Adoko**) is in the final year pursuing the MSc in AMSE here. His topic for Research is **Potential for Integration of Industrial Robots in Steel Manufacturing Industries**. Thus, your organization was identified as suitable for his research. We therefore, kindly request you to assist him and grant him permission to do his research with you.

On behalf of the Department of Mechanical and Graduate School of Kyambogo University, I wish to inform you that this research is purely for academic purposes and the student is under strict rules to keep all information about your Company that he might come across confidential. In case you have any query, feel free to contact me the undersigned.

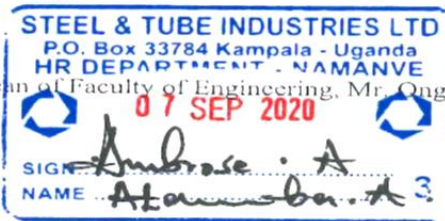
Thank you

Yours Sincerely

Titus Watmon
Dr. Titus Bitek Watmon
Head of Department
Mechanical and Production Engineering
Email: twatmon@kyu.ac.ug
+256 784 111 862



Cc: Dean Graduate School, Dean of Faculty of Engineering, Mr. Ongom Christopher Adoko, Project Coordinator, File



OK
He can go ahead
and conduct
Research
Ambrose . A
HR. Muger

APPENDIX 4: NON-DISCLOSURE AGREEMENT LETTER



NON-DISCLOSURE AGREEMENT

I, DNGOM CHRISTOPHER ADOKO, a research student from Kyambogo University has been allowed to conduct academic research by Steel & Tube Industries Limited (hereinafter referred to as "the Company") **I HEREBY UNDERTAKE** that, either during or after my research at the Company,

In no circumstances will I,

- a) Disclose to any person whatsoever any of the secrets, concerns, affairs of the company.
- b) Communicate with any third party regarding affairs of the company.
- c) Make any copy of the whole or any part of a document belonging to the company except where expressly authorized to do so.

I understand and agree that a breach of this Non-Disclosure Agreement amounts to indiscipline actions and the Company has the right to put a case against me.

Signature: *[Handwritten Signature]*

Date: 11/09/2020

Signed & Stamped (For STIL) *Ambrose Atambese*

