ANALYSIS OF DEMONSTRATIVE-KINESTHETIC TEACHING ON ROBOT MANIPULATOR FOR EFFICIENT INDUSTRIAL MATERIAL HANDLING APPLICATIONS

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A Thesis Submitted to the Department of Mechanical and Industrial Engineering in Partial Fulfilment of the Requirements for the Award of the Degree of Master of Science in Industrial Engineering and Management of Masinde Muliro University of Science and Technology

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DECLARATION

I hereby declare that this thesis is my original work prepared with no other than the indicated sources and has not been presented for a degree or any other award in any university or institution.

Signed……………………………………Date……………………………

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CERTIFICATION

We, the undersigned, certify that we have read and hereby recommend for acceptance of Masinde Muliro University of Science and Technology a thesis entitled **"Analysis of Demonstrative-Kinesthetic Teaching on Robot Manipulator for Efficient Industrial Material Handling Applications."**

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DEDICATION

This work is dedicated to Mr. Pilot Khaemba, Mrs. Praxidice Kimoi, Neville, Cyril, and John for inspiring and blessing all the others around them.

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ABSTRACT

Robots significantly improve productivity and production efficiency due to process optimisation and low production costs. Job enrichment and fulfilment can be achieved through improved workflows and role distribution. This will also lead to an improved capacity to handle complex assignments, perform tedious and sophisticated tasks quickly, enhance workers' safety, and improve the customization of goods and services. The adoption of robots in Kenyan small and medium-sized enterprises (SMEs) manufacturing industries has been gradual and faces many challenges. Key among the challenges is the few skilled labourers with robot programming capabilities for the varying manufacturing environments. This has led to the need for more competitiveness in the manufacturing sector with other countries, especially on the global stage. This can be immensely magnified in flexible manufacturing systems, especially when switching product types to robotised systems requires higher costs and time. The inferior skill set of people interacting with the robots warrants designing and generating user-friendly programming approaches using kinesthetic teaching and augmented and virtual reality. The Kenyan government's development agenda aims to achieve the 2030 goals using emerging innovative technologies, including robotics, machine learning, and artificial intelligence (AI). This research purposed to analyse the demonstrative-kinesthetic teaching (DKT) approach to robotic manipulators for efficient material handling applications. The robotic arm was programmed using structured texts and DKT to determine coordinate configurations, the desired position's accuracy, and the DKT's efficiency. A control platform was created using Visual Studio to allow the arm to be programmed demonstratively using the lock arm button. This allowed the arm to record the demonstrations while the user did the programming. Palletizing and contour path welding experiments were conducted to validate the study and collect the requisite data. Structured texts were used as the control for the experiment. The results found that the mean inverse kinematics were the same for both methods at the α=0.05 significance level, F=0.03, $P=0.86$, *and* $F_{critical}=5.98$. Joint 2 had a low percentage error at 2.12 % and a high for joint 4 at 5.24%, majorly due to user level of accuracy. The DKT had an 80% and 66.67% efficiency on experimental time for palletising and contour path welding, respectively, compared to structured text. The conclusion was that DKT provided a means of finding the joint configurations in concurrence with analytical solutions. The robotic manipulator was able to trace paths and desired positions accurately. DKT provided more accessible programming for non-skilled floor operators than structured texts. Some recommendations were the inclusion of wearable devices in the DKT approach and shifting the control platform created to universal set-up platforms.

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LIST OF ABBREVIATIONS AND ACRONYMS

3D	Three Dimension
4IR	4^{th} Industrial Revolution
AI	Artificial Intelligence
ANOVA	Analysis of Variances
AR	Augmented Reality
Cobot(s)	Collaborative Robot(s)
Cos	Cosine
CPSs	Cyber-Physical Systems
DH	Denavit-Hartenberg
DKT	Demonstrative-Kinesthetic Teaching
DOF	Degree(s) of Freedom
FK	Forward Kinematics
H_n	Hypothesis
HRC	Human-Robot Collaboration
HSMM	Hidden Semi-Markov Model
HT	Homogenous Transformation
IK	Inverse Kinematics
IoT	Internet of Things
Kg	Kilogram
kNN	K-nearest Neighbour Network
Ksh	Kenyan Shilling
KT	Kinesthetic Teaching
LAN	Local Area Network
LfD	Learning from Demonstration
ML	Machine Learning

mm	Millimetre(s)
OLP	Off-line Programming
PbD	Programming by Demonstration
pHRI	physical Human-Robot Interaction
PiH	Peg in Hole
RL	Reinforced Learning
SCARA	Selective Compliance Assembly Robotic Arm
Sin	Sine
SMEs	Small and Medium Enterprises
Tan	Tangent
Tan^{-1}	arc Tangent
TKT	Tele-Kinesthetic Teaching
TLP	Texts-based Language Programming
USA	United States of America
USB	Universal Serial Bus cable

LIST OF SYMBOLS

θ	theta
α	alpha
δ	delta

CHAPTER ONE

INTRODUCTION

1. Introduction

The chapter starts with a brief look at background information, then a closer look at the problem statement and the study objectives. The justification follows the scope, and the chapter concludes with the conceptual framework.

1.1 Background Information

Man has always sought to find beings capable of carrying out repetitive and cumbersome tasks, which led to the robot's development. An industrial robot is a programmable automatic system, mechanically controlled, with multiple degrees of freedom, which can be stationary or mobile (Bartoš *et al.*, 2021). A robotic manipulator is an electro-mechanical device consisting of joints and links that are driven by motors or other actuators (Jahnavi and Sivraj, 2017). The automatic control and mechanical structure allow it to perform repetitive tasks accurately. The accuracy is found by the closeness of the manipulator in reaching the target area in the workspace or how accurately a robotic arm positions an end effector at the target point; thus workspace limits (Abdelaal, 2019).

The standard available basic robot configurations based on link arrangement and joint movement are cylindrical, cartesian, spherical, selective compliance assembly robotic arm (SCARA), and articulated. The articulated robotic manipulator is the most preferred for the study task of palletising as it mimics the human hand (Jahnavi and Sivraj, 2017); hence, it is called an anthropomorphic manipulator. The workspace of the articulated configuration is spherical. The manipulator should be considered more than just a set of mechanical components (Abdelaal, 2019). It comprises software programming, sensors and actuators, a computer interface, a source of power and a gripper (Christian Kohrt *et al.*, 2008; C Kohrt *et al.*, 2013). The efficiency of the manipulator can be determined by taking note of the reaction time, time taken to complete a task, and margin of error (C Kohrt *et al.*, 2013).

The advancement of robotics faces challenges such as the absence of universal platforms and standards thereby needed by enthusiasts to build from base (Gates, 2007), and the training and experience required for programming non-trivial and robust applications are significant (Rossano *et al.*, 2013). As a result of the exposure of robots to non-experts, there is a need for more accessible, newer, and intuitive ways of robot programming and management. Conventional or manual programming methods, such as text-based, graphical, and teach-pendant programming (Amar *et al.*, 2020), are tedious, non-intuitive, and laborious (Zhou *et al.*, 2020). Automatic programming means are Learning from Demonstration (LfD), reinforced learning (RL), augmented reality (AR), machine learning (ML) technologies, speech-recognition-based, one-shot learning (Mosavi and Varkonyi, 2017; Orendt *et al.*, 2016), and kinesthetic teaching (KT).

Kinesthetic teaching or guidance is a programming approach where the programmer shows new behaviours via learner robot body manipulation as it records through its sensors (proprioception) (Calinon, 2018; Villani *et al.*, 2018; Zieliński, 1995). The techniques employed are physical manipulation (DKT) and robot movement control through interfaces (tele-kinesthetic teaching (TKT). TKT technique offers an opportunity for remote programming. Still, it faces the limitations of additional lengthy user training on the interfaces, availability of the chosen input hardware, and additional effort required to develop the selected interface. The DKT technique was adopted because it naturally allows for programming; the onboard sensors record the state of the robot during interaction (Ravichandar *et al.*, 2020), provides an intuitive approach with minimal training requirement (Eiband *et al.*, 2023; Tykal *et al.*, 2016) as it does not burden the programmer with the requirement of knowledge of programming languages such as Python (Heimann and Guhl, 2020). It provides an avenue for exploring the physical human-robot interaction (pHRI) (Landi *et al.*, 2017).

The continuous innovations and technological advancements, as explained by Clabaugh and Matarić (2018), have contributed immensely to cyber-physical systems (CPSs) growth (Castillo *et al.*, 2021). Lee and Seshia (2016) define CPSs as an incipient method of networking, computing, and physical processes, with cyber and physical element interaction (Hentout *et al.*, 2019) in time and space. Robots are in the very presence of the human environment, as noted by Gates (2007); due to increasing consumer affordability, technology is growing more intelligent and powerful. Today, robots are widely used in controlled industrial environments (manufacturing, service, processing) (Karabegović *et al.*, 2011) and uncontrolled settings such as healthcare, delivery services workplaces, entertainment purposes, and exploring new resources. Imperviousness to a hostile environment, reliability, predictability (Adriaensen *et al.*, 2022), and ever-availability are some of the machine qualities that favour using robots in industries.

A significant development in robot hardware and software has enabled the development of industrial robots and collaborative robots (Cobots) in the application in the running of smart factory activities such as object grabbing, assembling, packaging, palletising, welding, and material handling (Abdelaal, 2019; Karabegović *et al.*, 2011; Vojić, 2020). Technologies' complex and dynamic nature (Van Dijk and Hacker, 2003) means adapting to changes can be a hurdle, mainly when relying on human labour. Robots are flexible to future changes and are a go-to labour solution. The constant interaction of robots with humans in ordinary workspaces helps realise the fourth industrial revolution (4IR) (Calitz *et al.*, 2017; Naudé, 2017). 4IR refers to CPS technical integration (Hentout *et al.*, 2016), usage of internet-of-things (IoTs) in industrial processes and organisation of work (Wisskirchen *et al.*, 2017).

The new trend of customisation along 4IR in SMEs' manufacturing industries poses a challenge, and the use of robotised systems is any enterprise's goal with aims such as improving productivity (Kwanya, 2023) due to collaboration between humans and robots (HRC) (Gobinath, 2021), optimised processes leading to production efficiencies (Castillo *et al.*, 2021), low costs of production (Castillo *et al.*, 2021; Eke *et al.*, 2023; Gisginis, 2021; Kadir *et al.*, 2018), high-quality product (Galin and Mamchenko, 2021), enriching and fulfilling jobs via role distribution and improvement in workflows (Kadir *et al.*, 2018; Margherita and Braccini, 2021), improved handling of even multifaceted projects (Simões *et al.*, 2019; Zhou *et al.*, 2020), floor operator safety enhancement (Fast-Berglund *et al.*, 2016; Zhou *et al.*, 2020), fast execution of dreary activities (Gisginis, 2021), custom consumables (Kopp *et al.*, 2021), and avenue for clean production technologies. Complex manufacturing processes are becoming an area of great interest, and the use of robotised systems gives an advantage in terms of a competitive edge (Arents and Greitans, 2022).

1.2 Statement of Problem

The espousal of robots in Kenyan SMEs' manufacturing industries has been slowly growing (Magachi *et al.*, 2017) and still faces many challenges (Mvurya, 2020). Among the challenges are the few skilled labourers with programming capabilities (Nganga, 2020) and the robots that can perform in fluctuating work environmental conditions. The result is inadequate competitiveness in the manufacturing sector with other countries, thus rendering the country behind in global industry levels. The challenge can be immensely magnified in flexible manufacturing systems (Achieng *et* *al.*, 2020), as switching to robots and specialised machines requires higher costs and time (Anitah *et al.*, 2019). There was a need to develop an intuitive and user-friendly approach for the shop-floor operators for programming the robots to alleviate the challenge of inadequate competitiveness by SMEs in the manufacturing sector

1.3 Objectives

1.3.1 Main Objective

To analyse demonstrative-kinesthetic teaching on robot manipulators for efficient material handling applications.

1.3.2 Specific Objectives

1. To evaluate the inverse kinematics using DKT relative to structured texts.
2. To determine the accuracy of the desired position of the end-effector of the robot manipulator using DKT relative to structured texts.
3. To calculate the efficiency of the DKT relative to structured texts.

1.4 Hypotheses

1. H_0: The mean coordinate configuration is the same for DKT and structured texts.

   H_1: The mean coordinate configuration is different for DKT and structured texts.
2. H_0: The mean accuracy of the desired target position is the same for DKT and structured texts.

   H_1: The mean accuracy of the desired target position is different for DKT and structured texts.
3. H_0: The mean efficiency is the same for DKT and structured texts.

   H_1: The mean efficiency is different for DKT and structured texts.

1.5 Justification

World economies are undergoing 4IR (Gobinath, 2021), and Kenya needs to catch up in improving its technologies. In its study, the World Economic Forum (2016) states that countries such as Switzerland, Netherlands, Singapore, Qatar, and the USA are well prepared for 4IR. The fundamental role of robotised systems in 4IR in Africa can't be downplayed, as noted by Schwab and Samans (2016). Africa is on the verge of renewing its' desire for (re)-industrialisation through animated policy and development debates attributed to factors such as 4IR (Naudé, 2017) driven by innovative technologies such as automation, additive manufacturing, and industrial internet (Schwab and Samans, 2016). The desire can be demonstrated by looking at the African Union Agenda 2063 (African Union, 2015) and the 2017 African Economic Outlook (Outlook: African Economic, 2017). The development has seen the establishment of local technology spaces and internationally driven established technology centres and hubs by companies such as Twitter, Amazon, Microsoft, Huawei, and Alibaba Group (Eke *et al.*, 2023). Despite the knowledge of the same robots, as noted by Naudé (2017), there is many potentials to be realised by the African countries as robot technology is still ignored (Isa, 2018).

Kenya is a budding nation that aims to reach a global level of technology, just as other countries do. Kenya is among sub-Saharan Africa's technologically advanced nation (Kwanya, 2023), thus dubbed 'Silicon Savanah' (Eke *et al.*, 2023; Kalusopa *et al.*, 2021). Kenya has built an excellent reputation with stable internet connectivity on the continent, attributed to the numerous underwater cables landing in it (Kenya) (Bramann, 2017), which proves justification for using innovative technologies. The country's government aims to achieve some of its 2030 goals using emerging creative technologies. According to Mvurya (2020), the mainstream use of machine learning technologies, artificial intelligence, and robotics is needed to achieve the government's development agenda. The idea of industrial robots and cobots in the economy is still experimental (Kwanya, 2023).

The utilisation of robotics plays a vital part in fast-tracking growth in manufacturing (Banga and te Velde, 2018). Kalusopa *et al.* (2021) note that the country expects to experience a robot influx in the next few years. The findings by Kwanya (2023) show that contrary to what might be believed to be the case that sub-Saharan Africa may be lagging in robotics, the inhabitants know the emerging trends and technologies in this field.

1.6 Scope

The study aimed to analyse the demonstrative-kinesthetic teaching of robot manipulators for efficient industrial material handling applications. It was restricted only to the contour path welding and palletising tasks for verification and validation of the study.

1.7 Structure of the Thesis

This thesis contains five chapters: Chapter one (Introduction), provides an introduction into the development robot use in manufacturing activities thus smart factories. The advantages gained through use of robotized systems are also discussed as well as mentioning some of the robot programming approaches both conventional and emerging ones. The chapter also explains the problem being tackled by this research, the objectives, hypotheses based on the specific objectives and scope of the research.

Chapter two (Literature Review), Contains literature from various scholars in the field of robotics specifically robot programming approaches from the conventional methods such as structured texts to emerging paradigms of programming by demonstration. The chapter reviews the use of TLP and compares to PbD approaches such as TKT and DKT. The robot kinematics are also handled in brief understanding of the manipulator kinematics involved and solutions to the kinematics problem. Research gaps from the reviewed scholars have also been identified and summarized in a table.

Chapter three (Materials and Methods), highlights the materials used in the research while the methods section is explained by the experimental set-up as well as the well laid out experimental procedure for each of the specific objective under research.

Chapter four (Result and Discussion), reports and discusses the inverse kinematics acquisition of the robotic manipulator using the DKT and compared against those acquired through the conventional method of structured text. The accuracy and efficiency of the DKT was also reported and discussed with analysis of each hypothesis under set specific objectives tested out.

Finally, chapter five (Conclusion and Recommendations), presents the conclusions and recommendations based on the results discussed in chapter four. It also goes on to highlight the scope for future work.

CHAPTER TWO

LITERATURE REVIEW

2. Literature Review

The chapter briefly looks at robot programming approaches and, in this case, structured texts-based and kinesthetic teaching techniques, their merits and demerits, and research works. The chapter concludes with a review of the kinematics of robot manipulators.

2.1 Robot Programming

Robot programming describes desired robot behaviour and is supported by a programming system (MacDonald *et al.*, 2003). Programming methods such as lead-through (Online) and Offline programming (OLP) eliminated the need for manual writing of the codes (Ong *et al.*, 2020). A requirement for the programming was in the provision of detailed follow-paths and motion-oriented instructions (Biggs and MacDonald, 2003; Lozano-Pérez, 1982).

2.2 Texts-based Language Programming (TLP)

One of the initial programming approaches offered the user a programming method similar to standard software development (Heimann and Guhl, 2020). It served as the baseline off-line programming (OLP) environment. The text-based environments are the generic programming languages (Java, Python, Logo, Pencil Code Text, C, and Visual Basic (Bravo *et al.*, 2017; Sun and Zhou, 2023) and specific programming languages (ROBOTC, LeJOS, Aseba Studio, and Robot Mesh Studio (Bravo *et al.*, 2017). The approach required users' comprehension semantically and syntax of text languages (TPLs). Text-based programming users can develop computational thinking skills (Sun and Zhou, 2023). It required keen attention to the syntax rules with the requirement of programming foundation on the user's part. For non-skilled programmers, text-based programming may run into complications. The tremendous amount of time required for first-time users may become a challenge, especially in SMEs' manufacturing activities, as high costs for training may prove too uneconomical. The actual programming aspect is tedious and time-consuming (Ong *et al.*, 2020) concerning the steps and time taken to complete a task. For these reasons, newer, intuitive, and user-friendly programming methods for example programming by demonstration (PbD) paradigms such as KT are being researched and shifted towards.

2.3 Kinesthetic Teaching (KT)

KT is also referred to as kinesthetic guidance (Heimann and Guhl, 2020). The programming approach where the programmer showed new behaviours via the learner robot's body manipulation (Calinon, 2018; Papageorgiou *et al.*, 2021; Villani *et al.*, 2018). There was an allowance for innate dexterity transfer between robots and humans. The human carrying out the demonstrations needed not have technical skills and minimal time involved (Papageorgiou *et al.*, 2021).

2.3.1 Tele-Kinesthetic Teaching (TKT)

Kinesthetic teaching by teleoperation (Tele-kinesthetic) (TKT) has been applied to high level abstractions, grasps, and task trajectories (Ravichandar *et al.*, 2020). External input to the robot through graphical user interface, use of joysticks, virtual reality (VR) devices, and wearable devices. TKT offerered room for remote programming and an opportunity for crowdsourcing demonstrations at a large scale. TKT faced the limitations of additional lengthy user training on the interfaces, availability of the chosen input hardware, and additional effort required to develop the selected interface. Some research works on the use of TKT in robot programming for industrial applications are as follows;

Neto *et al.* (2009) identified a gap in intuitive robot programming and control. They developed an accelerometer-based system to control industrial robots with accelerometers attached to the human arms to capture their behaviour. The results indicated that while the system controlled the robot intuitively compared to the use of the teach pendant, there was a need for improvement in the recognition rate with a system response time of 160 milliseconds. Future works were recommended to use more accelerometers and gyroscopes in the system. Additional sensory devices may prove costly, especially for SMEs with constrained budgets.

Tanwani and Calinon (2016) identified a gap in work relating to clustering models concerning subspace clustering models. They proposed a framework that combining subspace clustering with adaptability of tasks, and ideal control for task manipulation learning by robots. For the pick and place, and valve operations, the learning aspect was carried out through teleoperation. With left arm being held by the human and right controlled through visual eedback from the on mounted camera, the robot was teleoperated. It facilitated the valve close and opening and the pick and place. The approach requires solid background knowledge of data learning and modelling methods such as semi-tied HSMM, which is unapproachable by non-expert users.

Tsarouchi *et al.* (2016) presented a way of abridging the programming of factory robot via visual sensors upon human motion detections. The human and robot motions were transformed using an external controller application. The technique allows for extensibility; thus, other means, such as voice commands and graphical interfaces, can be implemented. The proposed framework allowed use on different robot platforms, opening up the possibility of a universal robot programming approach. Future works aimed at using more reliable devices for better recognition results. The developed lexis of both hand and body motions poses a question whether users must memorise the motions before engaging in robot operations.

Ong *et al.* (2020) presented a system comprising a head-mounted augmented reality overlay and the use of a handheld tracking device for 3D space point definition. The definition was done using the handheld device for points surrounding the fillet weld. Colour changes relating to the weld gun depended on the robot's pliability in the given orientation for user feedback. A 90% reduction in the fillet weld programming time was achieved as the path deviation was kept a millimetre less within. The approach provides an avenue for high-quality demonstrations to be gathered. Still, it requires well-shaped, designed reward functions and substantial robot interaction time, which may prove challenging to meet by even robotic experts.

Meattini *et al.* (2022) noticed a gap in the functionalities of modern robots, such as the provision of performance of smooth interactions for the KT framework. Wiring as well as modulated robot compliance levels through trajectory planning using KT. Safe human interaction especially whilst executing tasks online was provided. The operator's ability to freely move was not in any way hindered by the well-designed wearable interface. It was experimented on a 7 DOF manipulator, with reported results indicating successful exploitation by the operator. Industrial applications and future applications were the conclusions arrived at through the adoption of the approach. The approach is still in the experimental and laboratory-based stages.

2.3.2 Demonstrative-Kinesthetic Teaching (DKT)

The (DKT) technique takes advantage of the onboard sensors to record the state of the robot during interaction (Ravichandar *et al.*, 2020), providing an intuitive approach with minimal training requirement (Eiband *et al.*, 2023; Tykal *et al.*, 2016) as it does not burden the programmer with the requirement of knowledge of programming languages such as Python (Heimann and Guhl, 2020). The correspondence problem is eliminated as the programmer directly guides robot (Bravo *et al.*, 2017; Sakr *et al.*, 2020), and there is no need for extra instruments beyond the robot's sensors and actuators. The demonstrations are restricted to the known kinematic limits of the robot (Guhl *et al.*, 2019; Heimann and Guhl, 2020). Research works on DKT are discussed as follows;

Hersch *et al.* (2008) presented an approach of using demonstrations achieved kinesthetically for acquiring robust robot skills. Despite environmental perturbation changes and initial conditions, the production of simpler goal-directed gestures was correctly done. Combining dynamical system control and statistical learning theory solves the inverse kinematic problem. Object grasp as well as placement in a box were used as validations for the approach. The demonstrations by the framework facilitated the robot's learning of far-constrained-reaching tasks. Suggestions for putting together a system capable of extracting relevant variables and selecting an automated model were put forth. The framework was restricted only to the simple tasks in the experiments as more complex ones require detailed models and elaborate environmental planning techniques. Using statistical learning theory means users must have a good knowledge of the subject and its applications for reinforcement for obstacle detection and avoidance.

Ghoshal *et al.* (2014), having identified difficulties in incorporating machine learning approaches in training new motor tasks to robots, put forward a simple framework for kinesthetic guidance without the need for a two-stage approach. The reinforcement stage was eliminated via appropriate kinesthetic stage modification and incorporating the domain experience of human teachers. The simulation results indicated success by removing the reward stage, which is of substantial importance to the quantifiable expertise teachings from the humans by assigning varying priorities to varying shots. The assumption was the teacher could demonstrate good shot movement and had enough expertise in that domain. Recalibration of parameters would be required should the experimental setup change—future works aimed at validation of the framework with a robotic manipulator. The fame work was only in simulation and was not tried on actual robots; hence, determining its effectiveness in industrial applications cannot be ascertained.

Zhu *et al.* (2018), presented an approach for learning grasping poses in assembly tasks conducted by a robot from human demonstrations. The approach had the task carried out in phases as a wrist camera was used in teaching. Workbench objects were scanned for SIFT feature extraction; reproduction phase was done by human demonstrations of the grasp of the object for learning on autonomous manipulation. The systems were experimented with using peg-in-hole (PiH) tasks, and the robot accomplished the task from the demonstrations without traditional dedicated programming. Further experiments were suggested to be carried out on the system's robustness over other assembly tasks, such as bolt screwing and chair assembly. A recommendation for optimisation of the force control strategy for even motion and accurate positioning of the assembly points in future works would extend between single and dual arm manipulation. Knowledge of machine learning algorithms such as SIFT and kNN is required to use the approach.

Valdivia *et al.* (2023) noticed a gap in the importance of demonstrators understanding what the robot learns far learning procedure focus and introduced an approach for communication on the internal state of the robot, especially throughout physical interaction using the robot-arm wrapped haptic displays. Chances of interruption whilst robot interaction and human involved in demonstration were eliminated, particularly while providing feedback in real-time. This feedback enabled kinesthetic teaching of robot arms effectively and more rapidly than the alternatives. Teach time decreased with an increase in the quality of demonstrations with a dependence on haptic display distribution and location. The approach was tested on arms of varying geometry or type with consistent results; hence, the arms were not tied to specific arms. Seamless communication and teaching resulted from using the multi-degree-of-freedom haptic displays for small space signal concentration. Future works would focus on the increased complexity of the rendered signals by the soft haptic displays. While reducing the teaching time, the approach requires expert knowledge of haptic devices and an understanding of the psychophysics perspective.

2.4 Kinematics of Robot Manipulators

Kinematics refers to a mechanics branch in which bodies and systems' motion is devoid of causative forces consideration. For kinematics involving robots, it is the application of geometry to the robust movement of multi-degree-of-freedom kinematic chains forming up robot manipulator structure. The kinematics involve rotation and translation displacement to bring about movement (Siciliano and Khatib, 2016). When no part of a rigid body remains at the start position with all straight lines maintaining parallel to their initial orientation during a displacement then it is a translation but a rotation if at least one point remains in the start position with not all lines remaining parallel their initial orientations (Siciliano and Khatib, 2016).

Forward kinematics (FK) is a transformation from joint space to cartesian space, providing the manipulator position information, while inverse kinematics (IK) is a transformation from cartesian space to joint space (Jahnavi and Sivraj, 2017).

2.4.1 Forward Kinematics

With forward kinematics, the idea is to determine end-effector orientation and positioning in relation to the base regarding known joint positions and geometric link values. An approach to determining spatial relations between the coordinate frames of succeeding links with the Denavit-Hartenberg (DH) parameters. Using the joint-link parameters, a homogenous transformation matrix can be obtained. Using DH parameters, robot link description can be done by assigning the link of a robot to the coordinate frames (Denavit and Hartenberg, 1955; Sheikh, 2019). The DH convention was adopted here because of its requirement of not six but four parameters for the relative location of reference frames.

- Joint angle (q_i): the angle measured about Z_i, from X_{i-1} to X_i,
- Link distance/Link Offset (d_i): the distance measured along the axis Z_i; from X_{i-1} to axis X_i,
- Link length (a_i): the length measured along X_{i-1}, from axis Z_{i-1} to axis Z_i, and
- Link twist at the link (α_i): the angle measured about X_i, from axis Z_{i-1} to axis Z_i (Sheikh, 2019)

The solution to FK for a robotic arm is determined via Homogeneous Transformation (HT) matrix calculation. Both end-effector positional and oriental information are contained within it. When crucial consideration for programming ease is necessitated then the homogenous transformations are combined. They are usually adopted when the ease of programming is the most crucial consideration. Assumption of perfectness of the rigid bodies in terms of shape and position especially regarding links composing the robot's mechanism is made.

The HT matrix is shown by equation (2-1).

$$ {}^{i-1}_{i}T = Rot_z(\theta_i).Trans_z(d_i).Trans_x(\theta_i)Rot_x(\alpha_i) \tag{2-1} $$

Where;T- overall transformation,

Rot- rotation,

Trans-translation

According to Craig (2013), the overall form transformation link between succeeding frames is given by:

$$ {}^{i-1}_{i}T = \begin{bmatrix} {}^{i-1}_{i}R^{3\times3} & {}^{i-1}_{i}P^{3\times1} \\ 0^{1\times3} & 1 \end{bmatrix} \tag{2-2} $$

Where;

${}^{i-1}_{i}R^{3\times3}$ It is a rotational matrix.

$$ {}^{i-1}_{i}R^{3\times3} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 \\ \sin\theta_i\cos\alpha_{i-1} & \cos\theta_i\cos\alpha_{i-1} & -\sin\alpha_{i-1} \\ \sin\theta_i\sin\alpha_{i-1} & \cos\theta_i\sin\alpha_{i-1} & \cos\alpha_{i-1} \end{bmatrix} \tag{2-3} $$

and ${}^{i-1}_{i}P^{3\times1}$ a vector given by :

$$ {}^{i-1}_{i}P^{3\times1} = [a_{i-1} \quad -\sin\alpha_{i-1}d_i \quad \cos\alpha_{i-1}d_i]^T \tag{2-4} $$

Thus, equation (2-4) is represented as ;

$$ {}^{i-1}_{i}T = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 & a_{i-1} \\ \sin\theta_i\cos\alpha_{i-1} & \cos\theta_i\cos\alpha_{i-1} & -\sin\alpha_{i-1} & -\sin\alpha_{i-1}d_i \\ \sin\theta_i\sin\alpha_{i-1} & \cos\theta_i\sin\alpha_{i-1} & \cos\alpha_{i-1} & \cos\alpha_{i-1}d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-5} $$

Equation (2-5) represents a 4 x 4 Homogenous Transformation matrix relating successive frames.

The overall Homogenous transformation matrix representing the frame concerning the base frame is shown by

$$
{}_{ef}^{0}T = \begin{bmatrix} \cos\theta_1 & 0 & \sin\theta_1 & \cos\theta_1\,(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2) \\ \sin\theta_1 & 0 & -\cos\theta_1 & \sin\theta_1(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2)) \\ 0 & 1 & 0 & L_1+L_3\sin(\theta_2+\theta_3) \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-6}
$$

From equation (2-6) , end-effector position (x,y,z) is as expressed in (2-7)

$$
{}_{ef}^{0}T = \begin{bmatrix} \cos\theta_1 & 0 & \sin\theta_1 & \cos\theta_1\,(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2) \\ \sin\theta_1 & 0 & -\cos\theta_1 & \sin\theta_1(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2)) \\ 0 & 1 & 0 & L_1+L_3\sin(\theta_2+\theta_3) \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} P_x \\ P_y \\ P_y \end{bmatrix} \tag{2-7}
$$

$$
\begin{bmatrix} P_x \\ P_y \\ P_y \end{bmatrix} = \begin{bmatrix} \cos\theta_1\,(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2) \\ \sin\theta_1(L_3\cos(\theta_2+\theta_3)+L_2\cos\theta_2)) \\ L_1+L_3\sin(\theta_2+\theta_3) \end{bmatrix} \tag{2-8}
$$

(Agnihotri *et al.*, 2015; Aktas *et al.*, 2017; College, 2018; Hock *et al.*, 2017; Islam *et al.*, 2019; Rahman, 2012; Sheikh, 2019)

2.4.2 Inverse Kinematics

A serial-chain manipulator's Inverse Kinematics (IK) involves the basis of the end-effector's positional and oriental relative to geometric base values parameters in determining its joint positions. However, non-linear equations derived from the transformation matrices pose a challenge in finding a closed-form solution. In fact, the possibility of no existing or numerous existing solutions is always there. For the viability of a solution, aligning and end effector placement essential fall within manipulator’s work environment (Siciliano and Khatib, 2016). In non-existent solution cases, numerical methods are required.

The infinite nature of the solutions of robotic manipulators renders their IK to be complex. The equations to be solved are rather non-linear and thus pose challenges especially when determining closed-form solutions (Sheikh, 2019). The joint values for target position can be calculated using IK if the object coordinate configurations are known relative to the base. The fast and ready nature of closed-form solutions in comparison to numerical solutions provides the possibility of identification of all solutions. Application preferences especially in sensor-supported systems for kinematic calculations regarding control measures amplify the use of closed-form solutions (KuCuk and Bingul, 2004). The solutions are not general but rather robot-dependent. The solutions can be determined algebraically or geometrically (Hock *et al.*, 2017; Sheikh, 2019).

2.5 Summary of Literature Works

A summary of the discussed literature on robot programming approaches was shown in Table 2-1.

Table 2-1: A Summary of Literature Works

	Author	Objective	Method	Results	Gap
1.	Valdivia *et al.* (2023)	• Developed and analysed the use of robot-arm-wrapped haptic devices for robot learning communication.	• DKT	• Effective and rapid teaching of robot arms in comparison to alternatives • Increased demonstration quality with reduced teaching time • Approach not tied to specific arm • Seamless communication and teaching	• Approach required user training on the use of a haptic interface
2.	Meattini *et al.* (2022)	• Demonstrated suitability of an approach that enables operators to perform trajectory kinesthetic guidance in wiring and modulation of compliance levels for smooth and	• TKT	• The approach provided an inducive application in real industrial tasks	• Still at experimental Stage

		safe human interactions.			
3.	Ong *et al.* (2020)	• Developed a system allowing the programming of fillet welds	• TKT	• Reduced fillet weld programming time by 90% • Path deviation kept at less than a millimetre • Provided avenue for high-quality demonstrations, gathering	• Required well-shaped, designed reward functions and substantial robot interaction time
4.	Zhu *et al.* (2018)	• Developed an approach for learning grasping pose in assembly tasks conducted by a robot from human demonstrations	• DKT	• Robot completed the PiH task using the system • Suggested further experiments of the system on other assembly tasks, such as bolt screwing, for evaluation of system robustness • Future works aimed at extending the system to dual-arm manipulation	• Machine learning algorithms knowledge was required
5.	Tsarouchi *et al.* (2016)	• Proposed simplification in programming industrial robots by visual sensors on detection of motions by human	• TKT	• Framework allowed its use on different robot platforms • It allowed for extensibility; hence, other means could be implemented	• Need for familiarisation and memorising of the vocabulary
6.	Tanwani and Calinon (2016)	• Developed a task adaptability and subspace combination framework which allows manipulation control learning by robot.	• TKT	• Pick and place alongside valve opening were used to verify the framework to avoid obstacles in unanticipated environmental conditions	• Solid background knowledge of data learning and modelling methods required

7.	Ghoshal *et al.* (2014)	• Introduced a simple framework for kinesthetic learning	• DKT	• Elimination of reward stage with the importance put on expertise obtained from a human teacher • Parameter recalibration in case of experiment setup change • Future works aimed at validation of the framework with a robotic manipulator	• Simulated only; still not tried out on actual robots
8.	Neto *et al.* (2009)	• Developed an accelerometer-based system to control industrial robots	• TKT	• Intuitive control of the robot in comparison to teaching pendant • Need for improvement in the recognition rate • Future works aimed to use more accelerometers and gyroscopes in the system	• Additional sensors may prove too costly
9.	Hersch *et al.* (2008)	• Developed a robust robot skill acquisition approach from the kinesthetic demonstrations	• DKT	• Enabled robot learning for constrained-reaching tasks • Framework restricted to simple tasks in the experiment	• Statistical learning theory means good knowledge of the subject and its applications for reinforcement for obstacle detection and avoidance.

The research works on various kinesthetic teaching techniques showed promise of developing more intuitive, less time-consuming, and less tedious approaches; they are too high cost economical. The incorporation of sophisticated sensors required user knowledge and training in the interface, and some are still in the laboratory experiments stage, and additional user knowledge on machine learning algorithms for implementation in robot programming by non-expert users in SME manufacturing activities. Having reviewed the works, it was clear that a user-friendly, costly, less time-consuming, and intuitive programming approach was required.

2.6 Conceptual Framework

The conceptual framework represents the relationship between the variables in the study. The DKT was the independent variable, the intermediate variable being coordinate configuration, conventional structured text as control, and the dependent variable as efficient material handling as shown in Figure 2-1.

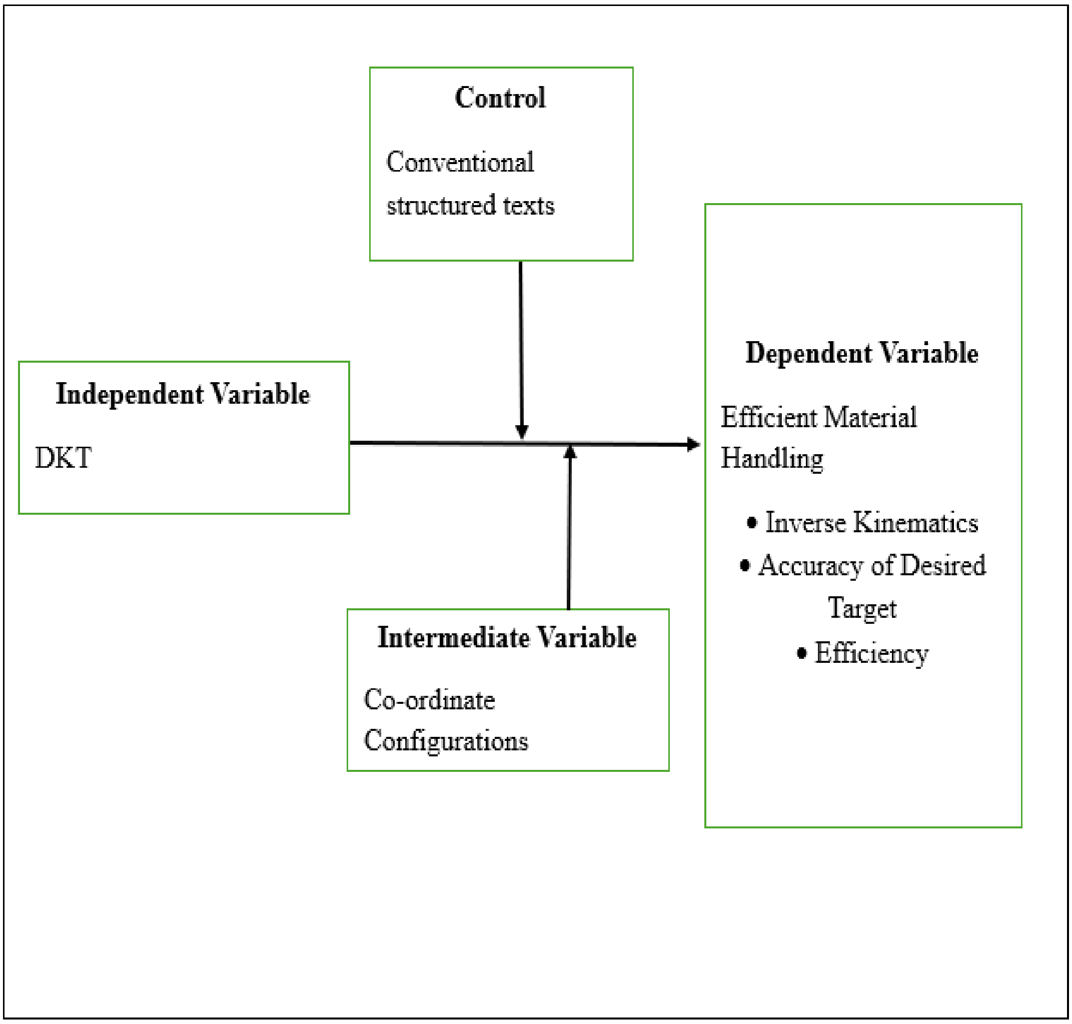

Figure 2-1: Conceptual Framework

CHAPTER THREE

MATERIALS AND METHODS

3. Materials and Methods

Location description begins the chapter, a look at the materials used, and the experimental setup and procedures conclude the chapter.

3.1 Location

The experimental research was carried out at Masinde Muliro University, located on Webuye-Kisumu Road, Kakamega County, Kenya as shown by map in Figure 3-1. The robot programming was conducted in the Robotics lab at Masinde Muliro University of Science and Technology.

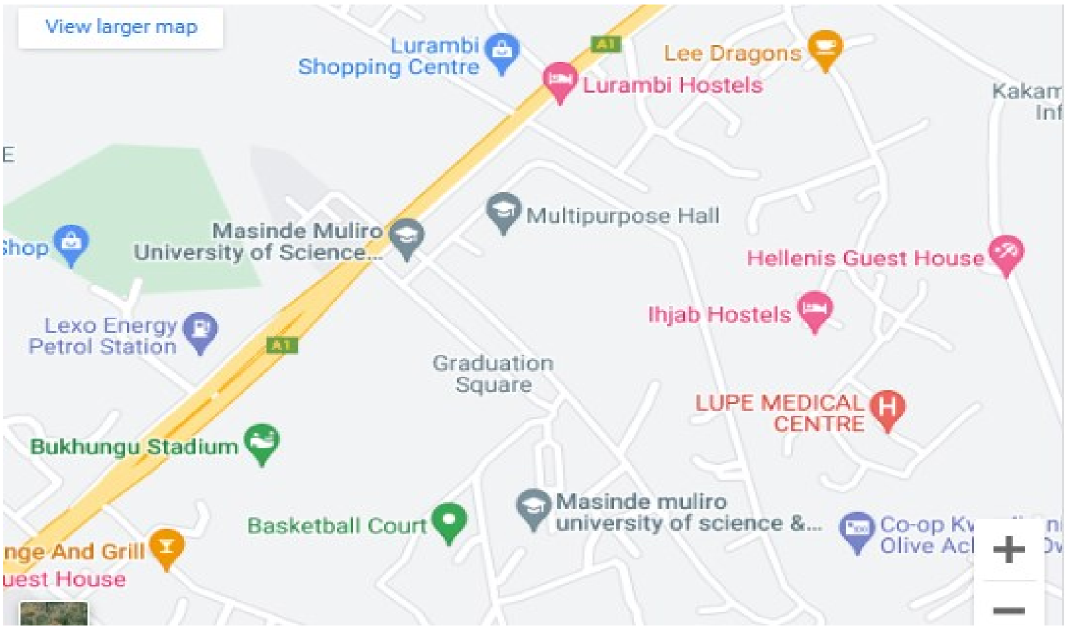

Figure 3-1: Study Location Map (Google)

3.2 Materials

The materials required for carrying out the robot programming were as follows:

- Robot manipulator (Dobot Magician)- carrying out the experiment
- Laptop (PC)- hosting the Dobot Studio user Interface software
- USB cables- a peripheral connection between the robotic arm and the laptop

- Power source- provide power to the laptop and robotic arm
- Wooden Block- items to be picked.
- Pneumatic Gripper- an end-effector
- Stopwatches- timing the experiments

3.2.1 Robot Manipulator Description

The robotic manipulator, Dobot Magician (referred to as such from here), is a multifunctional desktop manipulator that allows anyone from essential to expert programmers to carry out practical tasks. It is a 4-DOF articulated robotic arm with 4-axes with 1-DOF contributed by the gripper movement. It has a position repeatability of 0.2mm, a work envelope of 320mm maximum reach, and a payload of 0.5kg (Shenzhen Yuejiang Technology Co., 2017). It consists of the forearm, rear arm, end effector, and base for support, as shown in Figure 3-2;

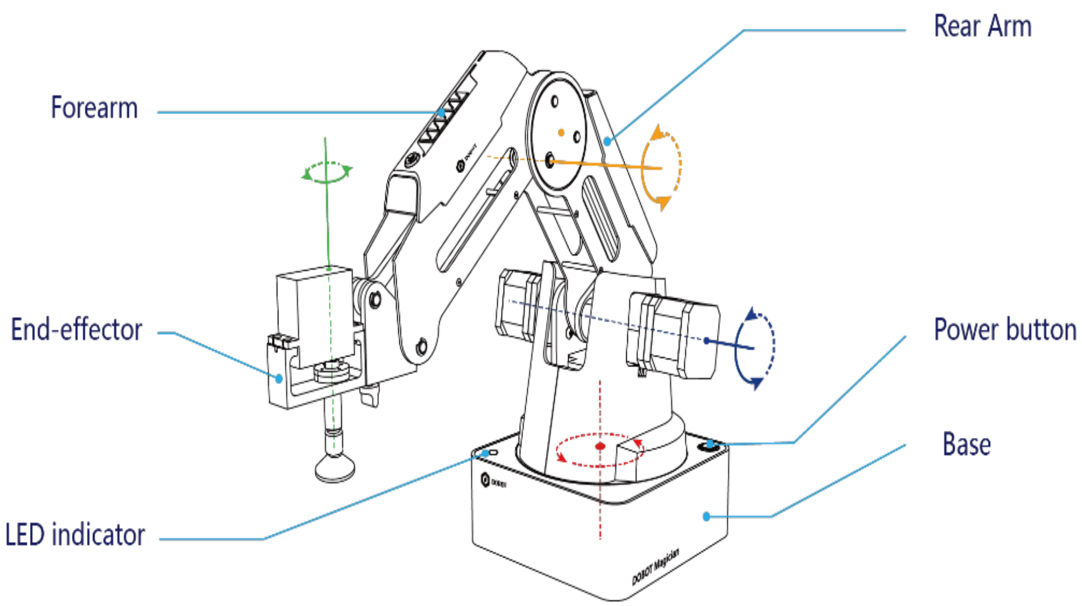

Figure 3-2: Dobot Magician (Adapted from Shenzhen Yuejiang Technology Co. (2017))

3.3 Experimental Set-up

To validate the study, the experiment was setup as shown in Plate 3-1.

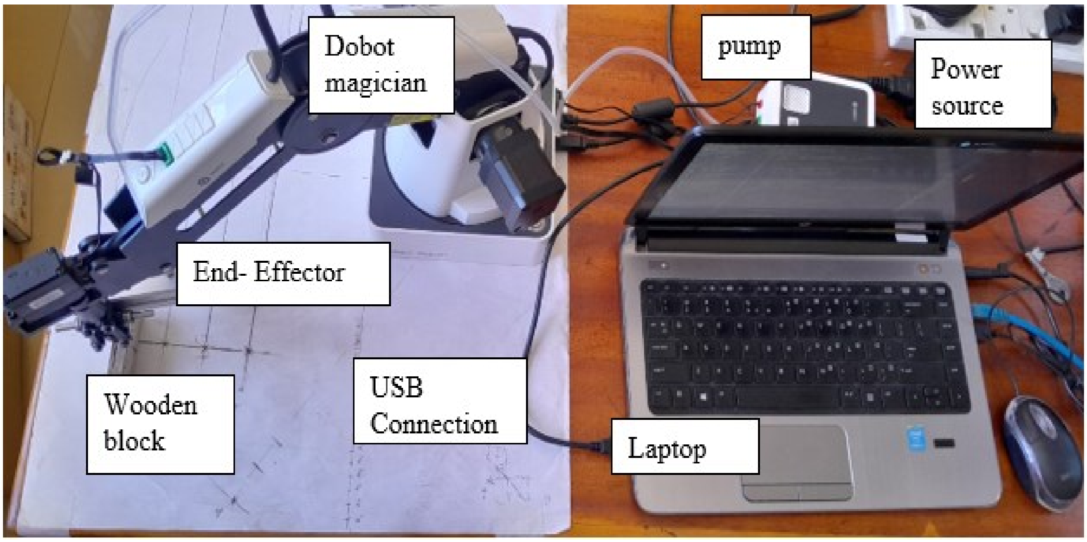

Plate 3-1: Photograph of Experiment Set-up

3.4 Experiment Procedures

3.4.1 Determination of the Inverse Kinematics

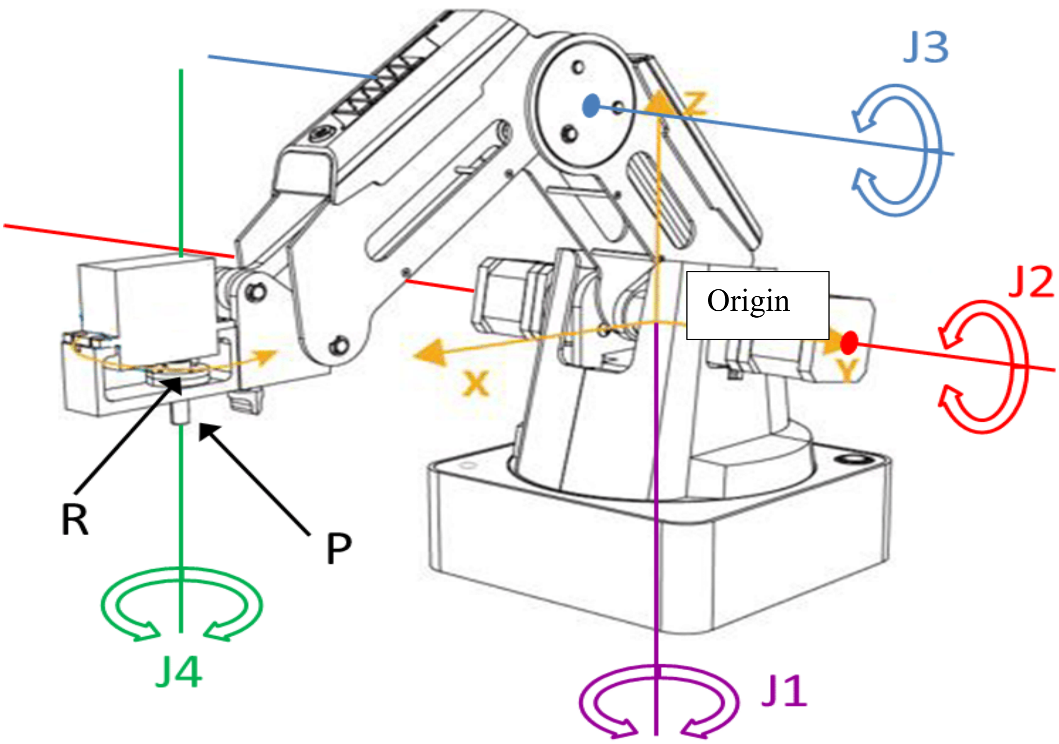

Figure 3-3: Joint and Cartesian Configurations of Dobot Magician (Adapted from Santoni *et al.* (2018))

Where J1-joint 1

J2- joint 2

J3-joint 3

J4-joint 4

R- roll

P- pitch

To determine the inverse kinematics, a control platform in Plate 3-2, based on Python language was created using Visual Studio IDE to control the robot demonstratively (DKT) by using the lock button on the forearm to capture end-effector positions and tabulate joint values in a pose.csv file as shown in Plate 3-2 For the control experiment, the same effector positions were captured using a Python program, and the joint positions were saved on the pose1.csv file using the getpose() command in the code, as shown in Plate 3-2.

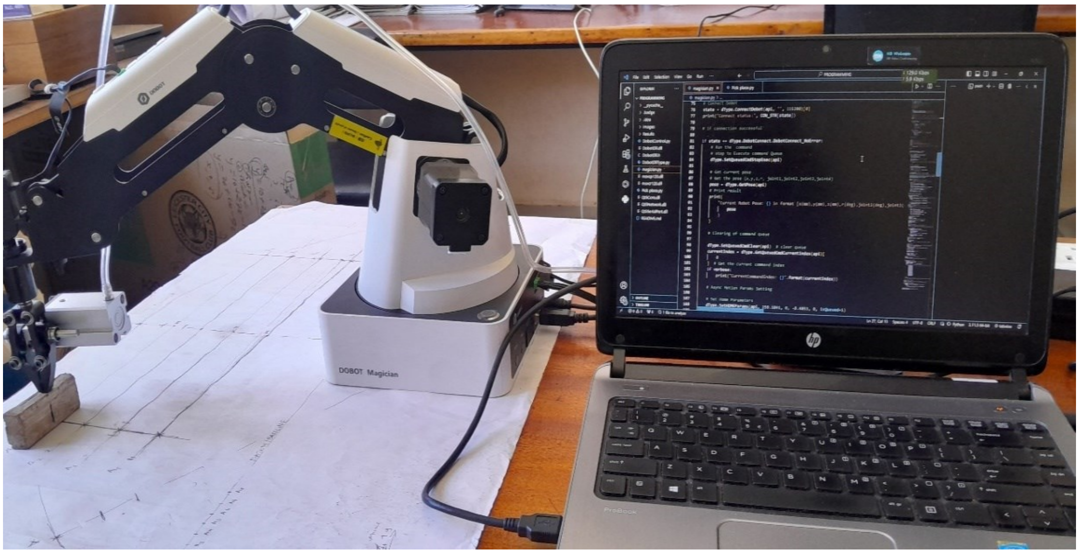

Plate 3-2: Photograph of the Control platform in VS studio and Dobot Magician.

The experiment was done over four levels. in Plate 3-3 and Plate 3-4.

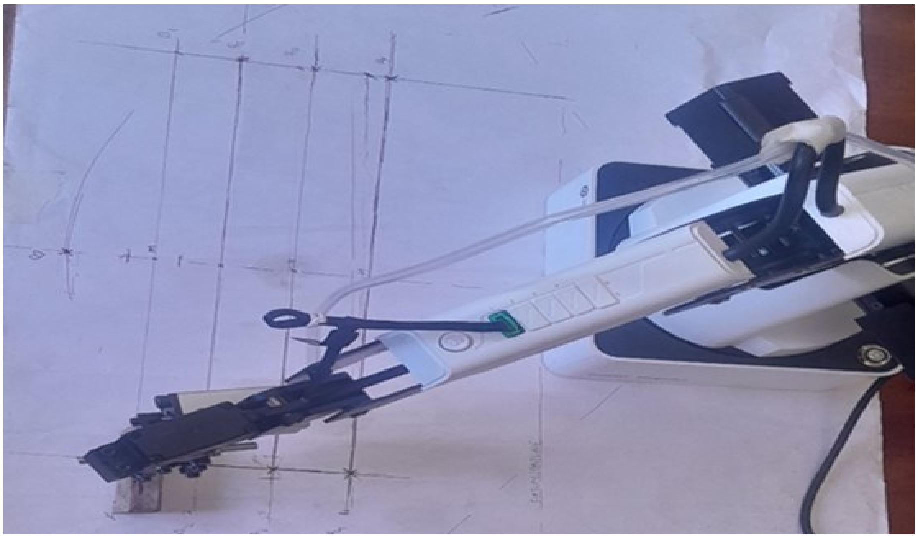

Plate 3-3: Photograph of the Start Position A_1

Plate 3-4: Photograph of the Stop Position B_1

The experiment was replicated for each level (A_2, B_2, A_3, B3, A_4, B_4). The joint values were recorded and stored in the CSV file for each replication and level. The modified DH parameters of the robot were also recorded as outlined in

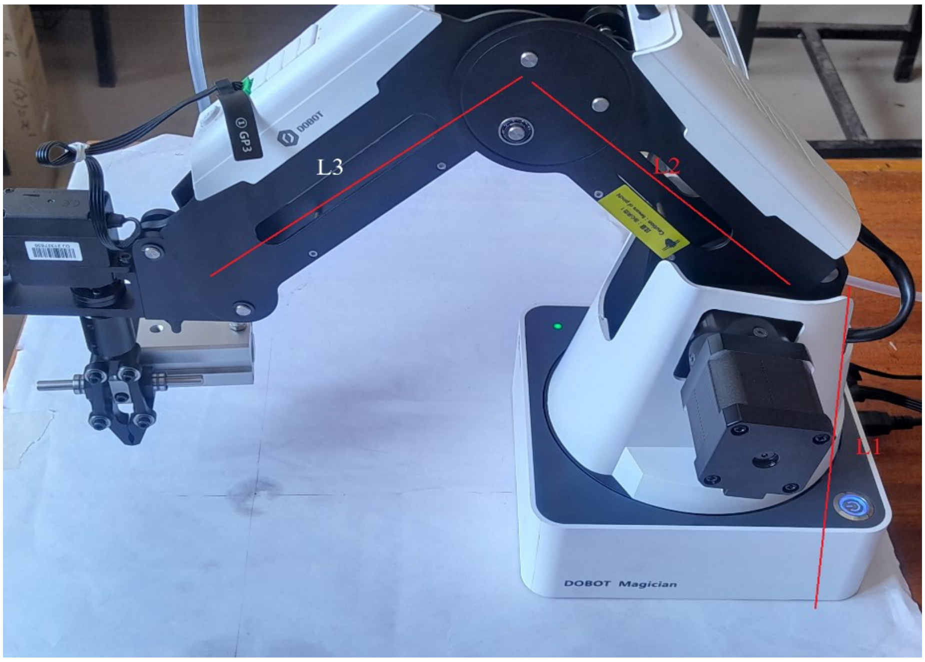

Plate 3-5: Photograph of the modified DH-Parameters

3.4.2 Determination of Accuracy of Desired Position

The experiment used the Control platform, as shown in Plate 3-2 . Palletising task and contour path welding experiments were conducted to verify the accuracy.

For the palletising task, the robot was used to carry out pick and place from initial start positions A_1 to the wooden piece placed at stop position B_1 for the various levels 1,2,3,4 with replications of the experiment for each level and joint values recorded and stored in the pose.csv file while using the DKT technique and pose1.csv for the Control experiment using coded pick and place program as shown in Plate 3-6 to Plate 3-10.

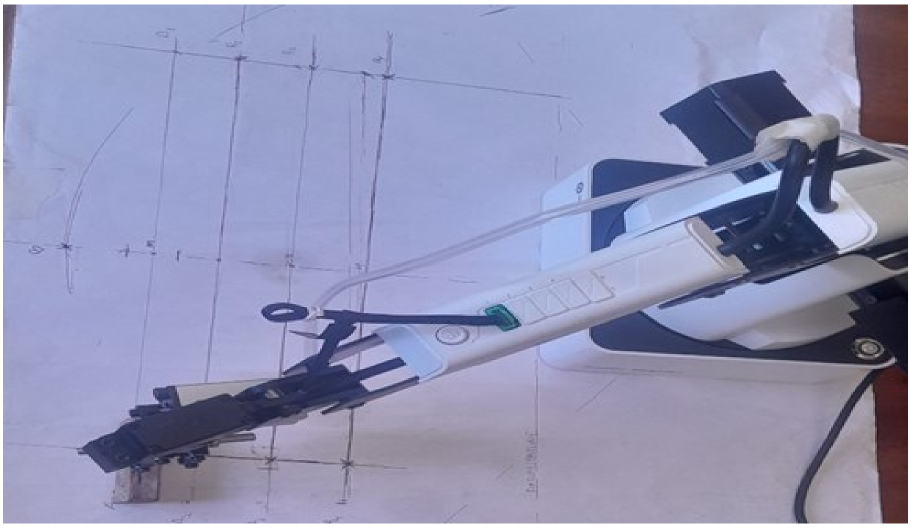

Plate 3-6: Photograph of the Pick Point A_1

Plate 3-7: Photograph of the Place Point B_1

Plate 3-8: Photograph of the Pick Point A_2

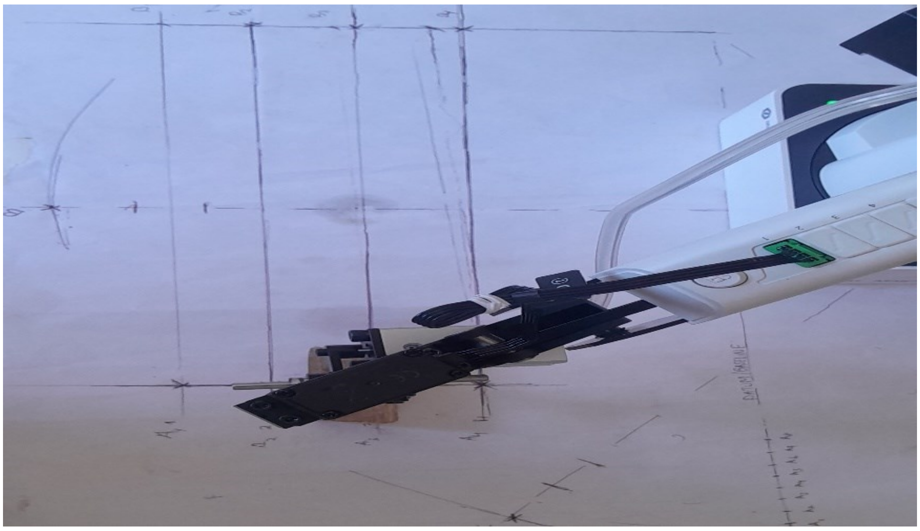

Plate 3-9: Photograph of the Pick Point A_3

Plate 3-10: Photograph of the Pick Point A_4

For the contour welding, the robot was programmed demonstratively using the DKT technique and platform, as shown in Plate 3-2, to collect the joint poses for three points A, B, and E along arcs of different radii to indicate the six levels with three replications carried out at each arc level. Points A, B, and E all lay on the same arcs but points A and E were not on straight lines for the six levels. Point A was the starting point, B between A and E, and E was the endpoint. The joints for the various positions were collected in the pose.csv file and pose1.csv file for the two methods.

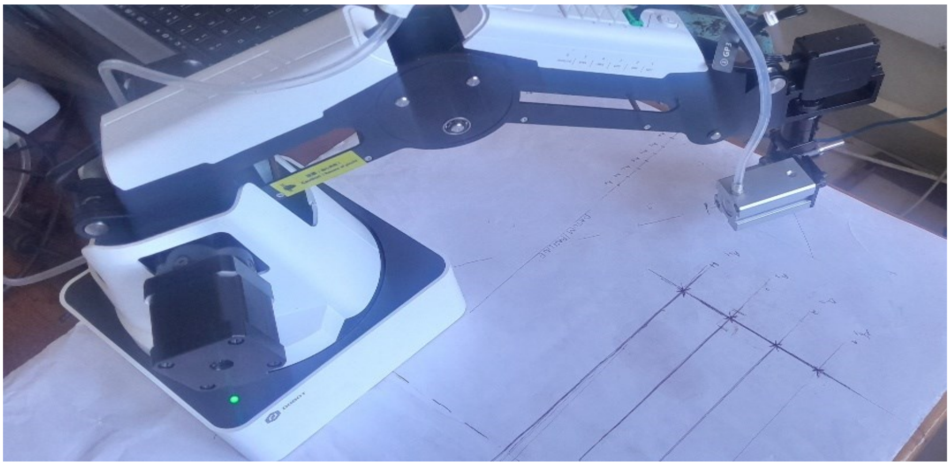

Plate 3-11: Photograph of the End-effector at Start Position A_1 on Contour1(arc1)

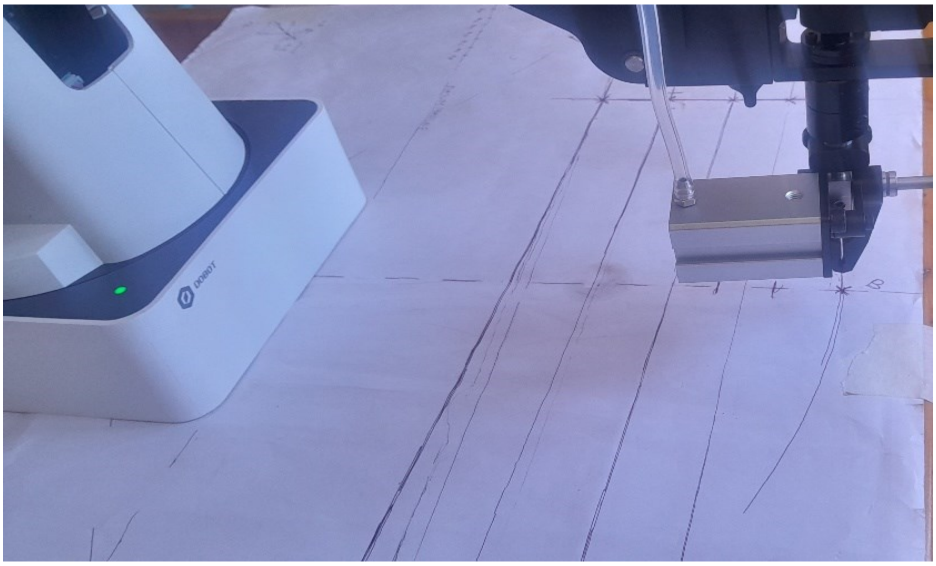

Plate 3-12: Photograph of the End-effector at Mid-Position B_1 on Contour1(arc1)

Plate 3-13: Photograph of the End-effector at End Position E_1 on Contour1(arc1)

3.4.3 Determination of Efficiency of DKT Technique

The efficiency was determined by measuring the time taken using the stopwatch to complete the experimental task's reaction time of Dobot Magician by both the DKT technique and structured text-based approaches while conducting the palletising and contour welding experiments. The times using the two methods were recorded, and tabulations of each task were recorded for each and subsequent replications for accuracy.

CHAPTER FOUR

RESULTS AND DISCUSSION

4. Results and Discussion

The results and discussions regarding determining the inverse kinematics, the accuracy of the desired position, and the efficiency of the DKT technique in comparison to the structured texts are handled in this chapter.

4.1 Determination of the Inverse Kinematics

A base frame that was fixed for the robotic arm was named '1'. The other positions of other frames were defined concerning the reference frame. The frames were numbered from numbers one to four. The modified DH parameters were obtained as shown by Table 4-1.

Table 4-1: Modified DH Parameters

Frame (i)	Joint angle (q_i)	Link offset (d_i)	Link distance (a_{i-1})	Link twist (α_{i-1})
1	θ_1	$d_1 = L_1 =$ 103mm	a_1 = 0mm	$\alpha_1 = 0^0$
2	θ_2	d_2 = 0mm	a_2 =0mm	$\alpha_2 = 90^0$
3	θ_3	d_3 = 0mm	$a_3 = L_2$ =135mm	$\alpha_3 = 0^0$
4	θ_4	d_4 = 0mm	$a_4 = L_3$ = 147mm	$\alpha_4 = 0^0$

For the Dobot Magician, the length from the base frame to frame 2, link offset $d_{1=}$ L_1 = 103mm, while the rest of the frame link offsets were 0mms. The link distances for frames 1 to 2 were 0mm, 0mm, while $a_3 = L_2$ =135mm, a_4 = L3 = 147mm. The link twists for frames 1, 3, and 4 were 0^0, and frame 2 had $\alpha_2 = 90^0$. The joint angles (θ_1, θ_2, θ_3, θ_4) were determined by carrying out the palletising and contour path welding experiments using DKT and structured texts (Control). Using the modified DH parameters, the homogenous transformation matrices can be obtained using equation (2-5) for the forward kinematics.

The FK give the position of end-effector with deference to the base, as was shown in equation(2-2). On the other hand, this research was primarily concerned with determining the inverse kinematics. Determining the joint angles is crucial in placing the end-effector at the expected cartesian points (x,y,z). The joint values can be algebraically obtained using equations outlined in the kinematics section from the literature's point of view. The joint values can be determined algebraically if the cartesian points and the respective DH- Parameters are known. For example, for a point (x: 261.2291, y: 172.4152, z: -14.8131), the joint 1 angle was $33.4254^{0,}$ which was also determined using equation (4-1)

$$\theta_1 = \tan^{-1}\left(\frac{y}{x}\right) \quad \text{(Hock } et\ al.\text{, 2017; Islam } et\ al.\text{, 2019) (4-1)}$$

$$\theta_1 = \tan^{-1}\frac{172.4152}{261.2291}$$

$$= 33.42542138^0$$

The joint angles (θ_1, θ_2, θ_3, θ_4) values were determined for the various positions using the control method and the DKT technique from pose.csv and pose1.csv files from the palletising and contour path welding experiments.

4.1.1 Joint Angle Values Plots for DKT and Control Modes of Programming

The individual joint (joint 1, joint 2, joint 3 and joint 4) angle values against each mode of programming were determined and contrived as shown in Figure 4-1.

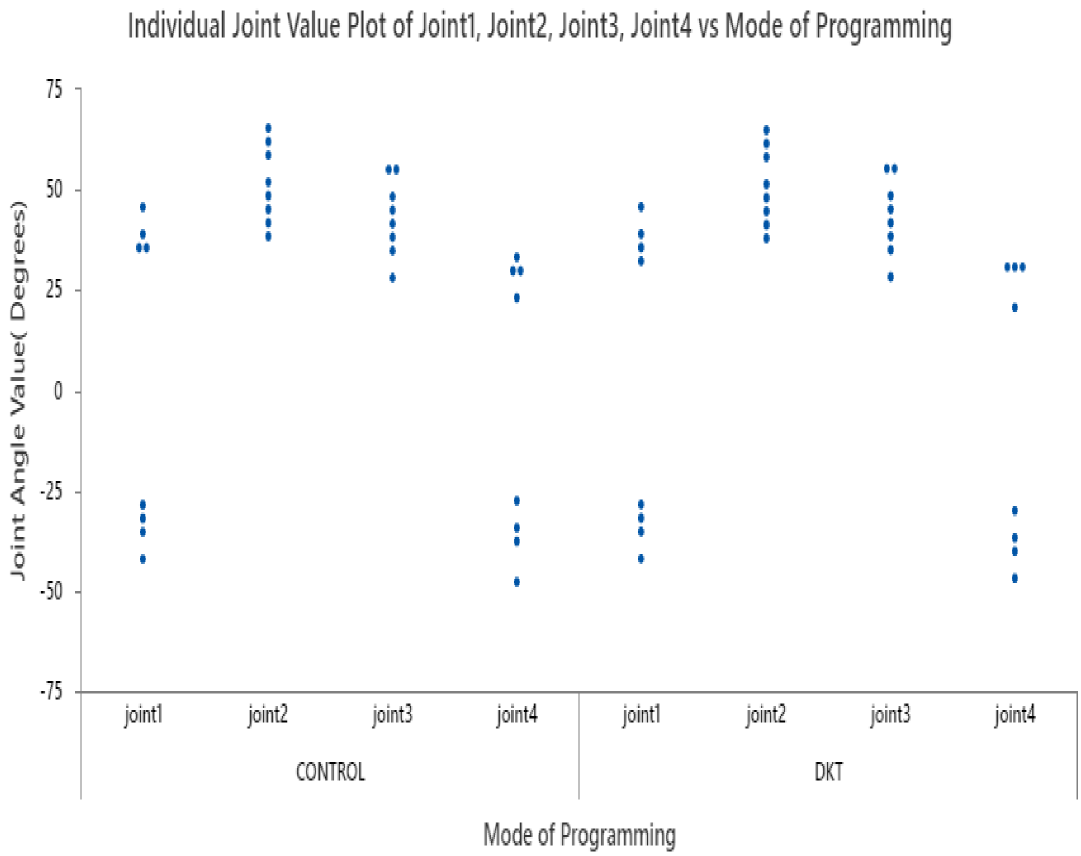

Figure 4-1: Individual Joint Angle Values Plot

Similarly, a plot of the individual joint angle values was as shown in Figure 4-2.

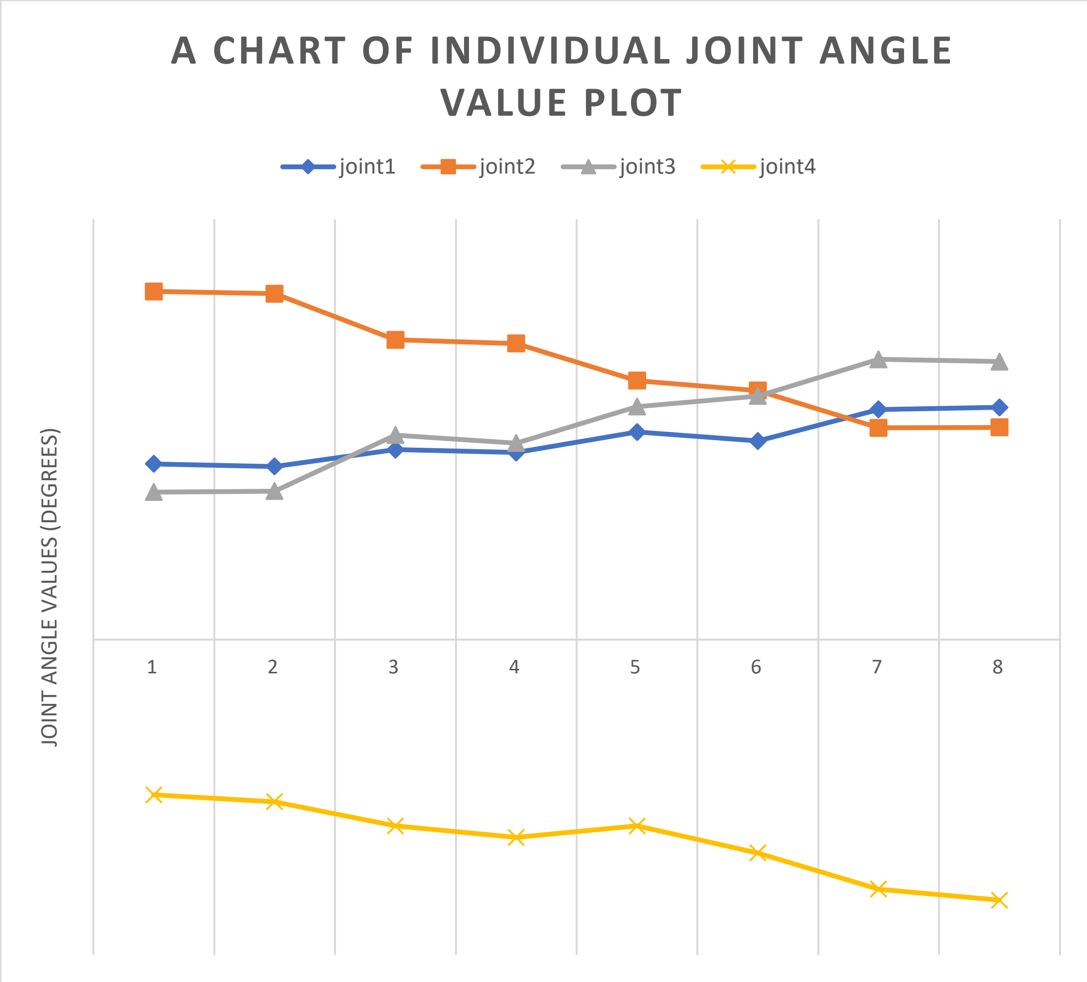

Figure 4-2: A Chart of Individual Joint Angle Value Plot

From Figure 4-1 and Figure 4-2, it was evident that the joint angle values for joint1 and joint 4 varied from positive and negative values for both DKT and Control as it related to the point of the item to picked or the point of placing the wooden box. The joint 1 angle values were in the positive values for the pick position and negative values. This was attributed to the fact the pick and place points were at the extreme coordinates of its joint configuration limits of $+135^0$ and -135^0 (Shenzhen Yuejiang Technology Co., 2017). The joint 4 angle values were mainly negative when the end-effector was on the lowering motion for the pick and place tasks as the wooden box was below its co-ordinate origin. The positive values were attributed to its raised position especially these were clearance heights for the arm to avoid dragging the wooden box along the floor. The joint 2 and joint 3 angle values were all positive values for both DKT and Control. The joint 2 has a range of axis movement from 0^0 to $+85^0$ (Shenzhen Yuejiang Technology Co., 2017) thus no chance of negative values. Whilst joint 3 has joint range of arm movement of -10^0 to $+95^0$ (Shenzhen Yuejiang Technology Co., 2017), for this particular tasks the arm was able to operate in the positive values only. The joint angle values can be obtained similarly to the structured-texts method of robotic arm programming using the DKT technique.

4.1.2 Surface Plots for Joints 1, 2, 3 in Relation to Joint 4

The interaction of joint4, being the joint primarily encompassing the final end-effector with other joints, was as shown by 3D surface plots in Figure 4-3, Figure 4-4, and Figure 4-5.

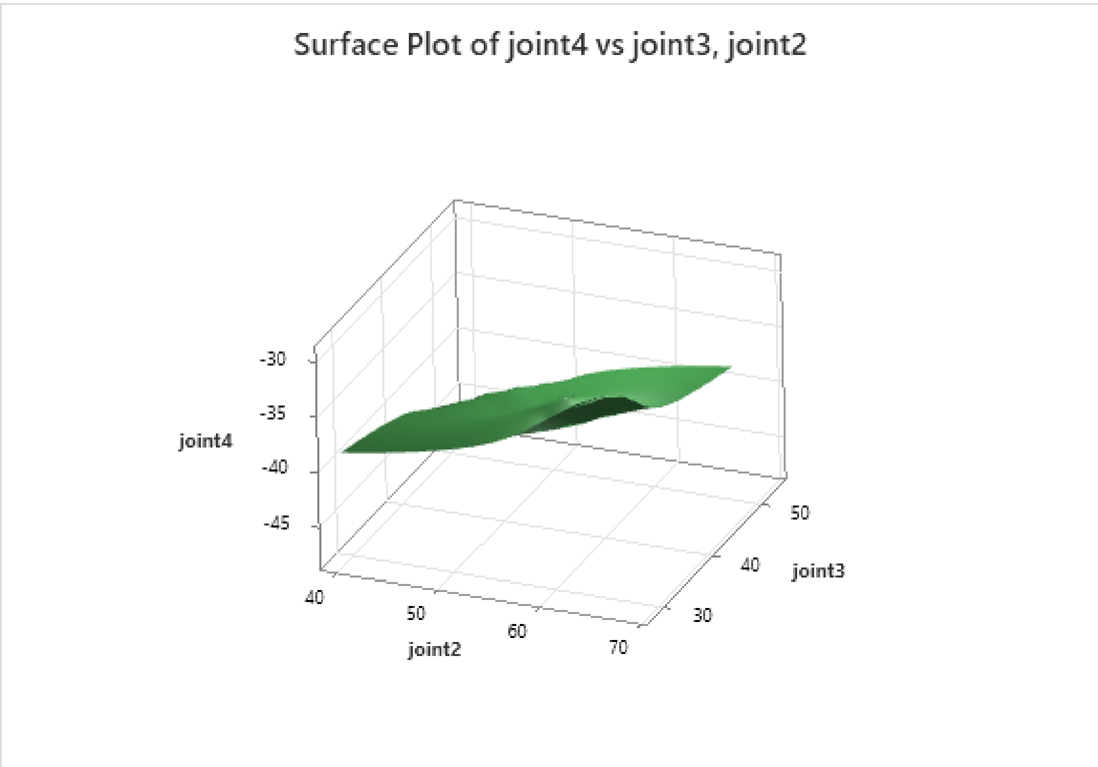

Figure 4-3: 3D Surface Plot of Joint 4 vs Joint 3, Joint 2

Figure 4-3 shows the 3D surface plot of the interaction between joint 4 against joint 3 and joint2. The joint 4 was the reference for checking the interaction with joints 2 and 3 as it was primarily involved in the placement of the end-effector in the final position.

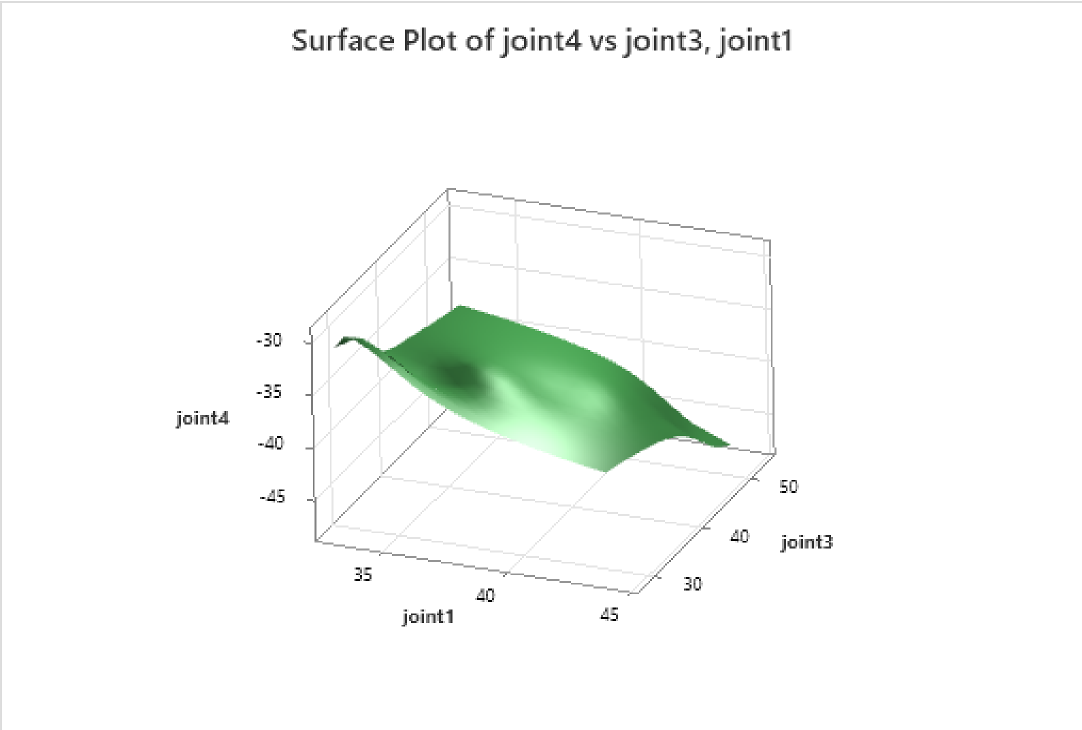

Figure 4-4: 3D Surface Plot of Joint 4 vs Joint 3, Joint1

Figure 4-4 shows the 3D surface plot of the interaction between joint 4 against joint 3 and joint 1. The surface showed a low joint angle value with reference to joint 4 since it was the base and since the robotic manipulator was majorly stationary at this joint, the values did not vary widely. The joint 3 values respond to those of joint 4 since the joint provides the position of arm to accurately reach the expected position.

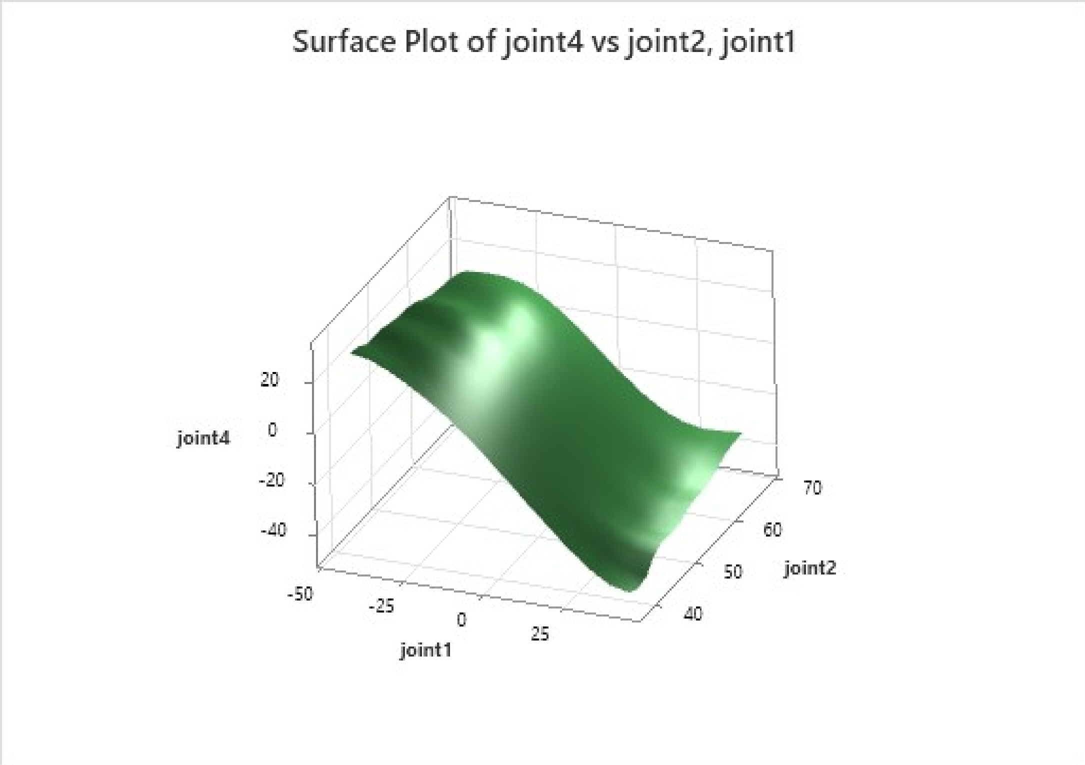

Figure 4-5: 3D Surface Plot of joint 4 vs joint 2, joint 1

Figure 4-5 shows the 3D surface plot of the interaction between joint4 against joint2 and joint1. Joint 2 values vary between the extreme positions of the initial and final positions of the end-effector for the validation tasks. The negative and positive joint 4 angle values were attributed to the reference from the common datum with negative to lowering of the end-effector while positive for the raising of the arm.

From Figure 4-3 to Figure 4-5, the results indicated that each of the joints 1,2,3, affected the final position of joint 4 and thus the actual positioning robot's arm in joint and cartesian configurations.

4.1.3 Joint Angle Values Descriptive Statistics

Descriptive statistics, especially mean, were the most sought-after to establish the relationship between the overall joint angle value means for the DKT and Control programming methods. Joint angle values descriptive statistics were also calculated and tabulated as shown in Table 4-2.

Table 4-2: Joint Angle Values Descriptive Statistics

Variable	Mode	Mean	SE Mean	StDev	Minimum	Median	Maximum
joint1	Control	1.7	13.9	39.3	-42.1	1.8	43.8
	DKT	1.5	13.9	39.3	-42.0	1.7	43.6
joint2	Control	51.25	3.47	9.83	38.38	50.81	66.26
	DKT	51.01	3.54	10.02	37.88	50.49	65.84
joint3	Control	42.71	3.32	9.40	28.06	42.79	54.84
	DKT	42.55	3.38	9.57	28.25	42.21	55.33
joint4	Control	-5.3	12.6	35.7	-47.8	-3.6	31.6
	DKT	-5.7	12.7	35.9	-46.8	-4.7	31.0

From Table 4-2, the joint angle value means for joint 1 was 1.45641 degrees for DKT and 1.65612 degrees for the Control. Joint 2 had means of 51.0095 degree for DKT and 51.2452 degrees for Control. Joint angle value means of 42.5454 degrees for DKT and 42.7061 degrees for Control were also determined for joint 3. Finally joint 4 had joint angle value means of -5.31689 degrees for Control and -5.71321 degrees for DKT. The distribution of the joint angle values was represented by histograms as shown in Figure 4-6.

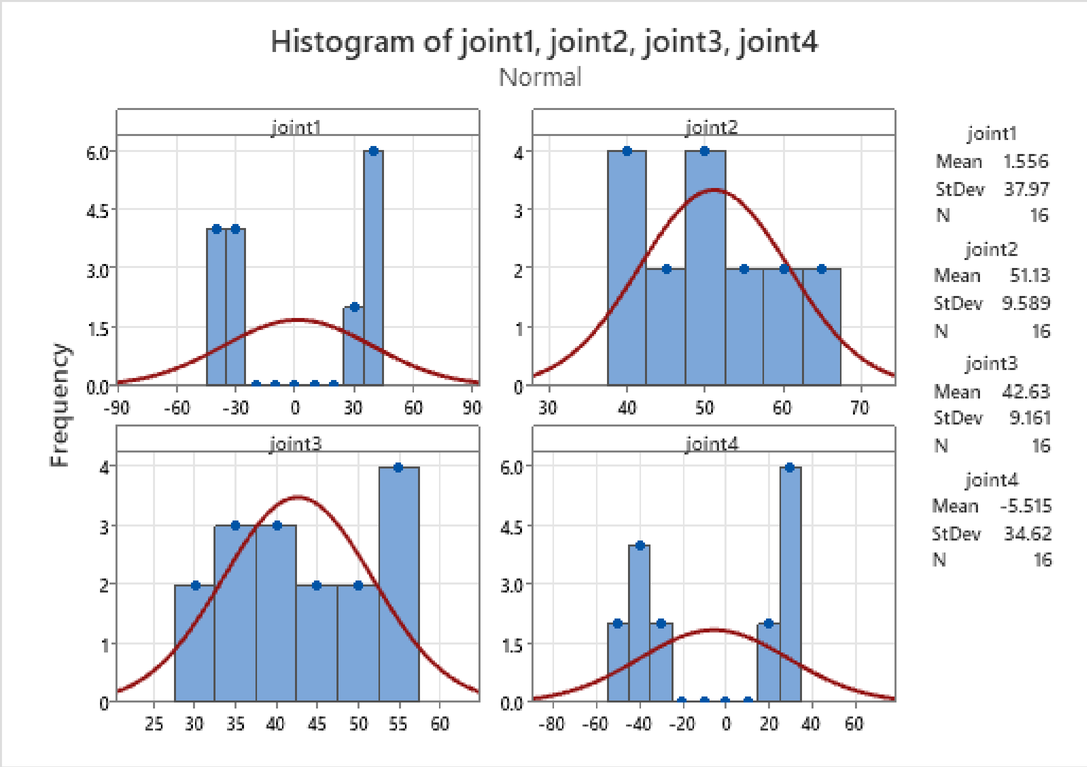

Figure 4-6: Histogram of Joint 1, 2, 3 and 4 Angle values

From Figure 4-6, the joint 1 and 4 angle values showed a unimodal distribution with a bell curve of the angle values obtained using the DKT and Control. The joint 2 angle values were rather symmetric in the distribution same as those of joint 3 angle values. The joint values obtained using the Control and DKT technique showed that it is possible to get the joint angle values as such with other geometric solutions and algebraic solutions; thus, the inverse kinematic solutions were determined.

4.1.4 Inverse Kinematics Hypothesis Test

The hypothesis was tested via the ANOVA test on each joint. An analysis of the inverse kinematics obtained using the two methods for an ANOVA test was carried out in Excel for each joint with a 95% confidence level and a significance level of $\alpha = 0.05$. The null hypothesis was that the mean coordinate configuration for DKT and structured texts (Control) was the same while the alternative hypothesis was that the inverse kinematics were different for both DKT and Control. The results of the ANOVA test on each joint angle values were as shown in Table 4-3, to Table 4-6

Table 4-3: ANOVA Test on Joint 1

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
CONTROL	4	152.89	38.22	20.03
DKT	4	150.56	37.64	23.02

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.68	1	0.68	0.03	0.86	5.99
Within Groups	129.17	6	21.53			
Total	129.85	7				

Table 4-4: ANOVA Test on Joint 2

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
CONTROL	4	212.88	53.22	122.45
DKT	4	209.94	52.48	121.98

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.08	1	1.08	0.01	0.93	5.99
Within Groups	733.28	6	122.21			
Total	734.36	7				

Table 4-5: ANOVA Test on Joint 3

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
CONTROL	4	177.03	44.26	88.40
DKT	4	173.43	43.36	86.18

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.61	1	1.61	0.02	0.90	5.99
Within Groups	523.74	6	87.29			
Total	525.35	7				

Table 4-6: ANOVA Test on Joint 4

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
CONTROL	4	-147.92	-36.98	56.87
DKT	4	-158.73	-39.68	60.37

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	14.59	1	14.59	0.25	0.64	5.99
Within Groups	351.73	6	58.62			
Total	366.32	7				

From Table 4-3 to Table 4-6, at $\alpha = 0.05$, it was determined that there were no significant statistical differences between the two methods as evidenced by the less joints' 1, 2, 3, and 4 , F values of 0.03, 0.01, 0.02 and 0.25 respectively against F_{crit}

value of 5.99. The *P*-values of 0.86, 0.93, 0.90, and 0.64 for joints 1, 2, 3, and 4 were higher than the significance level of $\alpha = 0.05$, failing to reject the null hypothesis.

4.2 Determination of the Accuracy of Desired Position

4.2.1 Scatterplots of Joint Angle Values

The accuracy of the target position was determined using the contour welding and palletising tasks. End effector positions were determined using structured-texts (Control) and DKT technique for the joint configurations. A comparison of the joint values for the structured text (Control) with the DKT was as shown in Figure 4-7, to Figure 4-10.

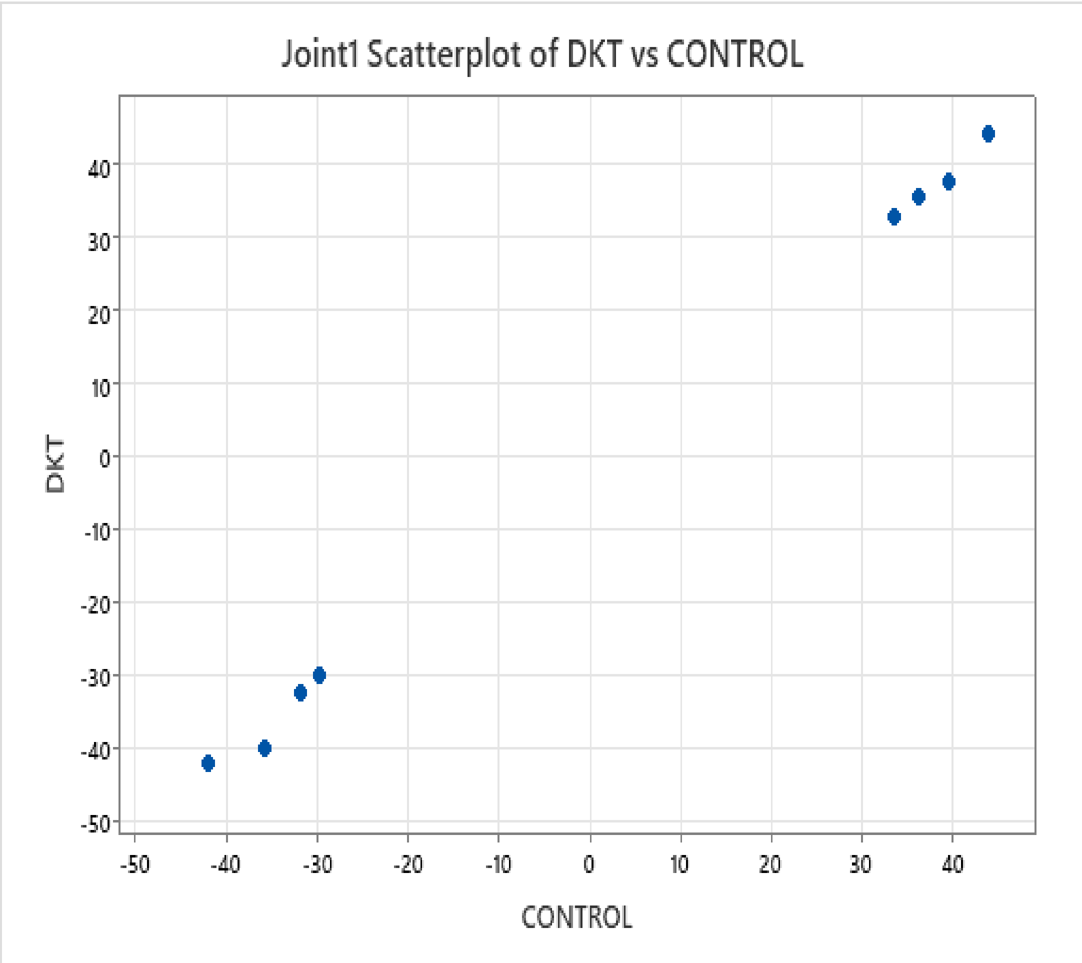

Figure 4-7: A Scatterplot of Joint 1 Values DKT against Control

From Figure 4-7, it was observed that there was a positive correlation between the joint values from the DKT and those from the Control mode of programming. The positive values indicated the pick point A, especially for the palletising application. In contrast, the negative values indicated place point B, which was anti-clockwise and had directions from the origin. This was in line with the joint 1 range of axis movement from -135^0 to $+135^0$ (Shenzhen Yuejiang Technology Co., 2017).

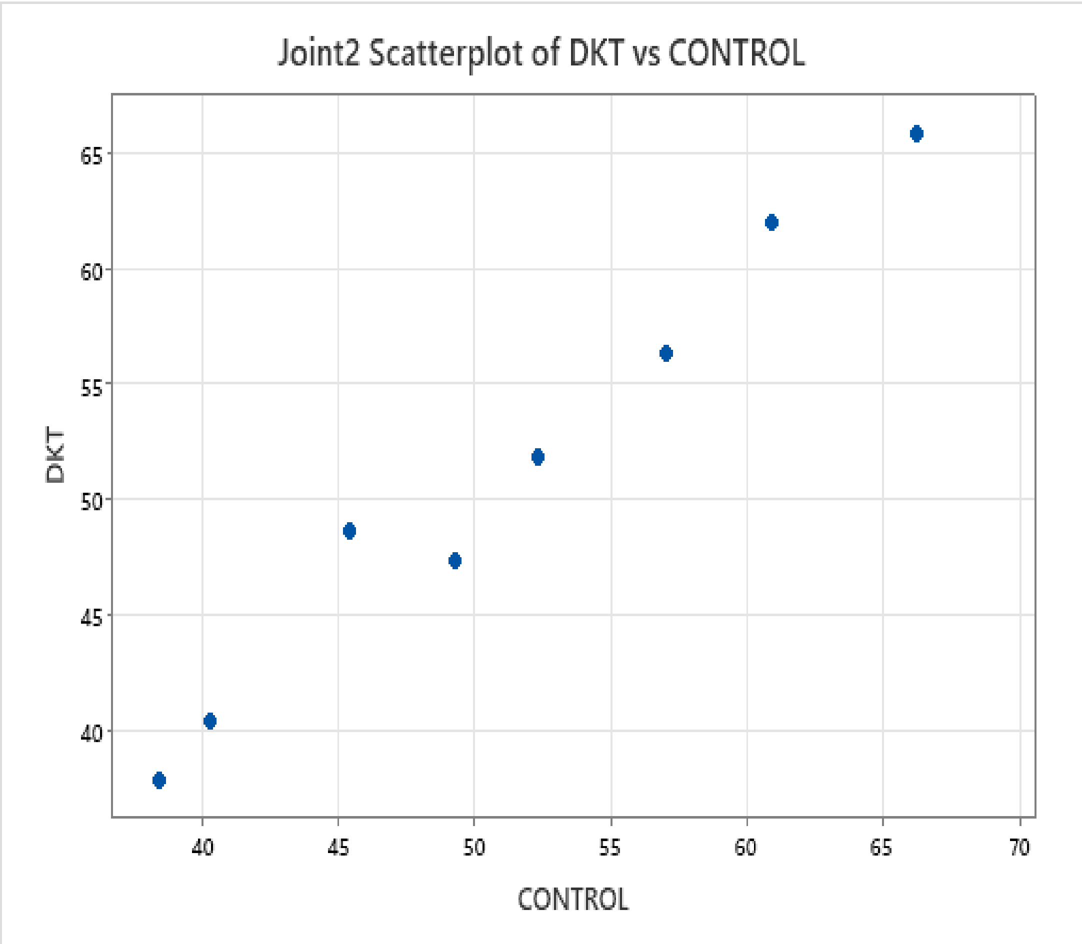

Figure 4-8: A Scatterplot of Joint 2 Values for DKT against Control

From Figure 4-8, it was observed that there was a positive correlation between the joint values from the DKT and those from the Control mode of programming. The positions of points A and B had no negative joint values. The joint values were all positive owing to joint 2's operational range of axis movement from 0^0 to $+85^0$ (Shenzhen Yuejiang Technology Co., 2017).

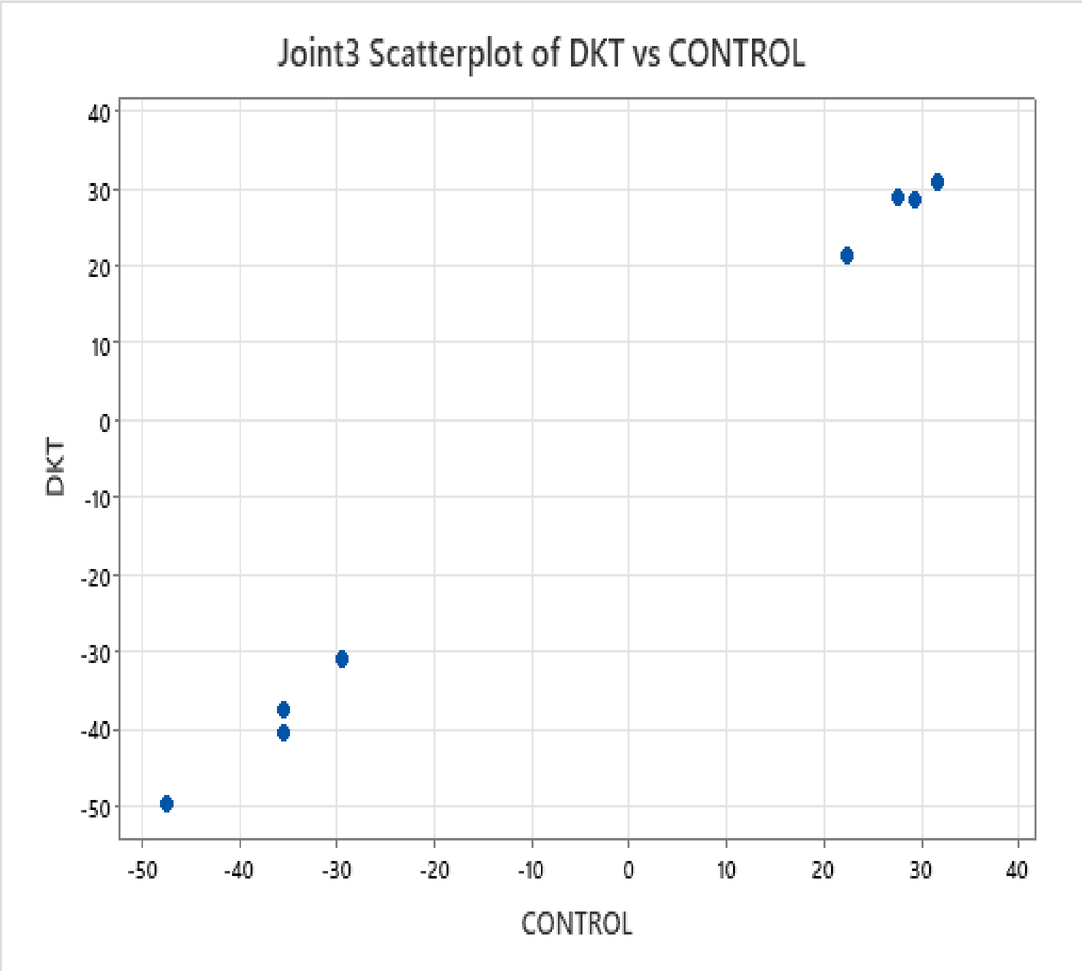

Figure 4-9: A Scatterplot of Joint 3 Values for DKT against Control

From Figure 4-9, it was observed that there was a positive correlation between the joint values from the DKT and those from the Control mode of programming. The joint values were a mixture of positive and negative values owing to the joint range of arm movement of -10^0 to $+95^0$ (Shenzhen Yuejiang Technology Co., 2017).

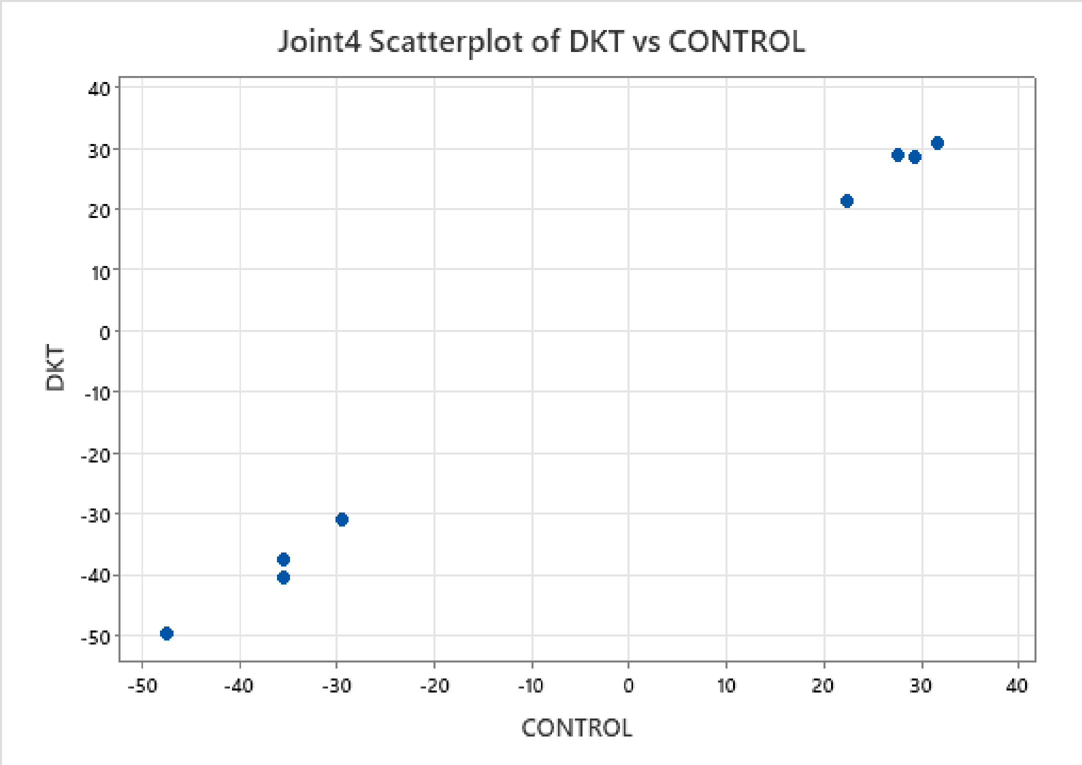

Figure 4-10: A Scatterplot of Joint 4 Values for Control and DKT

From Figure 4-10, it was observed that there was a positive correlation between the joint values from the DKT and those from the Control mode of programming. The joint 4 values had both negative and positive values. This was seen in the orientating of the pneumatic gripper in a bid to maintain exact orientation of the item picked at point A (positive values) to place point B (negative values). Joint 4 has an operational range of arm movement of -90^0 to $+90^0$ (Shenzhen Yuejiang Technology Co., 2017).

Joint Angle Values Percentage Error

The joint angle values' absolute and percentage errors were calculated using equation(4-2) and (4-3).

$$Absolute\ Error = Control - DKT \qquad \text{(Frost)} \qquad (4\text{-}2)$$

$$Percentage\ Error = \frac{Absolute\ Error}{Control} * 100\% \qquad (4\text{-}3)$$

The percentage errors of the joints for the various points of the end-effector were as plotted in Figure 4-11, and overall joint mean percentage errors as shown in Table 4-7.

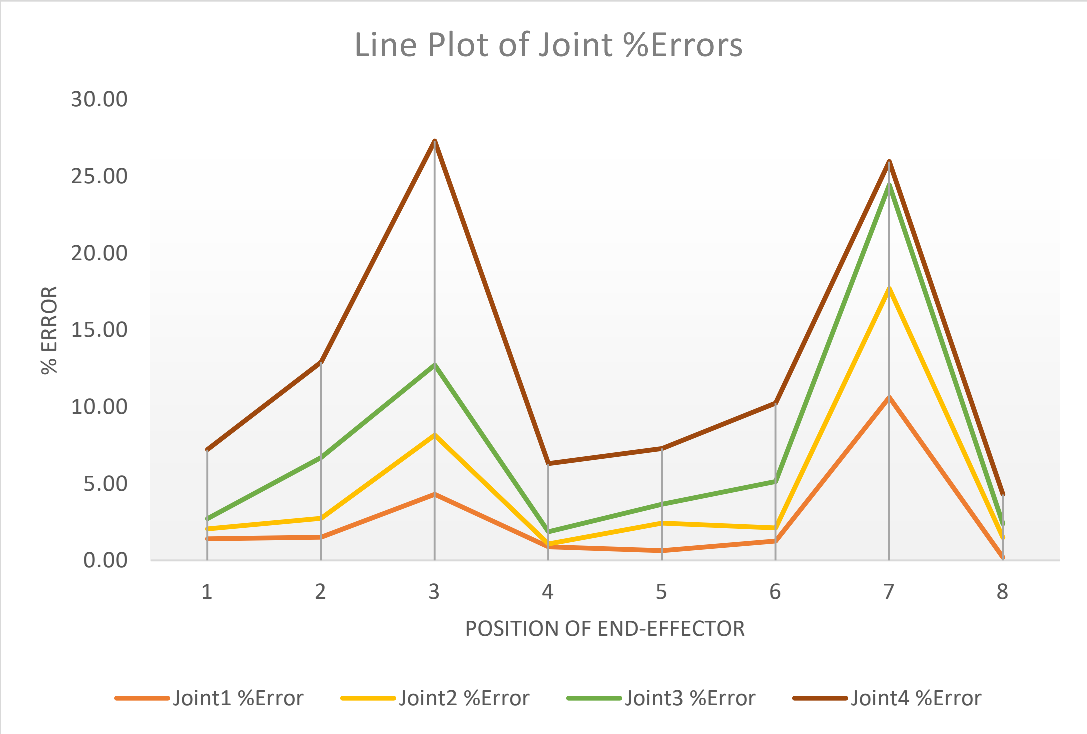

Figure 4-11: Joint Angle Values Percentage Errors

Table 4-7: Joint Angle Values Mean Percentage Errors

Joint1	**Joint2**	**Joint3**	**Joint4**
2.60	2.12	2.73	5.24

From Figure 4-11 and Table 4-7, it was determined that joint 4 had the highest mean percentage error of 5.24%, while joint 2 had the lowest mean percentage error of 2.12%. The low mean percentage error on the joint was due to the possible least number of sources of inaccuracies in comparison to the high value on joint 4, which may have been contributed by user-related inaccuracies, especially in placing the end-effector in the desired position demonstratively, computational errors, computer-control algorithms (rounding off errors in a computer) and, link bending due to gravity and loads.

From the palletising task, in this case, pick and place, the robotic arm could pick the wooden box from the start positions of A and place it at place position B as required, as shown in Plate 3-11 and Plate 3-12 as Pick and place points A and B were chosen using the Control program, which provided the basis for determining accuracy.

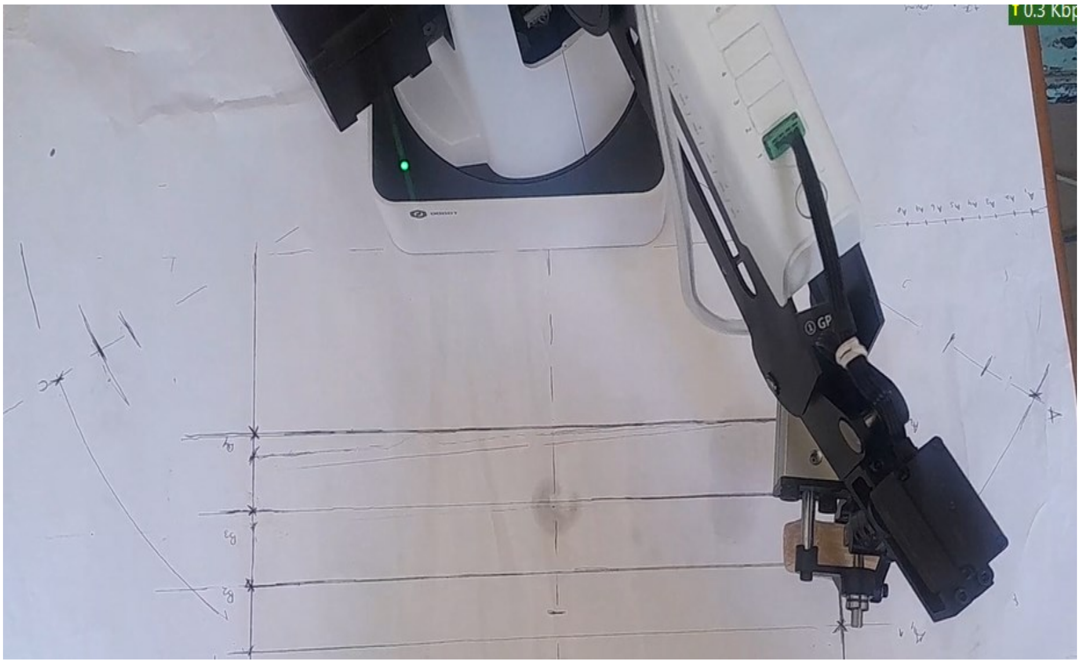

Plate 4-1: Photograph of Dobot Magician Performing the Palletizing Task from Pick Point

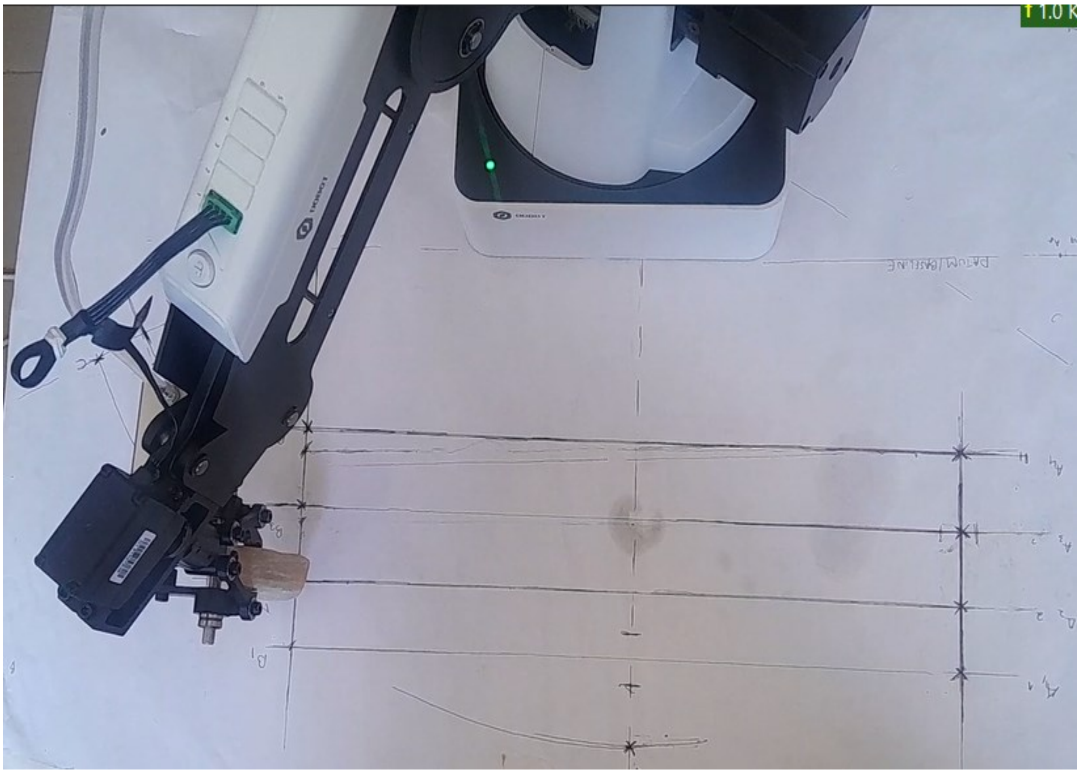

Plate 4-2: Photograph of Dobot Magician Performing the Palletizing Task at Place point

With respect to the contour welding path, the robotic arm was able to retrace the paths with the joint values at the various points A, B, and E, which were noted using the DKT and Control program. The varying radii did not influence the robotic arm's ability to follow the contour arcs so long as the contours were within the workspace envelope. The contour path welding task was shown in Plate 4-3.

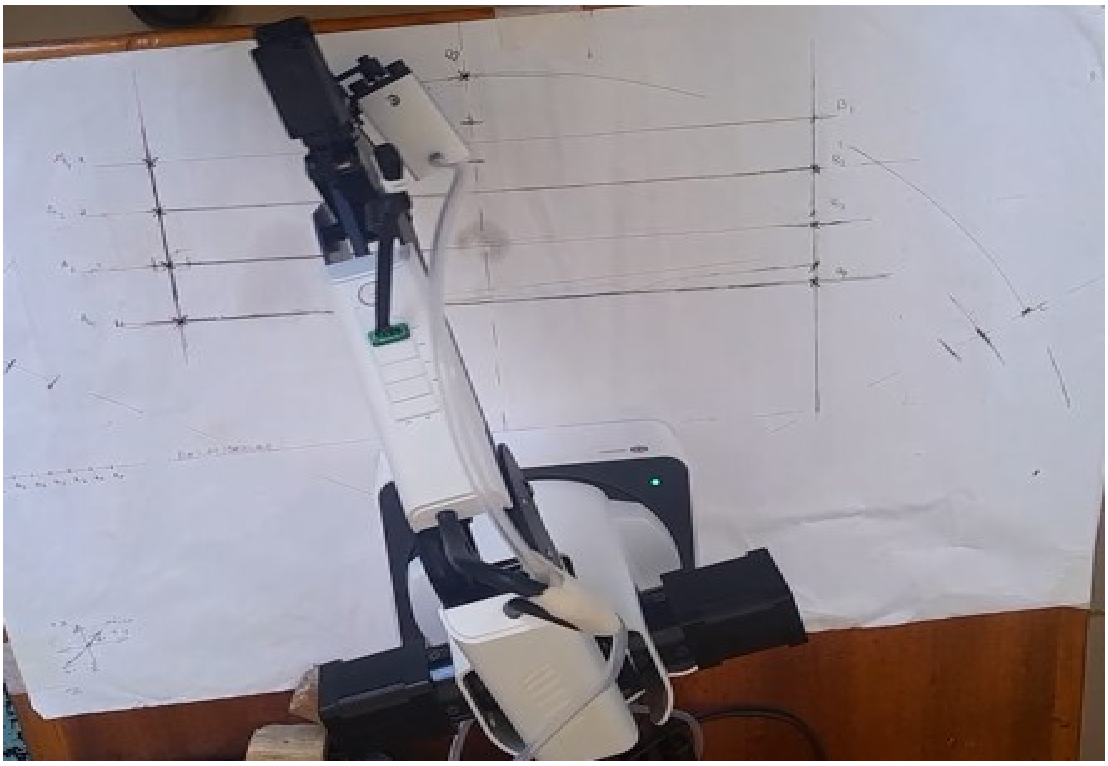

Plate 4-3: Photograph of Dobot Magician Carrying out Contour Welding Path

Any contour paths outside the safe workspaces of the robotic arm were not carried out as the alarm indicator would immediately be lit, thereby halting any operation till the alarms were cleared. It is not strange to this fact as contours outside the robotic arm limits would not be possible owing to the manufacturer's settings regarding safe manipulator operation mechanical limitations to the joint movements.

4.2.2 Accuracy of Desired Position Hypothesis Test

A hypothesis was tested to determine the desired position's accuracy. The null hypothesis in this case: mean accuracy of the desired position of the DKT was the same as that of structured texts (Control) while the alternative hypothesis was that the mean accuracy of desired position was different between DKT and Control. An ANOVA test at 95% confidence level and significance level of $\alpha = 0.05$. The results of the ANOVA test on each were as shown in Table 4-8, to Table 4-11.

Table 4-8: ANOVA Test on Joint 1

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
CONTROL	4	152.89	38.22	20.03
DKT	4	150.56	37.64	23.02

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.68	1	0.68	0.03	0.86	5.99
Within Groups	129.17	6	21.53			
Total	129.85	7				

Table 4-9: ANOVA Test on Joint 2

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
CONTROL	4	212.88	53.22	122.45
DKT	4	209.94	52.48	121.98

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.08	1	1.08	0.01	0.93	5.99
Within Groups	733.28	6	122.21			
Total	734.36	7				

Table 4-10: ANOVA Test on Joint 3

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
CONTROL	4	177.03	44.26	88.40
DKT	4	173.43	43.36	86.18

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.61	1	1.61	0.02	0.90	5.99
Within Groups	523.74	6	87.29			
Total	525.35	7				

Table 4-11: ANOVA Test on Joint 4

Anova: Single Factor

SUMMARY

Groups	Count	Sum	Average	Variance
CONTROL	4	-147.92	-36.98	56.87
DKT	4	-158.73	-39.68	60.37

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	14.59	1	14.59	0.25	0.64	5.99
Within Groups	351.73	6	58.62			
Total	366.32	7				

From Table 4-8 to Table 4-11, it was determined that there were no significant statistical differences between the two methods getting an accurate position of end-effector in a workspace as evidenced by the less joints' 1, 2, 3, and 4 , F values of 0.03, 0.01, 0.02 and 0.25 respectively against F_{crit} value of 5.99. The P-values of 0.86, 0.93, 0.90, and 0.64 for joints 1, 2, 3, and 4 were higher than the significance level of $\alpha = 0.05$, failing to reject the null hypothesis.

The small percentage of errors indicated a high level of accuracy of the DKT technique. Hence, it can be used to carry out robot programming for tasks requiring a high accuracy level.

4.3 Determination of the Efficiency of the DKT Technique

4.3.1 Time Durations for Tasks

The time durations of the experiment and robot reactions were recorded using the stopwatches and time monitor embed in the code of the control platform to display respectively. The recorded times were as shown in Table 4-12.

Table 4-12: Time Durations for Tasks (Palletizing)

Serial	Activity	DKT	Control
1	Robot Reaction Time (average)	3 seconds	3 seconds
2	Experimental Time (average)	3 mins59s (approx)	5 mins 01s (approx)

For the palletising application, time required for experimenting was an average time of approximately 3 minutes and 59 seconds for DKT whereas approximately 5minutes and 01 second for the Control as shown in Table 4-12. The experiment was carried out for various experimental trials and a graph of the same was as shown in Figure 4-12.

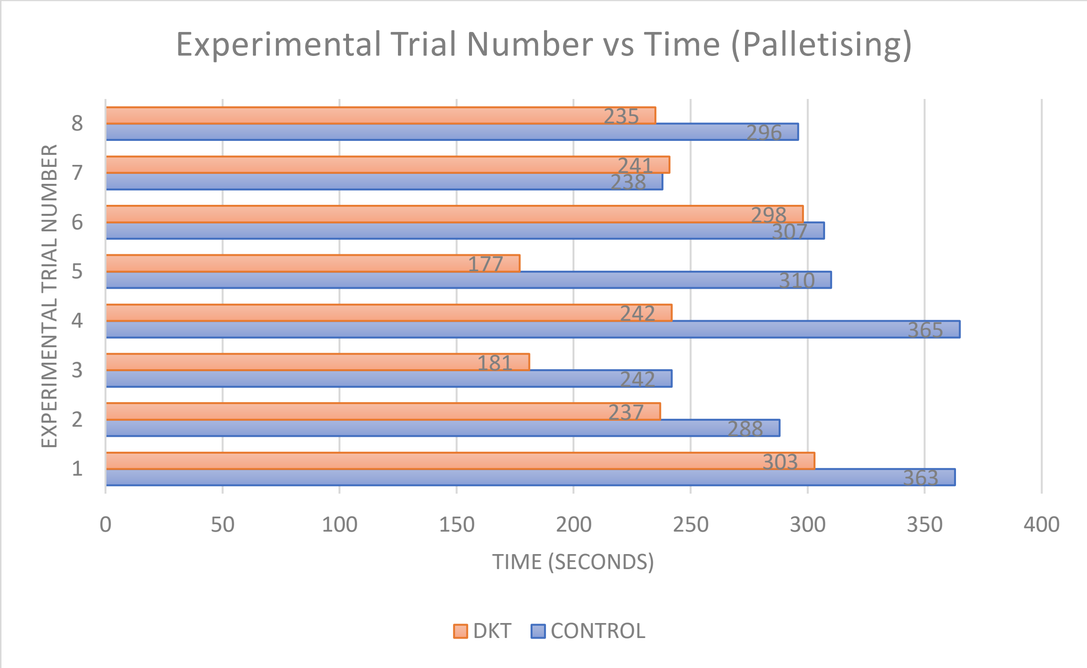

Figure 4-12: Palletizing Experimental Time

For the contour path welding application, the time required for carrying out the experiment was an average time of approximately 30 for DKT whereas approximately 45 for the Control as shown in Table 4-13, and the experimental time was as shown in Figure 4-13 for the two programming modes.

Table 4-13: Time Durations for Tasks (Contour Welding Path)

Serial	**Activity**	**DKT**	**Control**
1	Robot Reaction Time (average)	1s	2s
2	Experimental Time (average)	30s	45s

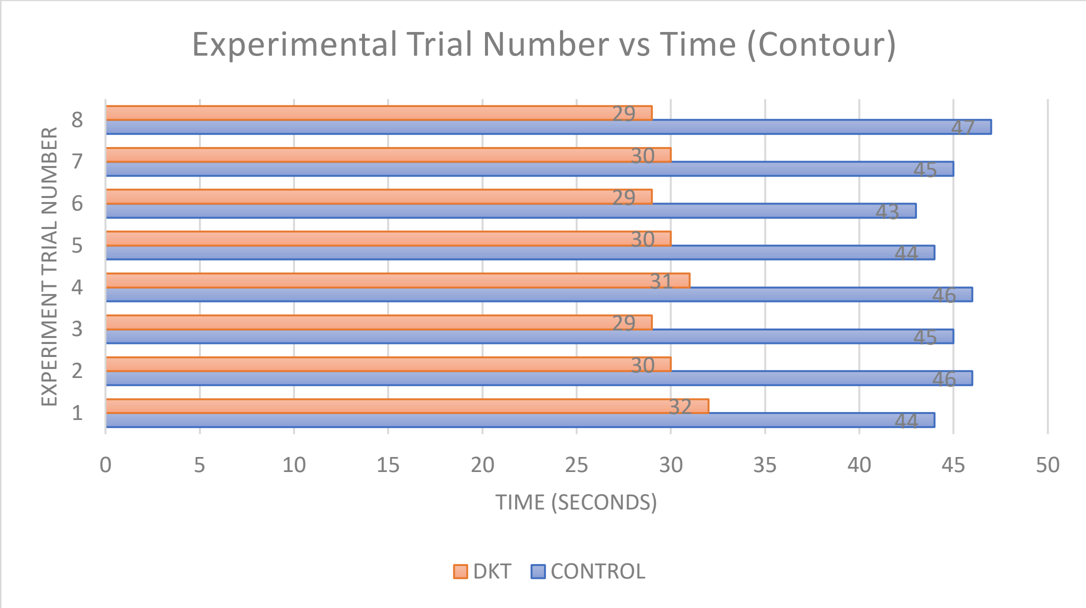

Figure 4-13: Contour Path Welding Experimental Time

From Table 4-13, the robot programming time of the contour path welding was lower than that of the palletising task, as the activity's complexity was lower. In this experiment, the robotic arm was only programmed to follow the contour path, reducing the time. The structured-texts approach required rechecking every code to determine whether the correct positions were entered for A, B, and E on all the arcs in the codes. There was no need for gripper function implementation in the code as the trajectory was only a matter of concern; hence, it took a shorter time than the palletising task.

The robot reaction time was also reduced during this task as the number of steps in the code were significantly reduced compared to the palletising code, which had functional code lines that required more processing time. However, the DKT method had the least time of 1 second compared to the 2 seconds of the text-based control, as the trajectory was stored in the robot's memory while being programmed. The text-based code required the robot's keen understanding of every line and the motion to be executed to reach the desired point, hence a longer reaction time.

The reduced complex nature of the contour path welding also meant reduced experimental times, hence the 30 seconds for the DKT technique and 45 seconds for the text-based control on average. The 15 seconds longer by the text-based control was attributed to the fact that the robot had to go through each of the lines of codes stepwise while executing the code as compared to the DKT technique, in which the robotic arm had already stored the motion and trajectory in its memory. From Table 4-12, it was seen that the reaction time of the robotic arm for both methods was the same, 3 seconds. This resulted from both methods relying on the execution of codes to connect to the robotic arm run by the same system. The DKT platform was executed on the Python code to control it, the same as the control code in Python for the text-based programming approach.

The programming time involved for both methods has differed sharply as it took 2 months and 1 week to code the Control code for the pick and place. This was for a more extended period compared to the DKT technique as an accurate code performance was required, hence writing and rechecking the code at every step of the code. The target points and the trajectory needed had to be considered to determine the kind of robotic motion required, whether MOVL, MOVJ, or JUMP, for the correct movement to the set coordinates.

While the DKT technique took only 2 days to program the robot, a huge chunk of the time was used to ensure the gripper performed as wanted, as it still required coding aspects for the opening and closing of the arms. Getting the right amount of time needed for the gripper hydraulics to pressurise for efficient functioning was highly considered. The actual demonstrative aspect only helped the robot to identify the positions of the pick points using the release and locking of the lock arm and the trajectory to be taken.

The experimental times for the two methods were vastly different (1 minute) as the DKT technique had only the execution of the gripper closing and opening commands to be read by the robotic arm. The 3 minutes 59s were due to the fact, at the same time, the user had to ensure the robot arm position was accurate at the desired positions; gripper's functioning still needed a lapse duration for full hydraulic pressurisation, thus opening and closing its arms. The text-based program also required the same time for the gripper function to be put in its code, but the careful approach to target positions meant more lines of code in steps before the robotic arm could reach the intended target points. The robotic arm had to execute each line by line of the code, taking more time to experiment.

From Table 4-12 and Table 4-13, it can be said that the DKT technique is more efficient than the text-based Control programming approach owing to the less time taken to execute the experiments. The text-based programming approach was quite cumbersome and tedious compared to the DKT, which, on the other hand, was more manageable, hence the less time, only 2 days for palletising and 3 hours for contour path welding programming. The experimental times also showed how, on average, it was more efficient to use the DKT technique than text-based programming, with 1 minute less for palletising and 15 seconds less for contour path welding experiments, respectively.

4.3.2 Calculations of Efficiency of DKT with Respect to Structured Texts

The efficiency of the robotic arm was calculated using equation (4-4) with the control being used as a baseline for calculations.

$$Efficiency = \frac{Output}{Input} \times 100\%$$ (Toppr, 2021)

(4-4)

$$Efficiency = \frac{Average\ \ Experimental\ Time\ (\ DKT)}{Average\ Experimental\ Time\ (Control)} \times 100$$

For palletising: $\frac{4}{5} \times 100\%$

=80%

For Contour Path Welding: $\frac{30}{45} \times 100\%$

=66.67%

4.3.3 Hypothesis Test on Efficiency of DKT

A test on the null hypothesis for an ANOVA test at a 95% confidence level and significance level of α = 0.05 was carried out on the two experimental applications. The null hypothesis was that DKT had the same efficiency as the structured texts (Control). The results of the ANOVA were shown in Table 4-14 ,Table 4-15.

Table 4-14: Palletizing ANOVA Test

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
CONTROL	8	40	5	0.57
DKT	8	32	4	0.57

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4	1	4	7	0.02	4.60
Within Groups	8	14	0.57			
Total	12	15				

Table 4-15: Contour Path Welding ANOVA Test

Anova: Single Factor

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Control	8	360	45	1.71

DKT	8	240	30	1.14

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	900	1	900	630	4.85E-13	4.60
Within Groups	20	14	1.43			
Total	920	15				

From Table 4-14 and Table 4-15, the *P*-values of 0.02 and 4.85E-13 for the palletising and contour path welding experiments, respectively, were below the significance level of $\alpha = 0.05$ and were inconsistent with the null, and thus favouring to alternative hypothesis, the null hypothesis was rejected.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5. Conclusions And Recommendation

The study was designed to analyse the use of the DKT technique in robot manipulators to handle industrial materials efficiently. Experiments involving palletising and contour path welding were conducted to test the validity of the methods. The results were analysed and discussed; the conclusions were drawn based on the set objectives and discussed

5.1 Conclusions

The results from the experiment designed around the determination of the inverse kinematics indicated the lack of significant statistical differences between the joint values obtained using the DKT technique and the Control method, which was anchored upon structural-text programming of the robotic arm. This was evidenced by the failure to reject the null hypothesis at a 95% confidence level with *P*-values of 0.86, 0.93, 0.90, and 0.64 for joints1, 2, 3, and 4, respectively, which were higher than the significance level of $\alpha = 0.05$. The joint values obtained were in concurrence with analytical calculations of the same joint values using the known equations concerning inverse kinematics determinations analytically.

The robotic arm was programmed to carry out tasks to validate the use of the DKT technique, which included the palletising task and the contour path welding. The robotic arm could pick items at set pick points and move them to the place points, and the points' accuracy level was determined. It was determined that joint 4 had the highest mean percentage error of 5.24% while joint 2 had the lowest mean percentage error of 2.12%. The significant percentage error in joint 4 was attributed to the user's accuracy level while selecting the target points using the robotic arm, which may have contributed to the value. A hypothesis test on the mean accuracy of the desired position at a 95% confidence level led to the failure to reject the null hypothesis as the *P*-values of 0.86, 0.93, 0.90, and 0.64 for joints1, 2, 3, and 4, respectively were higher than the significance level of $\alpha = 0.05$.

Evaluation of DKT technique efficiency was carried using programming time spent, the average robot reaction time, and the average robot experimental time. It was observed that robot programming time using the structural texts was longer than that using the DKT technique, hence proving the need to embrace the DKT, especially in high manufacturing processes that meet consumer demands. The DKT had an 80% efficiency for the palletising tasks and 66.67% for the contour path welding, thus showing the high reliability of the method as a means of robot programming.

It can be concluded that compared to the structured text of robot programming, DKT proved to be better for programming, especially for workforces that are not proficient in programming languages. While the method is more straightforward and quite going for some tasks, it may prove futile, especially where the geometry of items is rather complex. The materials to be handled are hazardous, thus requiring distance between the material and the demonstrator. Other methods, such as TKT, teach-pendant, and text-based, may be more helpful in handling such operations.

5.2 Recommendations and Scope for Future Works

5.2.1 Recommendation

It was recommended the use of DKT especially for simpler geometry objects whilst applying in the palletizing application. For the contour path welding paths ought to be within the arms work envelope.

5.2.2 Scope for Future Works

1. The inclusion of learning algorithms in the DKT control program to adapt to sudden environmental changes.
2. Blending wearable devices with the DKT, especially in hazardous environments.
3. Establishment of a universal control program for the DKT, as the current program was vendor-specific.

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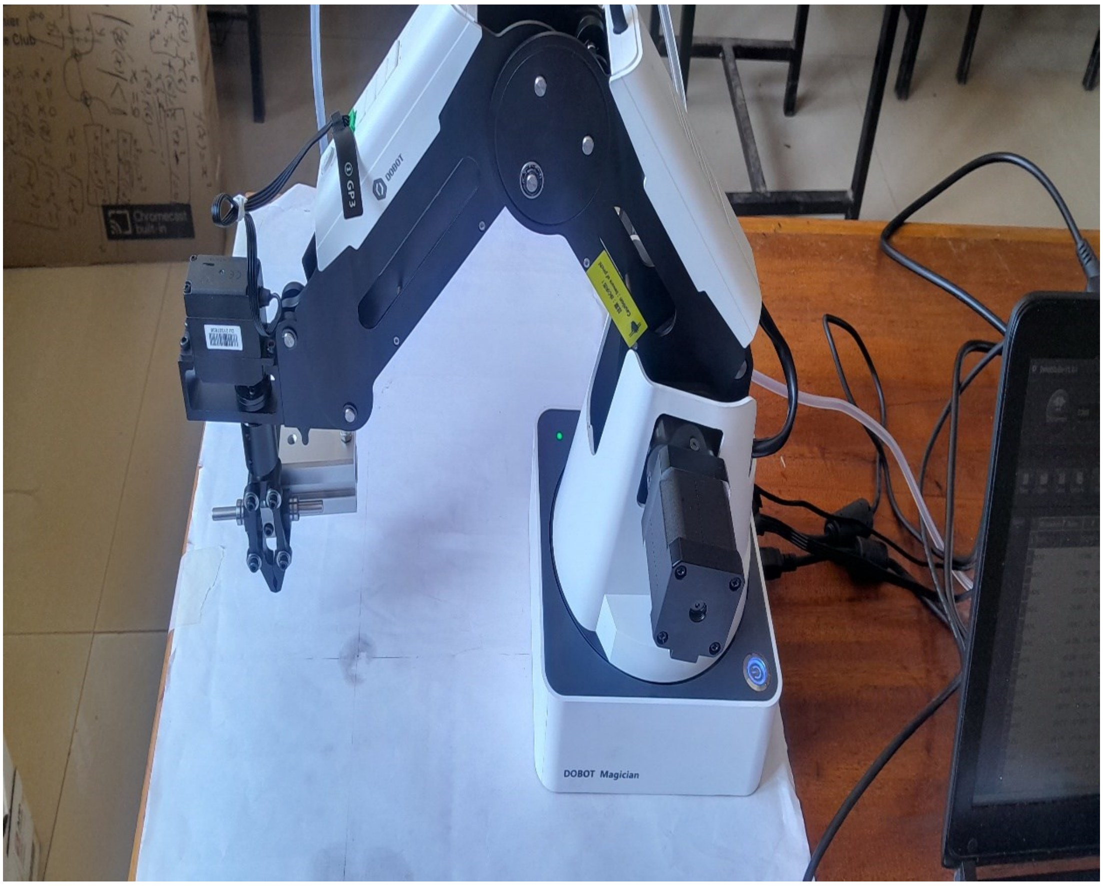
Appendices

Appendix 1: Dobot Magician



Appendix 2: Control Platform Code

```
# importing the dll files and other relevant imports
import DobotDllType as dType
import time  # for sleeping
# Load Dll and get the CDLL object
# Load the dobot magician dll to allow it to be used
api = dType.load()
# error terms
CON_STR = {
    dType.DobotConnect.DobotConnect_NoError: "DobotConnect_NoError",
    dType.DobotConnect.DobotConnect_NotFound: "DobotConnect_NotFound",
    dType.DobotConnect.DobotConnect_Occupied: "DobotConnect_Occupied",
}
# Verbose mode
setTCP = True  # if this bool is set to True then the Tool Center Point for the dobot magician is set.
verbose = False  # if this bool is set to True then additional information is printed
# Helper Functions
def inputNumber(message):
    """Get an input number from user. Prompt is str @message"""
    while True:
        try:
            userInput = int(input(message))
        except ValueError:
            print("Not an integer! Try again.")
            continue
        else:
            return userInput
            break
def yes_or_no(question):
    """Get a y/n answer from the user"""
    while "the answer is invalid":
        reply = str(input(question + " (y/n): ")).lower().strip()
        if reply[:1] == "y":
            return True
        if reply[:1] == "n":
            return False
# Main Program Start                   #
# ----------------------------------------#
print("")
print("========================")
print("")
print("Hello! This program will:")
```

```
print("")
print(" 1. Home the dobot magician robot")
print(" 2. Pick an item from point A and place at point B")
print("")
print(
    " The settings for this program are currently: verbose = {}, setTCP = {}. The default for these settings is
'True'".format(
        verbose, setTCP
    )
)
print("")
# Connect Dobot
state = dType.ConnectDobot(api, "", 115200)[0]
print("Connect status:", CON_STR[state])
# if connection successful
if state == dType.DobotConnect.DobotConnect_NoError:
    # Run the  command
    # stop to Execute command Queue
    dType.SetQueuedCmdStopExec(api)
    # Get current pose
    # Get the pose (x,y,z,r, joint1,joint2,joint3,joint4)
    pose = dType.GetPose(api)
    # Print result
    print(
        "Current Robot Pose: {} in format
[x(mm),y(mm),z(mm),r(deg),joint1(deg),joint2(deg),joint3(deg),joint4(deg)]".format(
            pose
        )
    )
    # Clearing of command queue
    dType.SetQueuedCmdClear(api)  # clear queue
    currentIndex = dType.GetQueuedCmdCurrentIndex(api)[
        0
    ]
```