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OPTIMIZATION AND SIMULATION OF A SMART ROBOTIC TO FACILITATE CONSTRUCTION ACTIVITIES

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Master's Thesis

Supervisor

Asst. Prof. Dr. Serdar AY

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The thesis titled OPTIMIZATION AND SIMULATION OF A SMART ROBOTIC TO FACILITATE CONSTRUCTION ACTIVITIES, prepared by RANYA ALLAOUI, and submitted on 00/08/2023 has been **accepted unanimously** for the degree of Master of Science in Mechanical Engineering.

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DEDICATION

I dedicate this study to my great father, who provided me with much support and energy to conduct this work. Also, I dedicate my thesis to my beloved mother. Without her love and care while I conducted my work, I could not reach this stage. Moreover, I dedicate this thesis to my supervisor, as he offered a part of his valuable time to advise me and help me improve my research outputs. Besides, I dedicate this research to the academic staff for their beneficial consultation and advice to enhance my thesis. Without their knowledge and experience, I could not promote my thesis findings.

PREFACE

I would like firstly to thank Allah for giving me the patience and energy to execute this MSc. I would also acknowledge the Mechanical Engineering Department and doctors who gave me the capability and knowledge to write and successfully complete this thesis. In addition, I would like to express my deepest thanks and gratitude to my work supervisor, Asst. Prof. Dr. Serdar AY, without his support, encouragement, and patience, I could not complete my study. I hope my advisor will be capable of reflecting upon this thesis with significant satisfaction. Moreover, I would like to thank all the examination committee members for their evaluation and for defending my work. Finally, I would like to extend my deepest thanks to all the academic and non-academic employees at Altinbas University for their continuous support.

ABSTRACT

OPTIMIZATION AND SIMULATION OF A SMART ROBOTIC TO FACILITATE CONSTRUCTION ACTIVITIES

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This master's study is conducted to examine and identify the beneficial contributions and rationale of implementing lightweight robotic systems that can achieve different repetitive tasks associated with lifting and transferring heavy objects and difficult-to-move equipment on the construction site. A case study of a grab excavator robot is addressed to help workers lift and move heavy construction equipment and objects with remarkable rates of flexibility and effectiveness. Simulations and numerical modelling are applied using the ANSYS software package. 4140 steel and carbon fiber materials are introduced and explored in this research. Based on the mathematical simulation and modelling results conducted in this research, the thesis findings indicate that the grabbing arm and connecting links in the grab excavator recorded meagre rates of Von Mises stress, elastic strain, and total deformations according to the numerical simulations conducted for the two scenarios in which ([a] 4140 Steel and [b] Carbon Fiber) are utilized. In addition, the study findings reveal that the maximum amounts of von Mises stress are 90.54 MPa and 90.8 MPa for the first scenario 4140 steel and the second scenario carbon fiber hydraulic. Besides, the elastic strain recorded for 4140 steel and carbon fiber is 4.5×10^{-4}m/m and 6.4×10^{-5}m/m, respectively. Further, total deformations of 4140 steel and carbon fiber are 0.00382 m and 0.00053 m, subsequently. The efficiency of the carbon fiber hydraulic grab excavator is improved because it can transfer more heavy objects as it is five times lighter and five times stronger than the one made of 4140 steel. Finally, it can be concluded that using carbon fiber in manufacturing the grab excavator hydraulic grabs and bucket grabs to carry out the ANSYS

simulation process related to the robotic system employed in construction of the grab excavator, which improves the performance parameters in term of increasing the strength of materials, reducing the weight and system energy consumption as it mitigates large amounts of von Mises stress, strain, and deformations.

Keywords: Smart Robots, Construction Industry, Performance, Lightweight Robots,Robotic Stystem.

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ABBREVIATIONS

AI	:	Artificial Intelligence
AWN	:	Automated Guided Vehicle
AGV	:	Autonomous Guided Vehicle
BIM	:	Building Information Modeling
CF	:	Carbon Fiber
CNN	:	Convolutional Neural Networks
DNN	:	Dense Neural Networks
DL	:	Deep Learning
FEA	:	Finite Element Analysis
ML	:	Machine Learning
NGN	:	Neural Graph Networks
R&D	:	Research and Development
RNN	:	Recurrent Neural Networks
SCO	:	Smart Construction Object
TCP	:	Tool Central Point
UAV	:	Unmanned Aerial Vehicle
VAE	:	Vibrational Auto-Encoder

1. INTRODUCTION

1.1 RESEARCH BACKGROUND AND TERMINOLOGY

When it comes to engineering, the construction industry is one of the most vivid and one of the most important industries for a country's GDP. Thus, ensuring that the construction industry works well is a significant aspect. Construction activities like the one shown in Figure 1.1 can handle infrastructure facilities, commercial and residential buildings, industrial and utility facilities, and urban projects, including bridges, roads, tunnels, and other amenities. The construction sector is also associated with maintaining old buildings and ancient structures. It can fix, renovate, and rehabilitate these aged facilities to increase their cultural value. The construction industry is also linked to other building activities, including demolishing and destroying facilities when they are obsolete or ending their service life [1] [3].

Figure 1.1: Examples of Large-Scale Construction Projects [1].

Robots are broadly used in the construction sector due to their substantial impacts and advantageous effects in the provision of multiple solutions and active techniques that can facilitate the construction process and achieve significant levels of cost, effort, and time effectiveness for mechanical engineers, workers, and consultants, including the following contributions:

a. Transferring a large number of heavy objects on the construction site that are challenging and difficult for laborers.
b. Performing some construction tasks under problematic working conditions, such as heavy rain and snow.
c. Achieving different repetitive activities and frequent jobs on the construction site that may be stressful for laborers.

Furthermore, many construction consultants and engineers depend on robots to offer some

a. Enhancing the speed of the construction process.
b. Eliminate the errors and faults that can result in rework issues due to worker's lack of experience.
c. Reduce the massive cost of labour needed in the construction project.
d. Conduct accurate inspection of daily activities and determine critical faults and errors that can contribute to severe problems that cannot be resolved flexibly later.

Besides, robot implementation in the construction sector is brought remarkable contributions to mechanical engineering consultants, seniors, and chief construction experts. Those high-knowledge engineers found that using robots in construction sites can overcome a challenging issue facing all project managers and engineers, reflected in the high amount of risks and hazards that may occur due to lower engineers' experience or dangerous weather conditions that would affect the achievement rate of the project. Therefore, construction risks, like submission delays, cost overruns, and claims, can be handled.

The research and development (R&D) efforts dedicated by numerous researchers and construction companies helped improve the effectiveness, durability, and reliability of robotic systems in conducting different types of activities and tasks, cutting down massive effort, time, and budget. R&D is also helped mechanical engineers and project managers monitor and achieve hard-to-do jobs and dangerous tasks that may result in severe impacts on workers. These circumstances include:

a. Working in the presence of a highly salty atmosphere.
b. Doing tasks in severe environments (which are associated with harmful chemicals).
c. Working in highly elevated buildings and facilities.

1.2 PROBLEM STATEMENT

Over the last few years, the construction industry witnessed significant levels of development, expansion and growth. With this growth, different novel techniques and practical tools are employed to facilitate construction work and mitigate risks. For instance, project management methods, intelligent machines, and heavy-duty mechanical devices are manufactured and designed. Notwithstanding, there are some problems and obstacles facing mechanical engineers and project managers, translated by the occurrence of different hazards and risks with workers they do some challenging tasks and complex activities on the site. Consequently, scholars and mechanical engineers implemented new solutions by which functional robotic systems are developed and innovated. Those robots are primarily practical and effective in handling different construction problems and building tasks that may cause adverse impacts and negative influences on workers [4]–[9]. However, robots used in the construction site may face some barriers mirrored by corrosion, degradation, or deterioration in their lifespan and mechanical performance in case severe working conditions exist. At the same time, heavy metals used in construction robots may reduce the overall efficiency and performance of those robots. Thus, lighter but more robust materials should is used [10]–[12].

In this context, this master's thesis is led to investigate the critical contributions of carbon fiber (CF) material implementation to offer boosted levels of efficiency, mechanical performance, and durability for grab excavators (monitored remotely) by virtue of a comparative analysis with 4140 steel (which is typically used for producing those excavators) [13].

1.3 RESEARCH SIGNIFICANCE

This study comes with some vital significances for mechanical engineers and the construction community. First, it categorizes different beneficial contributions and crucial advantages of robots for the construction sector supported by the cost, effort, and time effectiveness using comprehensive review and secondary data collection from different web journals and internationally recognized periodicals. Those web journals and global scientific magazines include IEEE, ScienceDirect, SCOPUS, Hindawi, MDPI, IOP Publishing, and Semantic Scholars. Another significance is reflected in the investigation and identification of helpful contributions and applicable rationales of carbon fiber in construction robots, a material that is used widely in the last years and brought variant added values for engineers. In this study, the material is used in a robot to do repetitive tasks and transfer heavy objects on the site to mitigate significant effort, time, and cost, facing laborers to do those construction activities. In addition, the significance of this study is reflected in replacing the heavy weight of 4140 steel with lighter carbon fiber material that can offer five times lower weight than 4140 steel while maintaining more considerable strength. It is vital to note that carbon fiber is five times more robust than 4140 steel. On the other hand, carbon fiber is five times lighter than 4140 steel. For those two reasons, it is predicted that utilizing carbon fiber in this context is helping to boost the performance of robotics and enhance their efficiency in performing different activities for workers characterized by difficult working conditions, repetitive tasks, or jobs involved in heavy objects required to transfer and place on the site.

1.4 RESEARCH MAJOR AIM AND MINOR OBJECTIVES

The major aim of this study is to provide different added values for mechanical engineers and project managers for several construction projects, mirrored by the mitigation of effort, cost, and time needed from laborers to achieve the demanded building task. Building on this goal, it is crucial to implement a set of secondary goals that can ensure the effective completion of this study, which include the following secondary objectives are:

a. To classify the major contributions of intelligent robotics and the key benefits of carbon fiber when it is implemented for robots with the help of a thorough literature review.

b. To select a case study in which difficult construction activities are required to perform by laborers in the presence of hazardous and challenging working conditions on the construction site.

c. To numerically analyze the grab excavator robot in term of using different type of materials, functioning and monitored remotely to lift different heavy objects to help workers achieve higher rates of tasks with significant speed.

d. To investigate the critical roles and benefits of carbon fiber in improving the performance and effectiveness of the grab excavator robot in executing challenging site tasks with the help of the ANSYS software package.

e. To modify, validate, and optimize the research results based on ANSYS simulation experts, construction consultants, and numerical analysis specialists.

1.5 THESIS STATEMENT

The title of this study is "OPTIMIZATION AND SIMULATION OF A SMART ROBOTIC TO FACILITATE THE CONSTRUCTION ACTIVITIES." Depending on this title, it is expected from this study that robotic systems in the construction industry should be amended and enhanced to increase their added value in the construction sector using some approaches and technologies.

1.6 RESEARCH QUESTIONS

This study is guided to help provide sufficient answers to the following research questions that are investigated and analyzed in this study:

a. What are the main contributions and vital positive impacts that can be attained from robotic systems in the construction sector?
b. Could the employment of robots help enhance and boost construction performance and project achievement ratios?
c. Would the deployment of carbon fiber enhance the strength and alleviate the weight of the grab excavator robot when this machine is made of it?
d. Can robots reduce significant rates of effort, cost, and time wasted on the site due to the lack of experience?
e. Can robotics minimize the massive budget, time, and effort required from workers because of challenging repetitive tasks or tough activities?
f. Would implementing robots in the construction sector reduce the cost of labour and mitigate financial losses for mechanical engineers and project managers?

1.7 RESEARCH HYPOTHESES

This study is conducted to examine the critical contributions of smart robots in facilitating the achievement of demanding construction activities. The research hypotheses are validated or invalidated based on the simulation findings of this study. Those hypotheses are represented in the following paragraphs:

a. Null Hypothesis, Ho – which assumes that: “Smart robotics could not help achieve higher accuracy, performance, or practicality in accomplishing construction tasks.”
b. Alternative Hypothesis, Ha – which assumes that “Utilizing smart robots in the construction industry can facilitate doing difficult and robust tasks done by the labour force.”
c. Sub Hypothesis, Ha,1 – which assumes that: “Using smart robots can offer alternative solutions to poor accuracy of construction activities achieved by humans.”
d. Sub Hypothesis, Ha,2 – which assumes that: “Smart robots can mitigate risks and injuries of the labour force who work in difficult working conditions.”
e. Sub Hypothesis, Ha,3 – which assumes that “Smart robotics can be implemented for hazardous environments and dangerous construction sites where the workers can barely accomplish activities.”

2. LITERATURE REVIEW

2.1 AIM AND INTRODUCTION

This chapter illustrates a comprehensive review through which major contributions and beneficial impacts associated with robotic systems and robot implementation in the construction system are reviewed and addressed. Also, this chapter highlights major modern approaches and innovative techniques that can enhance the performance of those robots used for different construction purposes and applications.

2.2 SMART ROBOT FOR FACILITATING VARIOUS CONSTRUCTION ACTIVITIES

In 2018, G. Yu et al. [10] a study is conducted investigating different building activities through which robotic systems ate employed in the construction sector. The authors reported that robots could play a critical role in enhancing and completing several tasks in the construction sector with significant degrees of performance, speed, and effort-effectiveness. Furthermore, the scholars carried out research on the use of robot coordination in prefabricated buildings, which takes into account modular and prefabricated construction. They provided a component-based method of building robots. Using a Smart Construction Object (SCO) strategy, several robots are used in the assembly of prefabricated homes, freeing up human workers to focus on other aspects of the construction process. To finish building the steel framework per the SCOs, multiple robots are used in a prototype with the help of a Building Information Modeling (BIM) simulation environment. Building on their studies, SCOs' fundamental characteristics are more complex BIM models and more precise robot models to enable collaborative simulation of a wider range of prefabricated construction processes and structures that are constructed off-site in a factory setting. Additionally, a component-based method of robot construction is provided. To free up human labour for other tasks, the smart construction object (SCO) strategy involves providing state and requirements to the components that drive many robots during the assembly of prefabricated houses. For the steel frame construction per the SCOs, multiple robots are used in a prototype Building Information Modelling simulation environment, as indicated in the partial UML Class Diagram in Figure 2.1.

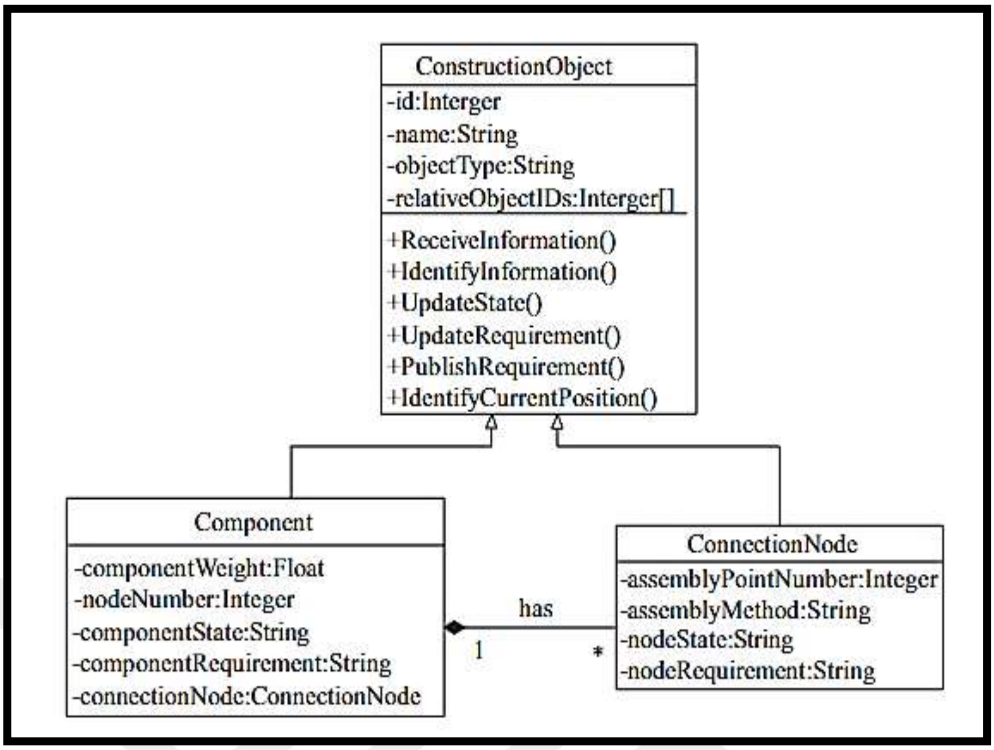

Figure 2.1: A Configuration of the SCO Strategy Implemented in the Construction Sector for Enhancing Robot Efficiency with BIM Technology [10].

In 2022, S. K. Baduge et al. [14] a numerical analysis by which accurate robot-based building simulations are executed. The authors considered some assessment criteria and validation pertaining to the robot's efficiency and reliability to help workers perform their tasks in various building projects. To enable more accurate robot-based building simulations. Time, cost, effort-effectiveness in tasks, reliability, and performance are some examples of vital outputs attained in their work. Besides, they discussed some factors determining SCOs for building projects. Additionally, this research needs to identify the difference between Connection Nodes and Components and inherit properties from the object used to build it. They provide a complete review of the present status of ML/DL algorithms, data gathering methods, AI, ML, and DL applications in construction and building 4.0, and the accompanying problems. This research outlines seven potential construction industry applications for artificial intelligence. As shown in Figure 2.2, For example, architectural design and visualisation, material design and optimisation, structural design and analysis, off-site manufacturing and automation, construction management and progress monitoring, safety, smart operation, building management and health monitoring, durability, life cycle analysis, and a circular economy are some of the current examples.

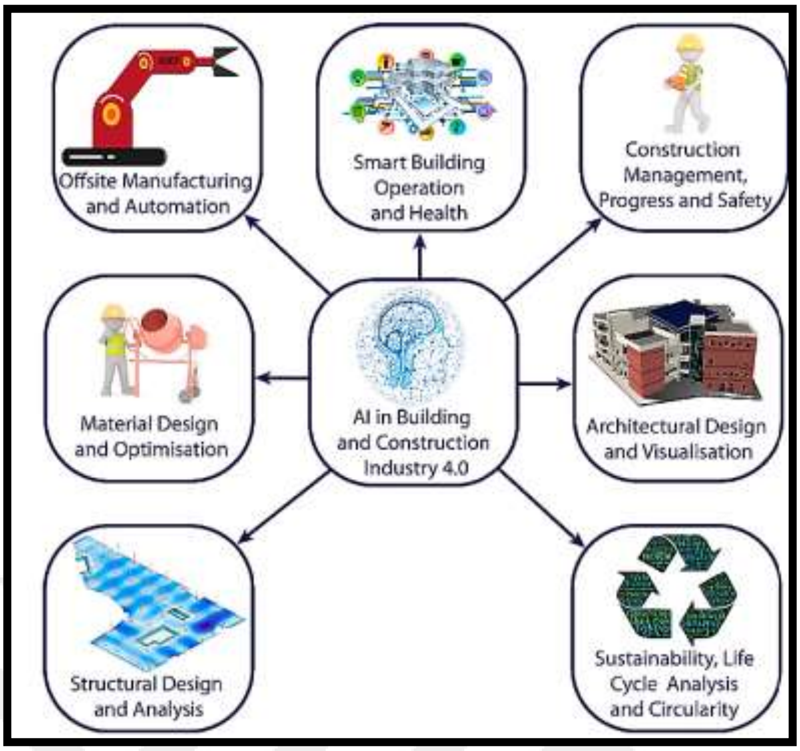

Figure 2.2: An Architectural Design and Visualization of the Research Materials, Design, and Optimization Implemented to Use Robots in Construction [14].

In Figure 2.2, it noted that these domains included things like architectural design and visualization, material design and optimization, structural design and analysis, off-site manufacturing and automation, construction management and progress monitoring, safety, smart operation, building management and health monitoring, and durability, life cycle analysis, and a circular economy. Further, as shown in Figure 2.2, these currently include things like architectural design and visualization; material design and optimization, structural design and analysis, off-site manufacturing and automation; construction management and progress monitoring; security, smart operation, building management and health monitoring; and longevity, life cycle analysis; As shown in Figure 2.2, these are the following domains: architectural design and visualization; material design and optimization, structural design and analysis, off-site manufacturing and automation; construction management and progress monitoring, safety, smart operation; building management and health monitoring; and durability, life cycle analysis, and a circular economy.

2.3 MACHINE LEARNING CRITICAL BENEFITS FOR ENHANCING ROBOTIC PERFORMANCE IN CONSTRUCTION

It is reported that Machine Learning (ML) is a type of Artificial Intelligence (AI) that, unlike conventional programming languages, it its own inimitable style, and in which computers analyze data and generate a model from the data that can be used to solve the problems. Traditional programming involves encoding rules in a computer language without making judgments based on facts. Additionally, compared to conventional programming, machine learning focuses on data to develop predictive models, which are then used to predict previously unknown data. There are some challenges for which building a rule-based program is exceedingly difficult due to the intricacy of the code, in these cases, ML are utilized if sufficient data relevant to the topic under discussion is available [14]. There are numerous ways to classify machine learning approaches. Moreover, a frequent criterion for identifying ML models is the level of assistance provided to the model during its training. In addition, ML models are divided into three major categories: supervised learning, unsupervised learning, and reinforcement learning, as depicted in Figure 2.3. In the case of supervised learning. The dataset contains both the predictors and the outcomes (or "labels") [14]. The first step in Figure 2.3 demonstrates the training of a supervised ML model on the labelled dataset, followed by the creation of inferences about unknown data. Supervised classification and regression tasks are two of the most popular applications. The classification problems predict a discrete class label, whereas regression tasks predict a continuous value. Popular supervised learning algorithms include K-Nearest Neighbours, SVMs, LR, LRNN, and LRNN [14].

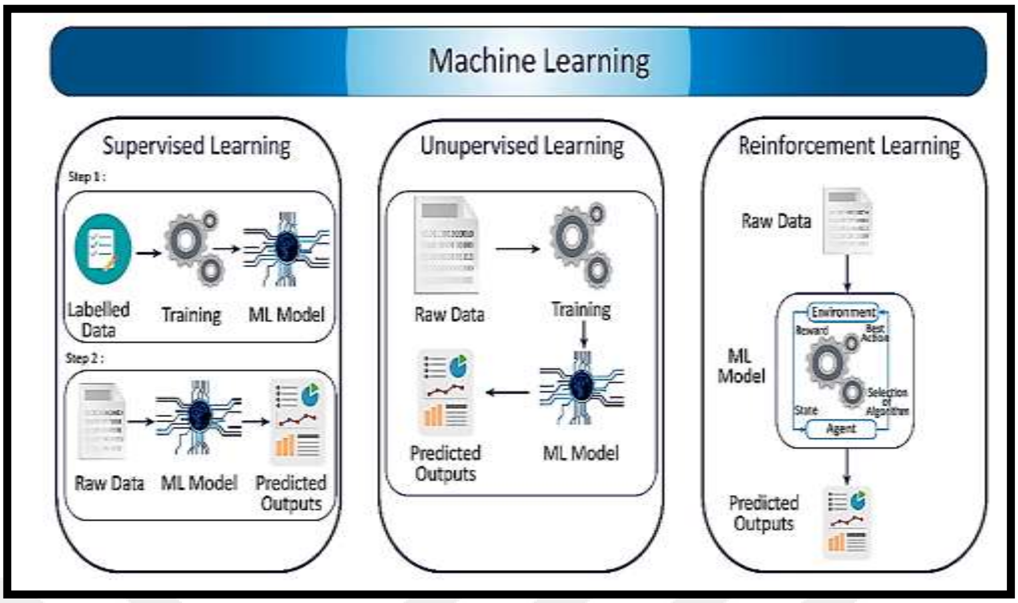

Figure 2.3: Categorization of Machine Learning Principles [14].

The construction sector is one of the engineering sectors that is booming and helps boost GDP. As a result, it is essential that the building industry can function normally. The construction activities depicted in Figure 2.4 are applied to a wide variety of building types and urban projects like bridges, roads, and tunnels, as well as infrastructure facilities, commercial and residential buildings, industrial and utility facilities, and residential and industrial buildings. The construction industry is also associated with maintaining historic buildings and structures. It can repair, renovate, and rehabilitate these ageing buildings to enhance their cultural significance. Additionally, the construction industry is connected to other building activities, such as demolishing and destroying facilities when they become obsolete or end their service life [15].

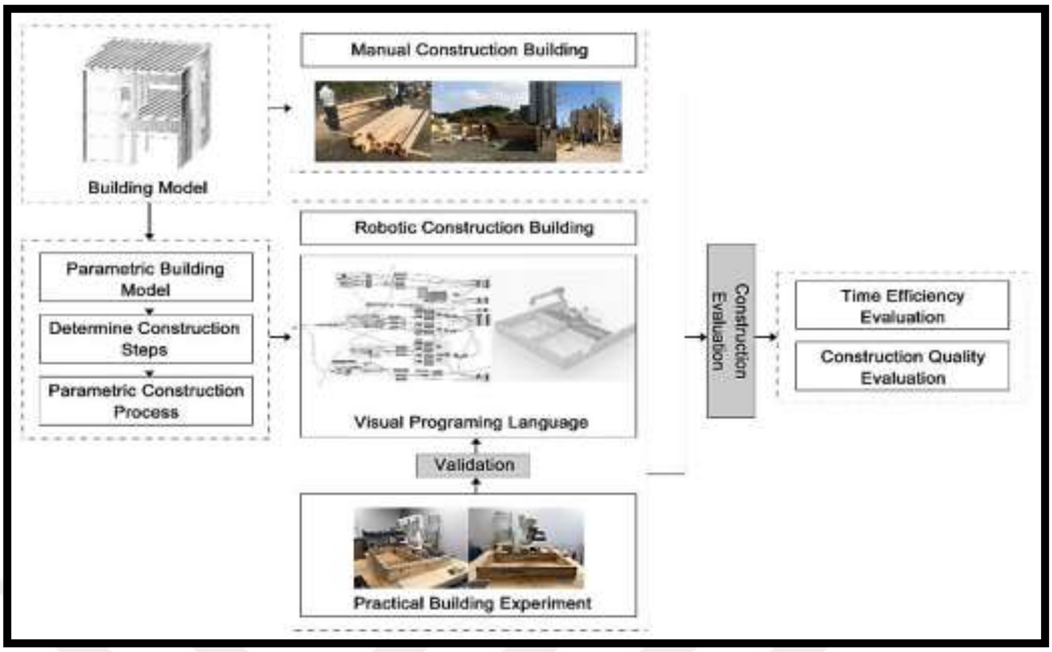

Figure 2.4: Construction Practices and Procedures [16].

Developers and users typically share a shared knowledge of a core and domain ontology. While the end-user domain ontology focuses on human-robot interaction, the core ontology consists of sensors, actuators, drivers, and operational systems. Three parts make up the human-robot system: the computer, the human operator, and the robot itself.

Figure 2.5 depicts the developer and user perspectives on the Core and domain ontology.

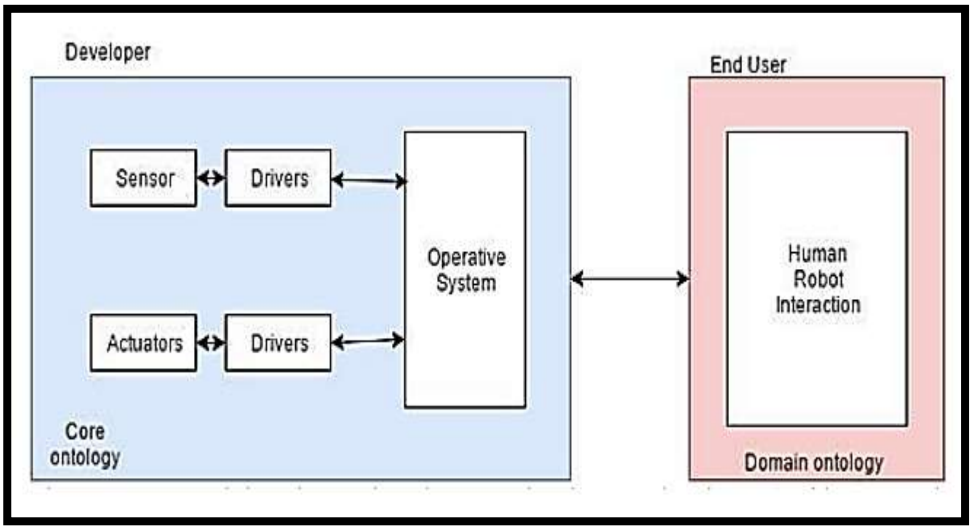

Figure 2.5: Users Sharing a Core and Domain Ontology [14].

Furthermore, Figure 2.6 indicates the interaction between machines, humans, and humanity.

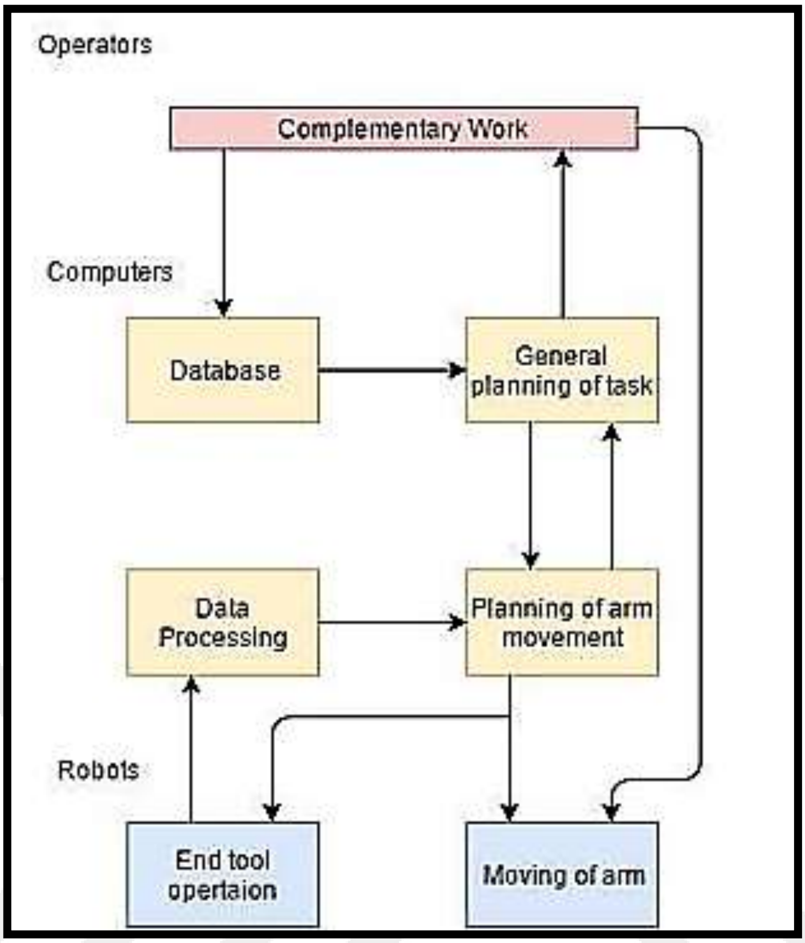

Figure 2.6: The Interaction Between Machines, Humans, and Humanity [14].

A human operator performs two interdependent tasks: preliminary work and additional tasks. Among the primary functions is entering the necessary information into a computer. Part of the preparation involves entering data into a computer. Other work includes gathering and organizing supplies, directing and positioning the robot, offering technical assistance, and acclimating the robot to its new surroundings. It needs additional effort to prepare the materials, control the robot, precisely place it, provide technical support, and accommodate it in the workplace [14].

2.4 THE BENEFICIAL IMPACTS AND ADVANTAGES OF ROBOTS FOR THE CONSTRUCTION INDUSTRY

Scholars reported that construction work often occurs in a disorderly setting filled with several dangers. Replacing humans in the construction business with robots it numerous potential advantages. This study mentioned that construction work often occurs in a disorderly setting with several hazards. Replacing humans in the construction business with robots it numerous potential benefits. Because of rising labour costs and a lack of available workers, the construction industry must adapt by adopting many robotic technologies to keep up with the latest trends in skyscraper tower construction [17]. Robot architecture is becoming increasingly popular as Southeast Asian countries attempt to meet the growing demand for skyscrapers. Many buildings don't adhere to the standard "up and down" layout, opting for more unique typologies. Scientists have developed one-fiftieth-scale model construction robots. Thanks to model-building projects, construction experts can visualize the final product in terms of aesthetics, structural soundness, and physical construction. Robots are currently employed in the most dangerous and tiresome of jobs. Bricklaying and paving are examples of repetitive tasks that robots can do. Bricklaying is a repetitive process, but accidents still happen on construction sites [17]. Bricklayers' workloads can be staggering. The most needed effort is for moving bricks in and out of a wheelbarrow from a height of 0 to 50 centimetres off the ground. A liker came up with one of the first automated methods for building brick walls that are 8 meters in length. Lehtinen built two-seam adhesive–using robots for glueing bricks. Slocum and Schema invented the "Blockbot," a device that dries out piles of concrete blocks. To this end, Pritschow proposed an on-site brick-laying robot to retrieve bricks from prearranged pallets, apply bonding materials, erect brickwork precisely, plaster bricks with mortar, and press them into place. Figure 7 depicts the manufacturing process of a robotic bricklayer [17].

Table 2.1 presents the building industry. Robots are being used to help with a variety of tasks, including the construction of buildings and infrastructure. Since these cases exist, it's clear that robots can be used outside of academic settings and industrial research facilities. Many of today's robots are developed to address problems with fabrication and building on the job site. These developments offer designers alternative fabrication methods and present a challenge to the standard method of building. Using this method, previously impractical architectural building practices can be adapted for use on-site [17].

Table 2.1: Robot-assisted Construction and Infrastructure Activities.

Construction	Building services and maintenance
	Housing and building construction
	Construction in special areas, for example, deep oceans, arctic areas, space and deserts.
Infrastructure	Bridges, container port, tunnelling and road construction
	Construction and deconstruction of power plants and dams

Robots come in various flavours, each suited to a specific web niche. Robots on-site are guided by computers or other stimuli to autonomously build the superstructures of buildings. For example, climbing robots have been used to keep bridges, high-rises, and highways. The hydraulic system that drives the underwater construction robot can withstand significant pressure. Motorized hand movement on the Traffic Marshal Robot signals drivers of impending roadwork.

Also, Figure 2.7 illustrates the method employed for producing bricklaying robots.

Figure 2.7: An Example of Robots Used to Facilitate Construction Tasks for Laborers [17].

Similarly, it takes a lot of people and time to put up large construction equipment, like exterior curtain wall panels [17].

However, robots can help reduce the number of workers needed on construction sites, such as the traffic-monitoring robot created by PN Safety Industries, whose hands move independently.

2.4.1 Wearable Robotics

The Automated Guided Vehicle (AWN)-03 offers lumbar support, monitors the user's activities, and transmits a signal to the motors that rotate the gears. The AWN-03 Suit envelops the wearer from the shoulders to the hips. It facilitates construction workers' mobility while handling and holding big materials. It presses the workers' thighs, provides additional support for their upper bodies, and relieves 15 kg of pressure from their lower backs. One AWN-03 robot suit can be purchased for around $8,100, and its battery pack can keep it running for up to six hours. Due to labour shortages and an ageing workforce in the construction industry, AWN-03 is expected to see increased demand. FORTIS is another wearable exoskeleton that helps users become more robust while providing them with more comfortable clothing to work. The instrument, like Iron Man, is lightweight and requires no power source. The strong exterior enhances the user's endurance. It facilitates the operation of heavy machinery and the transportation of oversized cargo, such as reinforcing bars. As construction workers stand or kneel, the exoskeleton transfers its weight to the ground. It imparts a feeling of weightlessness when transporting or planning big goods. Due to its ergonomic design, the exoskeleton may be altered to fit persons of varied heights and body types. It looks like the bucket of a cherry picker or a man lift and can hold an instrument weighing up to 36 pounds. This tool can securely store machines like grinders, demo hammers, and rivet busters that operate in either vertical or horizontal planes [17].

2.4.2 Robotic Arms in Construction

The small in size but significant in potential, robotic arms are often mentioned in the same breath as their larger robot counterparts. The usual appearance of robotic arms is shown in Figure 2.8. Infrared distance sensors, USB cameras, angular orientation feedback, force sensors, and accelerometers are part of a robotic arm's toolkit for determining whether or not it can grasp an object [17].

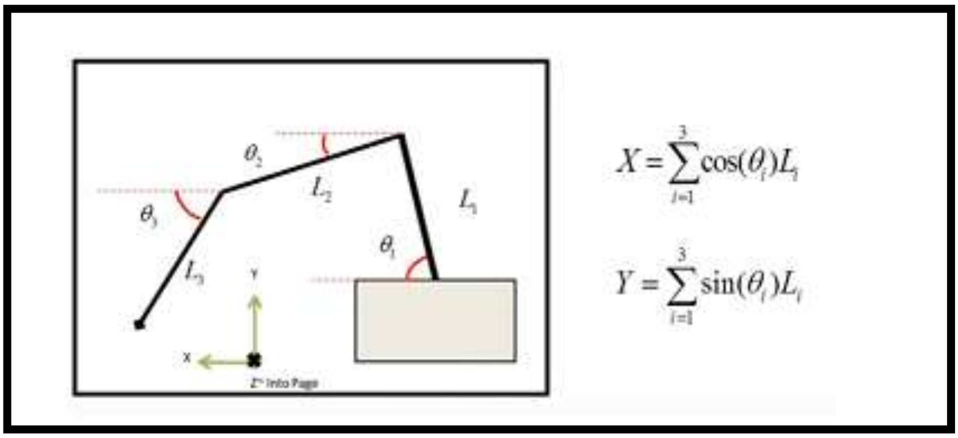

Figure 2.8: Design of Robotic Arm and Critical Parameters Considered [17].

Lightweight and rigid aluminium servo brackets create robotic arms that convincingly mimic human components. Furthermore, Aluminium is also used to construct the robot's gripper for the same purpose. A large percentage of people think that the fact that robots can do manual labour instead of humans is the most important reason why they should improve safety. For instance, a structural engineer in Hong Kong asserts, "There is no question that construction robots have their uses. Using robots to demolish a wall is a promising way to reduce the need for human labour and the associated risks. In addition, it can predict the challenges that may arise during construction." A Hong Kong, labour union leader, argues that robots can replace humans in the gathering and placement of traffic cones. For instance, a structural engineer in Hong Kong asserts, "There is no doubt that robots are useful in the building. There's no denying the construction industry could benefit from robots. The use of robots in demolition work it the potential to reduce the need for human labour and the associated risks. A Hong Kong labour union leader argues that robots can replace humans in gathering and placing traffic cones. Considering the number of construction workers killed or injured by reckless drivers in recent years, it makes sense to replace dangerous manual labour with robots. Robots can also function underground, where the environment is too hazardous for humans due to the presence of toxic gases that are not yet fully understood to cause harm to them." A CEO of a safety investigation business asserts that "robots can work in dangerous conditions, such as those containing asbestos." He also gave the example of a fire explosion in a Hong Kong warehouse that killed two fire-fighters. His client requested that their company deploy robots to take photographs. He concludes that robots can be useful planning assistants for some high-risk jobs [17].

Despite the safety concerns, he acknowledges that robots cannot yet replace all human labour. One example is the need to recruit a robot watchdog. It's challenging to use a robot to keep an eye on other robots. Humans, with their limited and finite resources, must make the call as to whether or not robots can be used safely and for what purposes.

2.5 COST-EFFECTIVENESS OF ROBOTIC SYSTEM IMPLEMENTATION IN CONSTRUCTION

On construction sites, the majority of construction professionals are sceptical of robots. Some believe that robots' financial consequences are their most significant drawback. Automation tools like 3D printing and virtual reality are seen as more cost-effective than robots on construction sites. And according to a professor in Melbourne, this sum doesn't include just the robots themselves but also the software and hardware engineers needed to program their unique applications by [17]. Not surprisingly, people are beginning to use robots in a wide range of work settings. Conventional wisdom holds that we do not employ robots because people are naturally afraid of being replaced by them. Therefore, the widespread use of robots on websites is still debatable. Some interviewees believe using robots on construction sites is impractical, impossible, and useless. A Swiss researcher is concerned that robots are exacerbate Europe's high unemployment rate. It could become a problem if everyone started doing this. Drones, if included, have been entrusted with the most dangerous jobs. In other words, no one it to do the risky work. There is a significant loss of employment opportunities worldwide if everyone uses digital devices. The fascinating field of "robot learning for smart manufacturing" combines the fields of robotics, machine learning, optimization, and manufacturing science. Their research provided a high-level overview of intelligent robotic manufacturing, machine learning, and robot learning concepts.

2.6 SMART ROBOTIC MANUFACTURING CONSIDERATIONS AND DESIGN PRINCIPLES

When everyone uses digital devices, individuals is eliminate many jobs worldwide. Robot learning for smart manufacturing is fascinating because it combines robotics, machine learning, optimization, and manufacturing science. Short descriptions and explanations of the core concepts of intelligent robotic manufacturing, machine learning, and robot learning are provided here [18]. The creation of computer-controlled robots with the ability to perceive and interact with the physical world. Robotic devices cover various fields and applications, from manufacturing and logistics to healthcare and social assistance, aerial exploration, and beyond. Manipulators make up the lion's share of industrial robots [19]. Proposed all varieties of robots are laid out for sale on the right side of Figure 2. In addition to the growing popularity of human-robot teams, these robot uses include transport, painting, packaging, and polishing. Robots have effectively liberated humans from monotonous and overburdened factory jobs and introduced a new generation of automation to the manufacturing industry. However, they did not go beyond the initial goal of robotics, which is to control objects in the real world from a digital interface.

Dynamism, uncertainty, and the need for flexibility all present obstacles. Intelligent robotic manufacturing is a by-product of the drive to advance robotics, with robots built to handle more intricate jobs with greater autonomy and intelligence [20]. Extended in their studies the Motors and the electricity that drives them physically propel robots. Robotic dynamics dictate that motors that generate force control the robot's mechanical body. According to the laws of robotics kinematics, the end effector also called the Tool Central Point (TCP), can be positioned in Cartesian space by rotating the robot's motors. Finally, these motions can be designed for various manufacturing projects using TCP tools.

2.7 PERSONALIZED ROBOTICS DEVICES EMPLOYED FOR CONSTRUCTION PURPOSES

The robot control operates on three distinct levels of abstraction.

a. The first level contains a force applied to a motor to function and is a significant focus in motor control. In gripping, levering, and haptic human-robot collaboration, force control is frequently utilized in the industrial industry employing torque sensors or sensor-less estimates. So in many cases, it is affected by the amount of power supplied to an engine and directly affects things through end effectors. The emphasis is also related to the rate at which a motor can spin [21].

b. Motor drivers and microcontrollers permit end users to program motor power (pulse width modulation). However, commercial robot manufacturers typically limit the motor power available to users, resulting in compromises. Collaborative robots equipped with torque sensors, such as KUKA, ABB, and UR robots, expand the scope of possibilities [22].

c. The second level: In the second level of Speed of motion, Industrial robotic applications, such as Autonomous Guided Vehicle (AGV) and Unmanned Aerial Vehicle (UAV) path planning and industrial robot trajectory planning, rely heavily on motion control, also known as motion planning. Positions in a sequence stand for actions in Cartesian or two-dimensional space. A robot's location and motion are encoded in the values of its joints' angular moments in time [22].

d. Researchers build robots with computer-controlled perception and action in the real world. Most factory robots are manipulators. Industrial robots, mobile robots, medical and surgery robots, rehabilitation robots, drones, and service robots are all examples of robotic devices.

e. The third level: The Task level. Motor and motion control are brought together in task control to form all-inclusive answers for industrial robotic tasks like packaging, shipping, cutting, welding, and polishing. Multiple independent tasks may contribute to the completion of a single study. Figure 2.9 depicts a task-based procedure. It is analogous to a planned trajectory for the actions of a robot performing a specific task.

Figure 2.9 depicts a task-oriented process [22]. When a thorough work cell is required, additional steps of a job include activating I/O signals, displaying alarms on user interfaces, and updating the database.

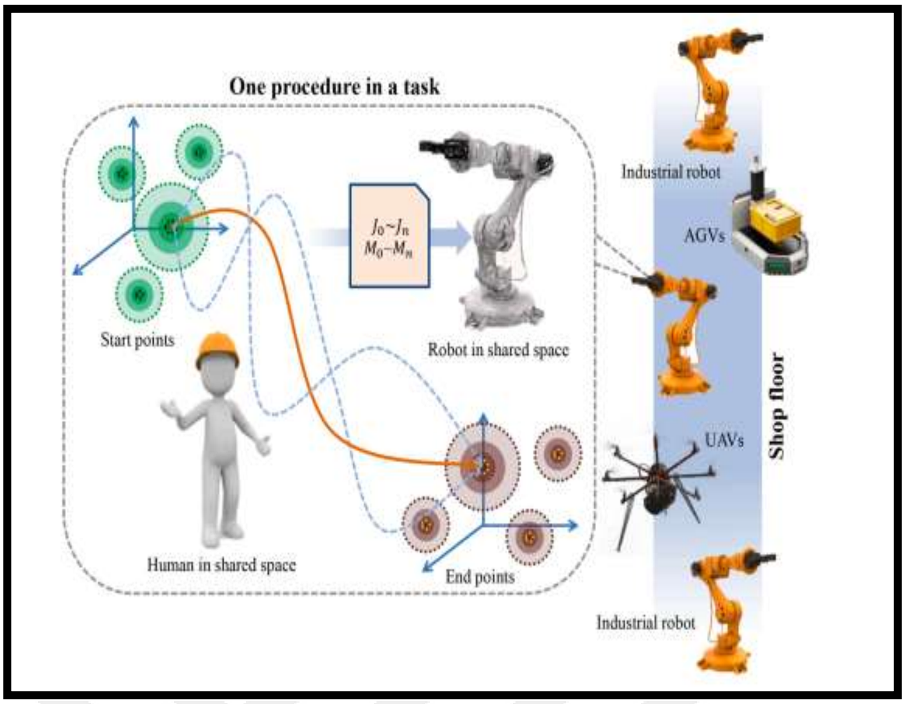

Figure 2.9: An Example of Intelligent Robotic Manufacturing Application [22].

Trajectories are Cartesian space curves connecting the origin and the final TCP posture. Since different approaches are taken, beginnings and endings are not always the same. By splicing trajectories progressively, a robot can generate logical, physical behaviours. It is essential to remember that trajectories are only one component of any given activity. Multiple independent activities can make up a single task. When applied to industrial robotic tasks like packaging, shipping, cutting, welding, and polishing, task control combines motor and motion control to provide comprehensive solutions.

Thorough work cell is needed, other job steps include triggering I/O signals, displaying alarms on user interfaces, and updating the database. Deep Q-networks, policy gradient, and actor-critic learning can all be trained simultaneously to produce a deep RL system [22]. A study revealed that the feature-based nature of traditional RL makes it challenging to represent high-dimensional data such as images adequately [23]. Figure 2.10 describes the framework of ML, RL, and LR-based robot learning systems.

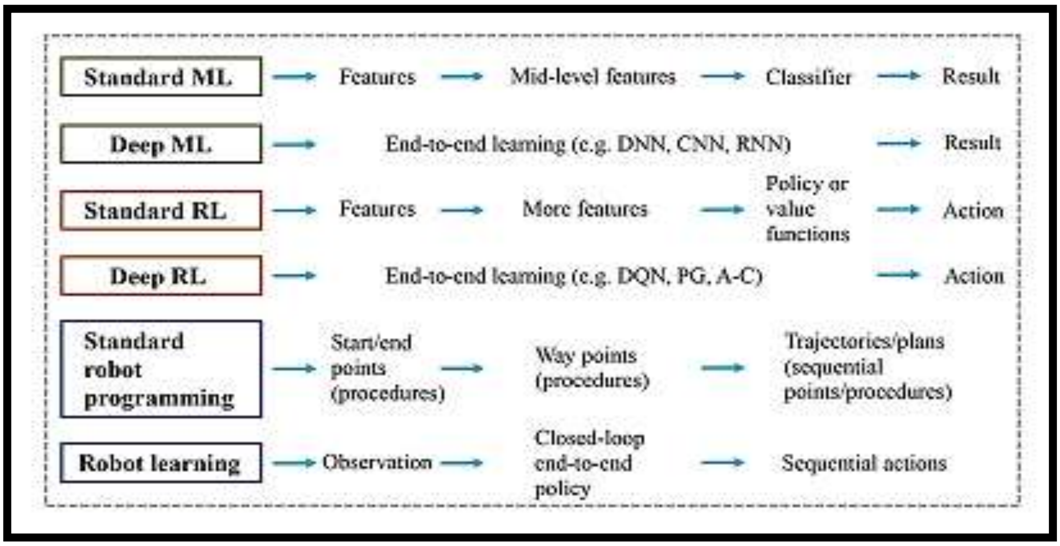

Figure 2.10: The Framework of ML, RL, and LR-Based Robot Learning Systems [23].

However, is typical of the procedure-oriented approach taken by conventional robot programming and is used by ABB industrial robots. Robot controllers do their motion planning and carry it out in an open loop. So, their action needs to start and stop somewhere. A complex closed-loop approach is played a more central role in robotic learning. Adaptability in automated sequences is increased by a policy that receives new observations faster [23].

As depicted in Figure 2.10, there are several essential procedure conditions upon which the category of robot learning rests. These fundamental elements are likewise derived from various disciplines, particularly reinforcement learning. Scholars mentioned that these three essential processes occur sequentially: first, applying the current policy to working robots or simulations allows for the collection of enriched data that can be used for ROI estimation, a process known as sample generation. Second, in model-based robot learning, the model approximation is employed, the user is some knowledge of the dynamic model of the environment. And third, improving a policy aims to increase its effectiveness by connecting observations with subsequent actions that produce better results. All of a robot's learning process boils down to this essential repetition [23]. Figure 2.11 indicates the structure of the primary steps used in robot learning algorithms.

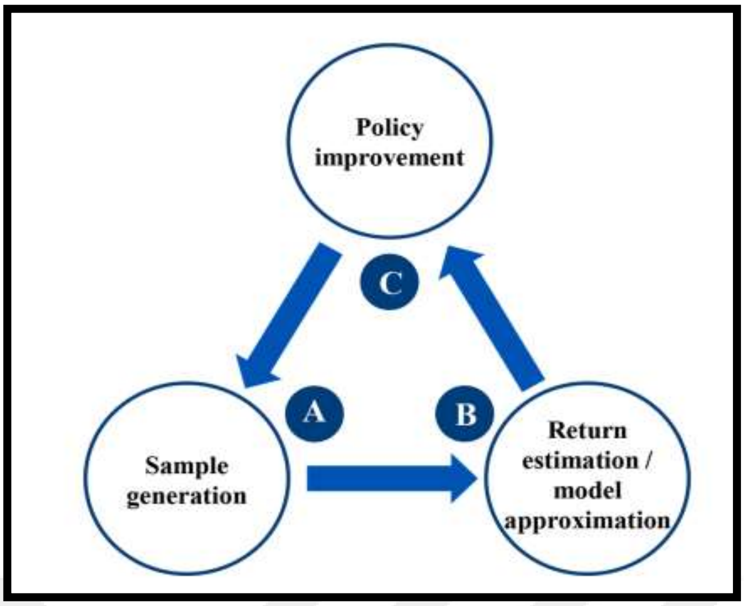

Figure 2.11: The Structure of The Primary Steps Used in Robot Learning Algorithms [23].

2.8 CRITICAL MACHINE LEARNING CONCEPTS FOR ROBOTIC SYSTEM PERFORMANCE ELABORATION

In addition to computation, statistics, information theory, signal processing, algorithms, control theory, and optimisation theory, machine learning is a multidisciplinary topic that is studied by [24]. Additionally, machine learning is one of the most exciting areas of AI right now. Data-driven function fitting is the most straightforward machine learning paradigm. An approximate model of untrained data is constructed using the trained function. When talking about "learning," the process is inferred to a weak position is strengthened by employing previously acquired information, like the learning capacity and operations of animals. ML is coined to describe this type of learning because it is the type of machine-like computers typically execute. By feeding data into itself, the fitted function in machine learning generates results from either raw data or a manually crafted feature. Before the development of deep learning, feature engineering is utilized to either manually or automatically extract data features. This strategy have been supplanted by using more powerful models, such as deep neural networks.

Different models are employed for this function; neural networks are just one. Using linear and quadratic models, as well as expressions of probability distributions (such as Gaussian estimates and Gaussian mixed models), and even discrete tables, is commonplace.

Comparable but less specialized architectures include Dense neural networks (DNN) are challenged by convolutional neural networks (CNN), recurrent neural networks (RNN), and neural graph networks (NGN). To address the current difficulties, numerous models have been offered. Learnable parameter models are a good option if the problem is easily represented or can be effectively handled with known probability distributions. Because neural networks have been demonstrated to be capable of modelling any nonlinear function in theory, they are increasingly used to solve complicated issues. The data dimension often influences the model's applicability—semantic information extracted from images. For example, these aspects are typically more data-dense than conventional numerical inputs, needing a better approximation, like deep neural networks. Networks of neurons can be as varied as the tasks they perform. Unlike RNN, which excels at processing sequential data like texts and sounds, CNN is best suited to data structured with geometrical shapes, like images. The learning phase involves estimating the model's parameters using the provided data, regardless of which model is chosen as the machine learning function.

Furthermore, [24] it was suggested that a model's type and internal settings (the sum of various Gaussian distributions, Hyper-parameters include things like the number of layers in a neural network. The incoming data's mathematical representation might be a scalar, vector, matrix, or tensor. Data can take the form of a picture, an audio file, a paragraph of text, or a series of numbers.. In the case of a Vibrational Auto-Encoder (VAE), for instance, the output may have more or fewer dimensions than the input. If you're using a vibrational auto-encoder, you can choose whether the study is the same or a different number of dimensions than the input (VAE). Contrast machine translation involves mapping sentences from one language to another, with machine generation (of artwork or poetry, for example) or dimension reduction, which consists in mapping any data back to itself. In particular, machines learn by understanding the function parameter.

Parameter tuning, however, relies heavily on the specific Machine Learning (ML) method employed. Three everyday subcategories for machine learning techniques are unsupervised, supervised, and reinforcement learning. Figure 2.12 shows the range of autonomy and complexity between industrial and service robots.

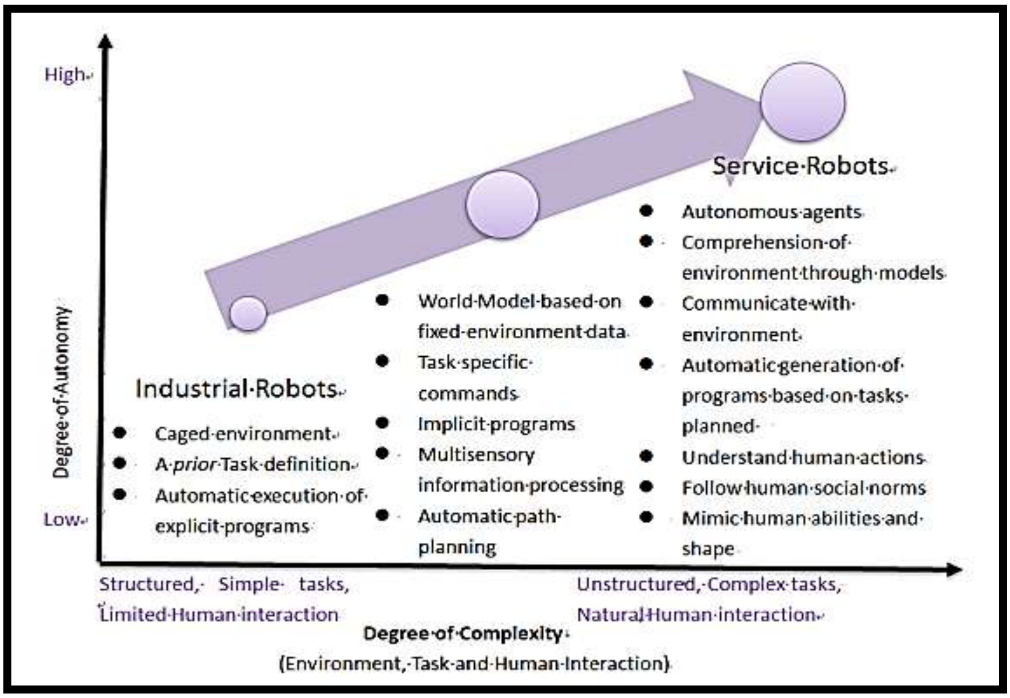

Figure 2.12: The Range of Autonomy and Complexity Between Industrial and Service Robots [25].

Clustering and other forms of data processing are examples of unsupervised learning. The user of a vibrational auto-encoder can specify whether the encoded output should have the same or a different number of dimensions than the input (VAE). While mapping sentences from one language to another is what machine translation is all about, mapping any data back to itself can be used for machine generation (like a painter or poet) or dimension reduction. In particular, machines learn to recognize the function parameter.

Moreover, books cannot fulfil all of your educational needs. "Reward is sufficient" by focusing on and refining the systems involved in acquiring and utilizing rewards. We may comprehend all forms of intelligence and their accompanying talents (or minimize the cost). In contrast to conventional teaching approaches, reinforcement learning is crucial to developing intelligent robots. Loss functions can be computed using supervision signals during supervised learning. A better answer is obtained by changing the parameters of the cost function. The most popular optimization strategy uses gradient methods, which are easily calculable on a computer. The "trial-and-error" paradigm is an alternative lens to examine reinforcement learning. Guided learning is comparable to learning from books, while reinforcement learning is like learning from experience. Some jobs traditionally performed by humans are being taken over by machines, which is an unsettling reality.

Robots have replaced human security officers in some locations, such as shopping centres. A Chinese bank are recruited a robot receptionist capable of answering customers' questions and persuading them to create bank accounts.

2.9 CRITICAL REMARKS ON THE PUBLICATIONS REVIEWED

Table 2.2 illustrates some significant findings and substantial outputs, summarizing the rationale of all publications addressed and discussed in this chapter.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed in Chapter Two.

No.	Author(s) and Year	Manuscript Title	Techniques for Enhancing Robots' Efficiency in Construction	Substantial Research Outcomes
1	Zhu, A., Pauwels, P., & De Vries, B. (2021)	Smart component-oriented method of construction robot coordination for prefabricated housing	Assigning state and requirements to the components that will drive multiple robots during the assembly of prefabricated housing constitutes the smart construction object (SCO) strategy.	Multiple robots are implemented within a prototype BIM simulation environment to finish the construction of a steel frame based on the SCOs.
2	Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., ... & Mendis, P. (2022)	Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications	Analyze the present state of atificial intelligence (AI), machine learning (ML), and Deep learning (DL) applications in the building and construction sector.	Analyze the current status of artificial intelligence (AI), machine learning (ML), and deep learning (DL) applications in the building and construction sector.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed in Chapter Two. "Tables Continued."

3	Li RYM, Ng PL. (2017)	Wearable robotics and construction worker's safety and health.	The concept of replacing construction workers with robots offers numerous advantages, including improved safety, quality, and efficiency. Current trends in skyscraper towers, coupled with rising labor costs and the inability to find qualified workers, necessitate the adoption of various robotic technologies within the construction industry.	The model-building projects allow construction professionals to envision the appearance, structural integrity, and actual construction of a new building. Currently, robots are primarily used for hazardous and laborious tasks. Because laying bricks and paving are repetitive tasks, robots can perform them.
4	Q. Liu, Z. Liu, W. Xu, Q. Tang, Z. Zhou, D.T. Pham. (2019)	Human-robot collaboration in disassembly for sustainable manufacturing,	Robotics is the science and engineering of creating robots that can sense and interact with their physical environment under computer control.	Most industrial robots are robotic manipulators. The advancement of computing technology, integrated circuitry, and robotics science has allowed for the development and widespread adoption of industrial robots in manufacturing settings.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed in Chapter Two. “Tables Continued.”

5	Y. Lu, X. Xu, L. Wang. (2020)	Smart manufacturing process and system automation–a critical review of the standards and envisioned scenarios.	The advent of industrial robots can be traced back to the early 2000s, when they are initially used in the state-of-the-art GM factory in Ohio. The names ABB, KUKA, UR, FANUC, and YASKAWA may seem familiar to you as leading producers of industrial robotic manipulators. .	In addition to transporting, painting, packaging, and polishing, these robotic applications include the emergence of human-robot collaboration.
6	Y. Qu, X. Ming, Z. Liu, X. Zhang, Z. Hou. (2019)	Smart manufacturing systems: state of the art and future trends.	Physical propulsion for robots is provided by motors and the electricity that powers individual motors. Motors produce force and regulate the robot’s mechanical body in accordance with robotic dynamics. According to the laws of robotics kinematics, the end effector, also called the tool central point (TCP), can be rotated to a new location in Cartesian space.	By rotating the robot’s motors in accordance with the rules of robotics kinematics, the end effector, also known as the tool central point (TCP), can be moved to a position in Cartesian space, and various TCP tools can be used to generate these motions for various industrial tasks.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed in Chapter Two. "Tables Continued."

7	Wang, L., Gao, R., Váncza, J., Krüger, J., Wang, X. V., Makris, S., & Chryssolouris, G. (2019)	Symbiotic human-robot collaborative assembly.	Motor level. Motor control emphasizes the amount of force necessary for a motor to operate. Frequently, it is influenced by the applied power to a motor and has direct effects on objects via end effectors.	The end effector, or tool central point (TCP), can be shifted to a new location in Cartesian space by reorienting the robot's motors in accordance with the laws of robotics kinematics.
8	Al-Yacoub, A., Zhao, Y. C., Eaton, W., Goh, Y. M., & Lohse, N. (2021).	Improving human robot collaboration through Force/Torque based learning for object manipulation.	Motor drivers and microcontrollers permit end users to program motor power (by pulse width modulation). However, commercial robot manufacturers typically limit the motor power available to users, resulting in compromises. Collaborative robots equipped with torque sensors, such as KUKA, ABB, and UR robots, expand the scope of possibilities	Grasping, levering, and haptic human-robot collaboration all make extensive use of force control, which is typically managed by a torque sensor or sensor-less estimation.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed in Chapter Two. "Tables Continued."

9	Liu, S., Wang, L., & Wang, X. V. (2021).	Sensorless force estimation for industrial robots using disturbance observer and neural learning of friction approximation.	Grasping, levering, and haptic human-robot collaboration all use force control, and typically rely on torque sensors or sensor-less estimation to achieve this.	In robotic learning, a sophisticated closed-loop methodology is emphasized more. A policy that receives new observations at a faster rate from beginning to end increases the adaptability of sequential robotic actions.
10	Liu, Z., Wang, X., Cai, Y., Xu, W., Liu, Q., Zhou, Z., & Pham, D. T. (2020).	Dynamic risk assessment and active response strategy for industrial human-robot collaboration.	Machine learning is a field that combines computation and statistics with information theory, signal processing, algorithms, control theory, and optimization theory.	The convolutional neural network (CNN) shines with data that has a geometrical shape, like images, whereas the recurrent neural network (RNN) is best with sequential data, like words and sounds. The learning phase involves estimating the model's parameters using the available data, regardless of the model selected as the machine learning function.

Table 2.2: Some Significant Findings and Substantial Outputs of All Publications Discussed In Chapter Two. "Tables Continued."

11	Liu, Q., Liu, Z., Xiong, B., Xu, W., & Liu, Y. (2021)	Deep reinforcement learning-based safe interaction for industrial human-robot collaboration using intrinsic reward function.	Often, machine learning methods are divided into three subcategories: unsupervised learning, supervised learning, and reinforcement learning. Unsupervised learning is the processing of data, such as clustering, without supervision signals.	The "trial-and-error" paradigm provides a different perspective on reinforcement learning. In terms of human learning, supervised learning is comparable to gaining knowledge through reading books, whereas reinforcement learning is comparable to gaining knowledge through experience.

2.10 CHAPTER SUMMARY

It can be inferred from reviewing different peer-reviewed papers and academic articles, and recent publications, that adopting intelligent technologies and techniques, besides innovative enhancement approaches in robotic systems, could foster and boost their vital contributions and substantial functionality in carrying out different types of challenging tasks and complex building activities associated with significant rates of risks, effort, time, and cost. Thus, using those practical concepts and beneficial numerical methods in robots could play a critical role in facilitating the construction process.

The following chapter investigates implementing those practical principles to improve the constriction phases.

3. RESEARCH METHODOLOGY

3.1 CHAPTER GOAL

To identify the critical benefits of carbon fiber material in enhancing the performance of robotic systems used in several construction applications, this chapter is developed. It covers various key research steps and master's work analytical approaches considered and applied to carry out the ANSYS simulation process related to the robotic system employed in construction. The research philosophy, analytical phases and preparation, and theoretical modelling of the critical algorithms studied and used in this work are all represented in the third chapter.

3.2 RESEARCH METHOD

This master's thesis uses some substantial research steps and analytical phases to make the necessary numerical modelling and simulation process associated with a robotic system that uses carbon fiber in the construction sector. This work started with a review of the literature that highlighted essential rationales and advantageous impacts of integrating carbon fibers into robot manufacturing and production that are widely utilized in construction and other industries. After this phase, the research examines a case study consisting of two scenarios:

a. The first scenario: It contains a grab excavator (hydraulic grabs and bucket grabs) that is made of 4140 steel.
b. The second scenario: Includes the same grab excavator with a different metal made of carbon fiber.

To examine and evaluate the mechanical performance of the grab excavator according to the two scenarios, simulations and numerical analysis of the grab excavator are implemented to explore its mechanical properties and effectiveness based on those two materials. Then, modifications and adjustments of the grab excavator are adopted to enhance the reliability and robustness of the research findings. This step is applied with the help of numerical analysis experts and ANSYS professionals, who can provide better validity of the thesis outputs.

The flowchart for the research method is shown in Figure 3.1.

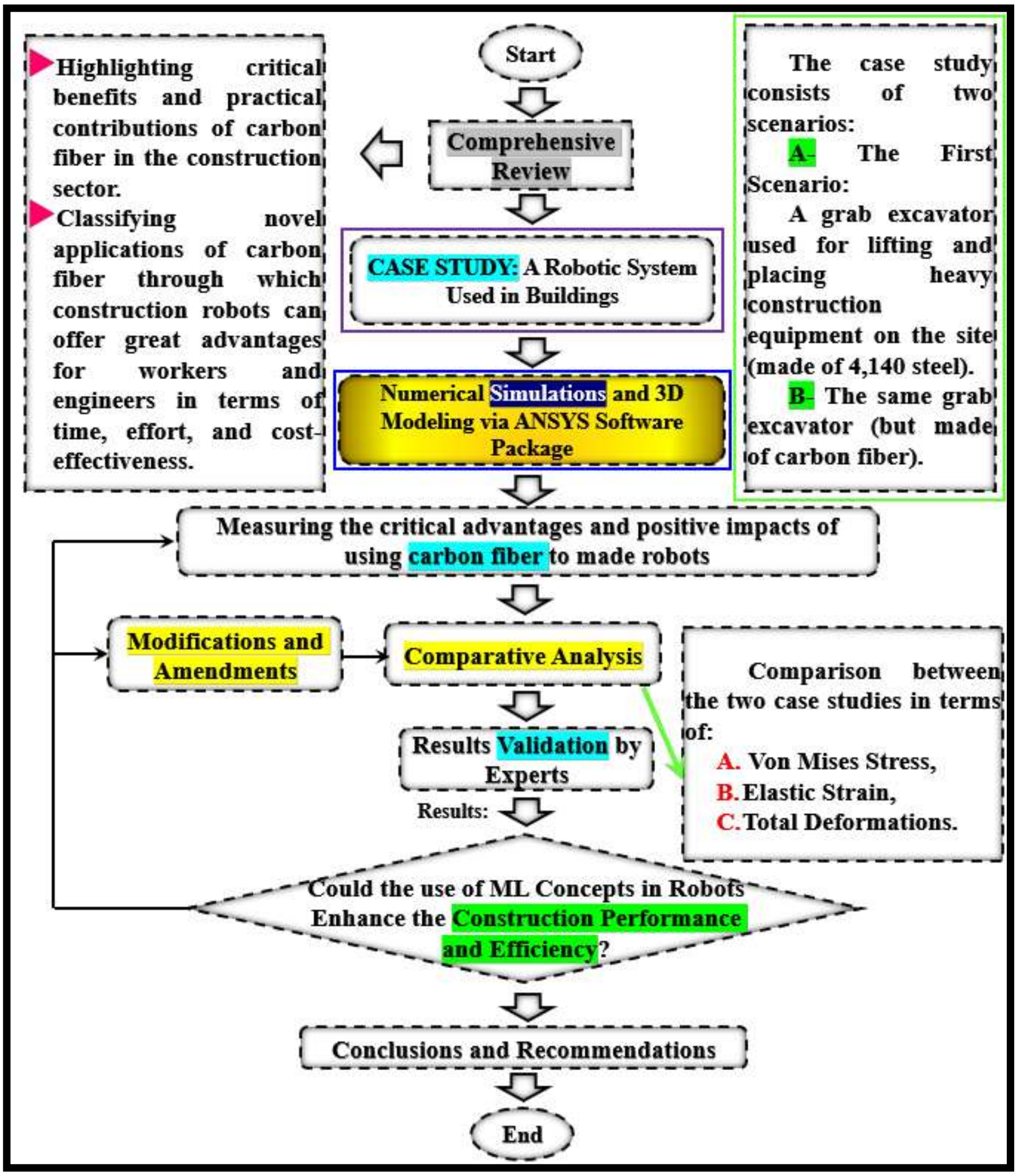

Figure 3.1: The Flowchart for The Research Method.

In the end, conclusions and suggestions will be made to help students, scholars, and researchers who are interested in robotic systems used in the construction industry conduct more research and make further improvements on the applications and implementation of carbon fiber in the construction sector. This aspect can improve the performance and reliability of those robotic systems. Thus, more elaborations in the construction sector can be achieved in terms of accuracy, cost-effectiveness, practicality, and risk mitigation.

3.3 THESIS PHILOSOPHY

The numerical analysis in this study is executed based on some dependent and independent parameters that are assessed and evaluated to examine the effectiveness and beneficial merits of carbon fiber utilization in construction robots to help achieve different tasks and perform complicated activities with significant degrees of flexibility, effectiveness, workability, and practicality.

Figure 3.2 shows the two types of study variables that are considered in this thesis.

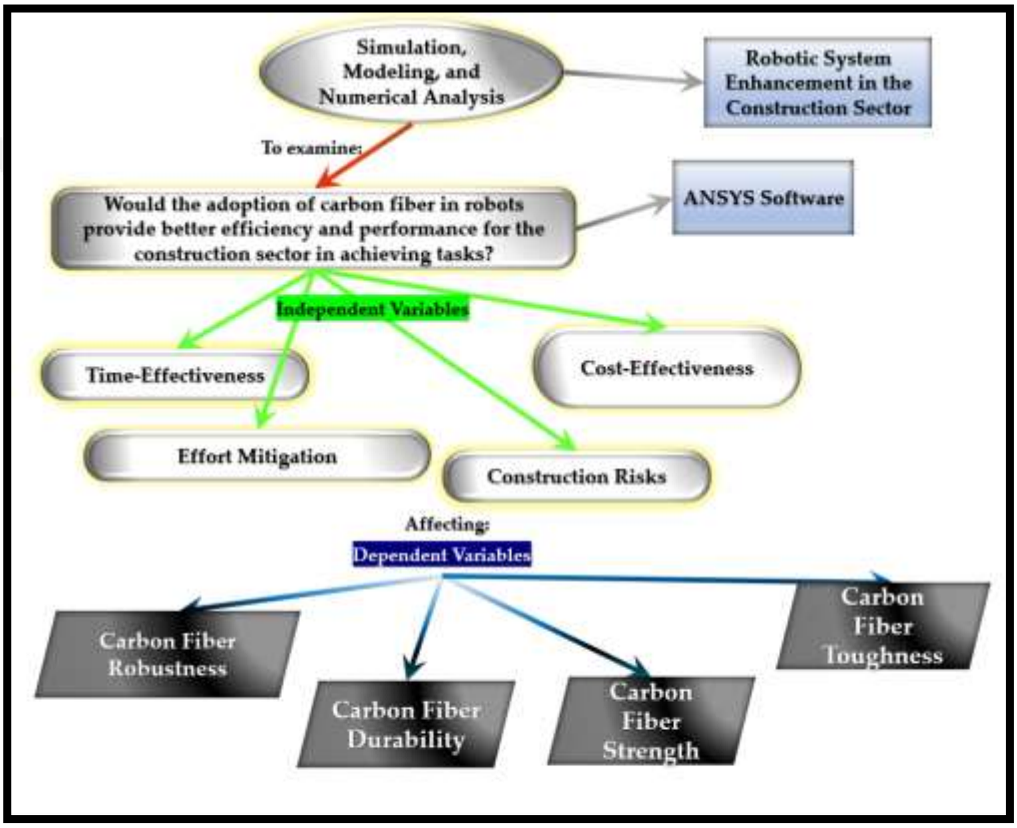

Figure 3.2: Dependent and Independent Parameters Considered in This Study.

3.4 CASE STUDY DESCRIPTION

The research's robotic system is an example of many similar robotic systems that are broadly employed in the construction sector, such as excavator. The implementation and use of those robots in the construction sector can cut significant rates of cost, effort, and time. Also, the accuracy and performance of the execution phases of variant construction activities can be elevated and enhanced.

Figure 3.3: Example of Robotic Application in the Construction Sector [79].

Figure 3.4: Wireless Remote Control Excavator for Heavy Equipment [80].

In the Figure 3.4 it provides us with a model of the excavator on the ground the remoquip system is an innovative technology that transforms a standard excavator into a versatile and remotely operated machine. It provides us with a model of an excavator that can be controlled from a distance, offering numerous benefits and applications. one of the key features of this system is its emphasis on health and safety. By eliminating the need for operators to be physically present in hazardous environments, it prioritizes safety and reduces the risks associated with various tasks. whether it's working in areas with smoke, fumes, radiation, or dealing with natural disasters like earthquakes and landslides, the remoquip system ensures that operators can carry out their work remotely and safely. Furthermore, this technology offers significant cost savings for contractors and businesses. ıt eliminates the need for investment in dedicated machines for specific tasks, allowing contractors to maximize the usage of their existing equipment. by simply retrofitting a standard machine with the remoquip system, it can be transformed into a demolition robot on demand, saving both time and money. the versatility of the remoquip system extends to a wide range of applications. ıt can be used for various tasks such as demolition, excavation, landmine removal, rock breaking, mining, construction work, and even handling emergency situations like chemical spills or the removal of hazardous goods. additionally, it enables disabled persons to operate equipment, making it inclusive and accessible. overall, the remoquip system revolutionizes the way tasks are carried out in challenging and dangerous environments. It combines technological advancements with a focus on safety, cost-effectiveness, and versatility, making it an invaluable tool for a range of industries and situations [79] .

In case study addressed in this study comprises a robotic system that can be used on the construction site by super hydraulic visors to mitigate significant rates of effort, time, and cost required by laborers and site workers to achieve some difficult tasks characterized by:

a. Higher rate of repetition and iteration.
b. A remarkable number of tasks in each construction task.
c. The large effort needed from workers to do their work.

The type of robot studied in this thesis comprises the wireless grab excavator, which can be shown in Figure 3.4.

Figure 3.5: The Grab Excavator Considered as A Case Study in This Thesis [80].

In the case study investigated in this study the lifting, transferring, and placing of heavy objects in large numbers are taken into account. Thus, using this category of robots can reduce large efforts from workers to do repetitive tasks. Common examples of the applications of the robot (shown in Figure 3.4) include:

a. Lifting a large number of heavy objects on the site.

b. Doing repetitive rebar tying or plastering.

c. Moving massive engineering equipment that requires significant effort.

On the other hand, a critical comparative analysis is implemented for this case study to help distinguish and identify the major contributions and rationales of carbon fiber material to do these repetitive tasks and challenging jobs for workers, taking into consideration some factors, which are:

a. Weight of carbon fiber (which is five times lighter than 4140 steel).

b. Strength of carbon fiber (which is five times more robust than 4140 steel).

c. Von Mises stress, elastic strain, total deformations.

d. Overall efficiency in doing the construction work.

To consider the third comparison item (von Mises stress, elastic strain, and total deformations), the ANSYS software package is employed. Generally, grab excavators are manufactured using 4140 steel. Therefore, the comparative analysis focuses on locating the major benefits of using carbon fiber instead of 4140 steel to provide different solutions and practical advantages for mechanical engineers and workers in terms of lower weight, speed, and strength.

The main components on which this master’s study focuses comprise the connecting rods/ links and the grabbing arm these components are subjected to significant forces and movements during operation, resulting in high levels of stress and deformation. So, there are several reasons why we focus on connecting rods links and grabbing arms for making comparative analysis after applying von Mises stress, elastic strain, and total deformations. First of all, tremendous stress and deformation are experienced by connecting rods and grabbing arms as they operate. They experience considerable stresses and motions, and if they fail, the results could be disastrous. The structural integrity of these components is also evaluated using two key metrics, von Mises stress and elastic strain. A material's maximum shear stress, or von Mises stress, is what determines whether it will permanently deform or not. A material's elastic strain, on the other hand, measures how much it deforms when stressed. A component's total deformation, which shows how much deformation it has experienced, is also crucial since it shows how much deformation it has experienced before failing. In order to identify which connecting rods and grasping arms are more durable and capable of withstanding greater loads and forces, we must compare the von Mises stress, elastic strain, and total deformation of the various components. Overall, it is crucial to concentrate on connecting rods and grabbing arms when performing comparative analysis after applying von Mises stress, elastic strain, and total deformations to make sure that these parts are built to withstand the stresses and forces they are subjected to and that they are safe and dependable.

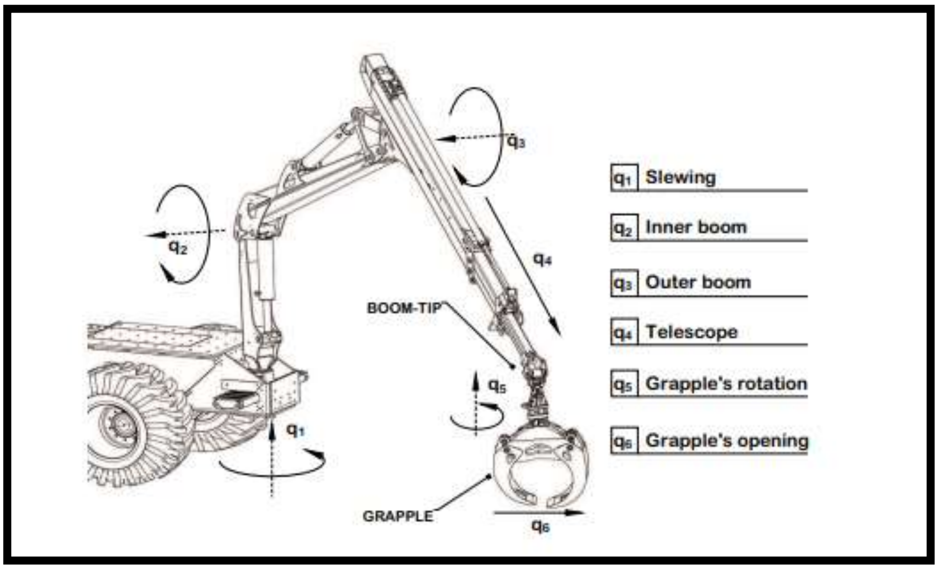

Figure 3.6: The Links and Grabbing Arm Studied in this Master's Thesis [81].

3.5 RESEARCH TOOLS AND ML ALGORITHMS APPLIED

The main study approaches deployed and applied to achieve this master's thesis formulated in this study include the following research instruments:

a. ANSYS software.

b. Comparative investigation.

c. Finite Element Analysis (FEA).

The following paragraphs provide detailed descriptions and illustrations associated with those three research approaches to determine the critical impacts and positive relevances of carbon fiber materials in the construction sector.

3.5.1 ANSYS Software Package

ANSYS software is a numerical program that can conduct different types of mechanical investigations and engineering exploration based on FEA and simulations. This software tool is the first introduced by some US institutions and used in limited applications, like military and space engineering. Nonetheless, after it is developed, modified, and amended several times in the last decades, its applications became numerous, and its adoption is elevated to serve in medical, mechanical, electrical, and industrial engineering, bioengineering, and manufacturing [29] [31].

For this reason, various industries and large-scale mechanical devices are designed and enhanced in terms of their accuracy, performance, and reliability with the help of the ANSYS software.

One of the beneficial advantages of this software is its potential and capability to execute high-precision simulations, 3D modelling, and numerical analysis that can mimic and simulate the real conditions and actual operating circumstances and environments existing in different engineering disciplines [32].

With the support of the ANSYS software tool, different industries have been boosted, elaborated, and enhanced, such as automobile engineering, airplane manufacturing, ship design, and the space industry. The vital significance and added values attained for mechanical engineering and organizations by the adoption of this program comprise the following advantages [33]:

a. Saving much time required to carry out experiments and real investigations for large-scale industries.
b. Alleviating massive efforts needed to conduct those experiments and real investigations.
c. Minimizing the substantial budget required to execute all those experiments and real investigations.
d. Providing sufficient potential and opportunities to guide and manage multiple numbers of experiments and investigations with substantial levels of accuracy, performance, and reliability.

3.5.2 Comparative Analysis

Investigations, in the main, depend on specific procedures and known steps to help discover some beneficial relationships and classify feasible merits of a mechanical machine or devices based on the definition of some boundary conditions and critical variables. On the other hand, in some cases, other investigation concepts can be implemented to study the mechanical device variables. One of those concepts is comparative analysis. According to this method, mechanical engineering scholars and researchers can depend on evaluating the mechanical properties and vital features of a mechanical tool by using some mathematical equations, empirical examination, or numerical explorations. Then, a comparison is conducted with another parameter (like the material of the mechanical device), considering some vital parameters [34]−[36].

Here, a comparative analysis is carried out using numerical 3D modelling and analysis. All boundary conditions are defined in this examination. But the only aspect that is different between the first and second scenarios is the type of material. The boundary conditions, forces applied, and other mechanical variables are similar to both scenarios. But 4140 steel is used in the first scenario. Meantime, the carbon fiber is deployed in the second one.

3.5.3 Finite Element Analysis

Finite Element Analysis (FEA) are defined as a type of investigation through which complex mechanical devices, structures, and geometries are examined and assessed based on the division and transformation of the whole structure into tiny parts that are studied separately. Then, an overall approximation of the solution is performed. Examples of mechanical devices that can be studied by virtue of FEA comprise ships, airplanes, automobiles, and large 4140 steel structures. In this setting, vessels or cars cannot be simulated or investigated when a drag force, momentum, or other types of boundary conditions are applied due to the following reasons [37]−[40]:

a. Complicated geometry.
b. The variation of force or momentum along the car/ aircraft.
c. The large size of the investigated shape.
d. No uniform cross-section.

To solve all these problems, cars, ships, or aircraft are divided into small elements. Then, forces and momentum are applied numerically. Then, the numerical solution can be attained from the whole mechanical structure.

3.6 CHAPTER SUMMARY

In this chapter, the primary research method, research philosophy, the study's dependent and independent variables, and the vital research techniques used in this master's thesis are explained and illustrated in detail. The main research techniques used in this study include (A) The REVIT software, (B) Comparative analysis, and (C) FEA. Furthermore, the third chapter provided a detailed description of the case study considered in this study. Also, it illustrated the two main scenarios addressed in this thesis to evaluate the beneficial contributions and vital merits of the grab excavator when the carbon fiber material is utilized compared with 4140 steel material.

4. RESULTS AND DISCUSSIONS

4.1 CHAPTER GOAL

This study provides an illustration of critical findings obtained from the numerical analysis, mathematical evaluation, and simulation outputs achieved to assess and examine the von Mises, elastic strain, and total deformations related to the grab excavator investigated in this study, considering two scenarios:

a. The first scenario: 4140 steel is used in the links and grabbing arms contains both chromium (Cr) and molybdenum (Mo).

b. The second scenario: carbon fiber is applied in the links and grabbing arms, as well.

Furthermore, the discussion of this study is also represented.

4.2 NUMERICAL SIMULATION OUTCOMES OF THE FIRST SCENARIO

In this scenario, 4140 steel is used for manufacturing the grab excavator. Von Mises stress, elastic strain, and total deformations are investigated and examined to evaluate the mechanical performance of this excavator. Figure 4.1 indicates the von Mises of the grab excavator when the 4140 steel is employed.

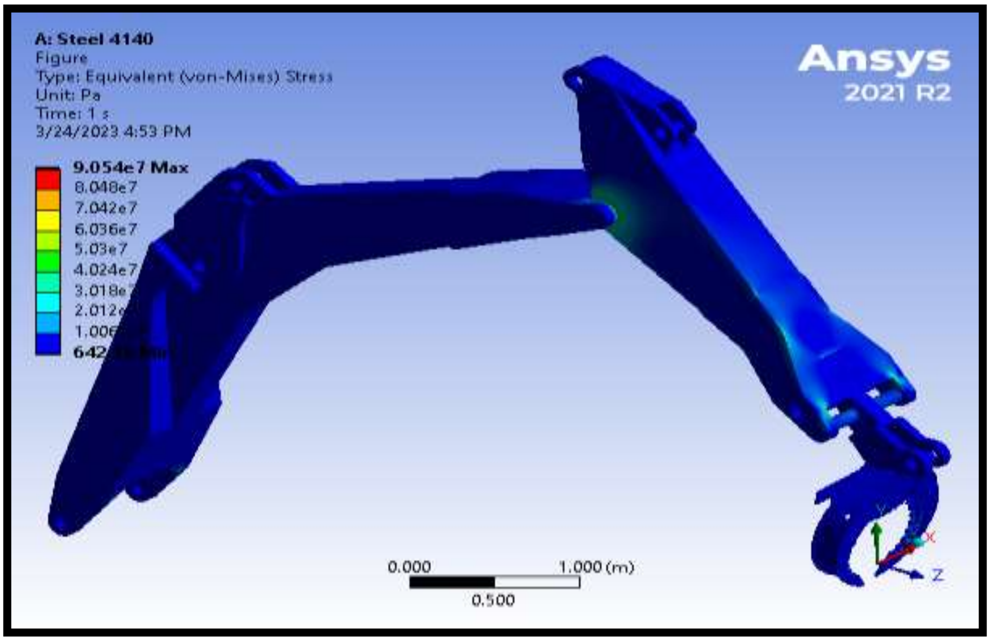

Figure 4.1: Numerical Results of Von **Mises** Linked to the Grab Excavator Made of 4140 Steel.

It can be inferred from Figure 4.1 that the maximum value of von Mises stress for the grab excavator used in this study amounts to 90.54 MPa. Also, it is indicated from this figure that generally, the von Mises in the whole structure of the grab excavator recorded its minimum values, which can be seen by the blue colour distributed on the overall parts of the grab excavator. At the same time, the research findings indicated the numerical simulation results of elastic strain for 4140 steel.

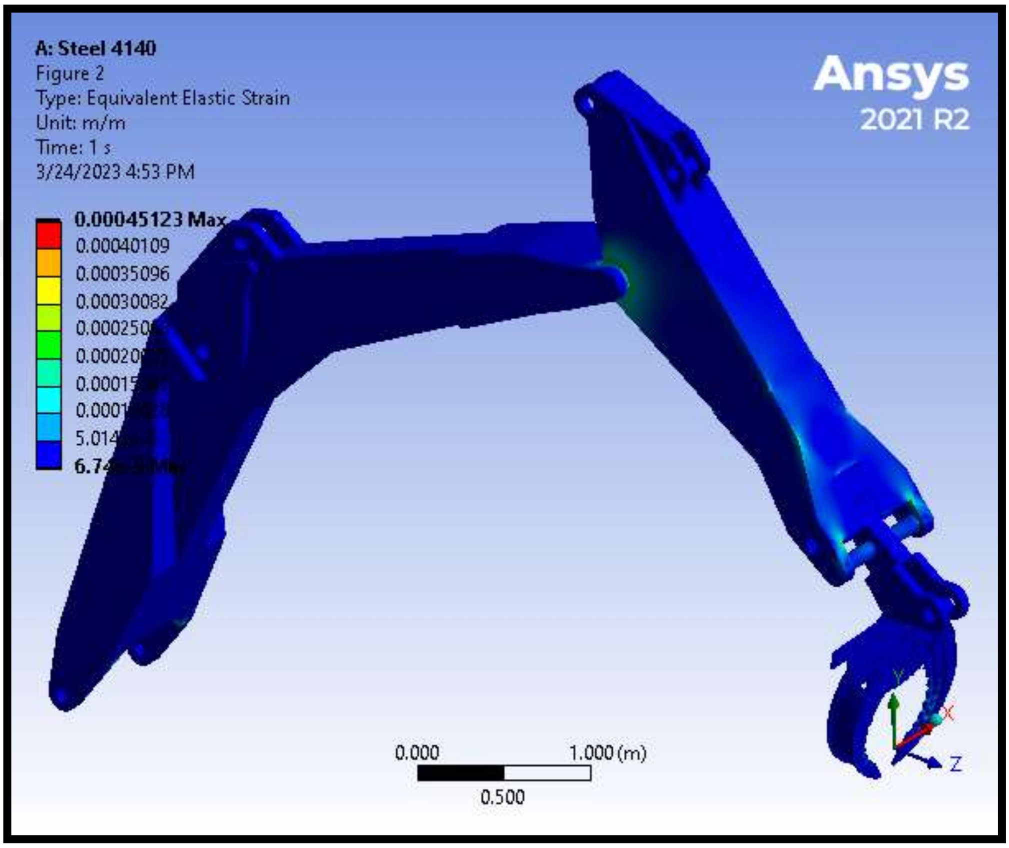

Figure 4.2: Numerical Results of Elastic Strain Linked to the Grab Excavator Made of 4140 Steel.

It is inferred from the results obtained in this figure that the elastic strain of 4140 steel recorded a maximum value of 0.0004512 m/m. However, approximately the overall structure did not attain this maximum value but recorded minimum amounts in all parts of the grab excavator. Also, Figure 4.3 illustrates the findings pertaining to the deformations of this mechanical equipment used in the construction industry.

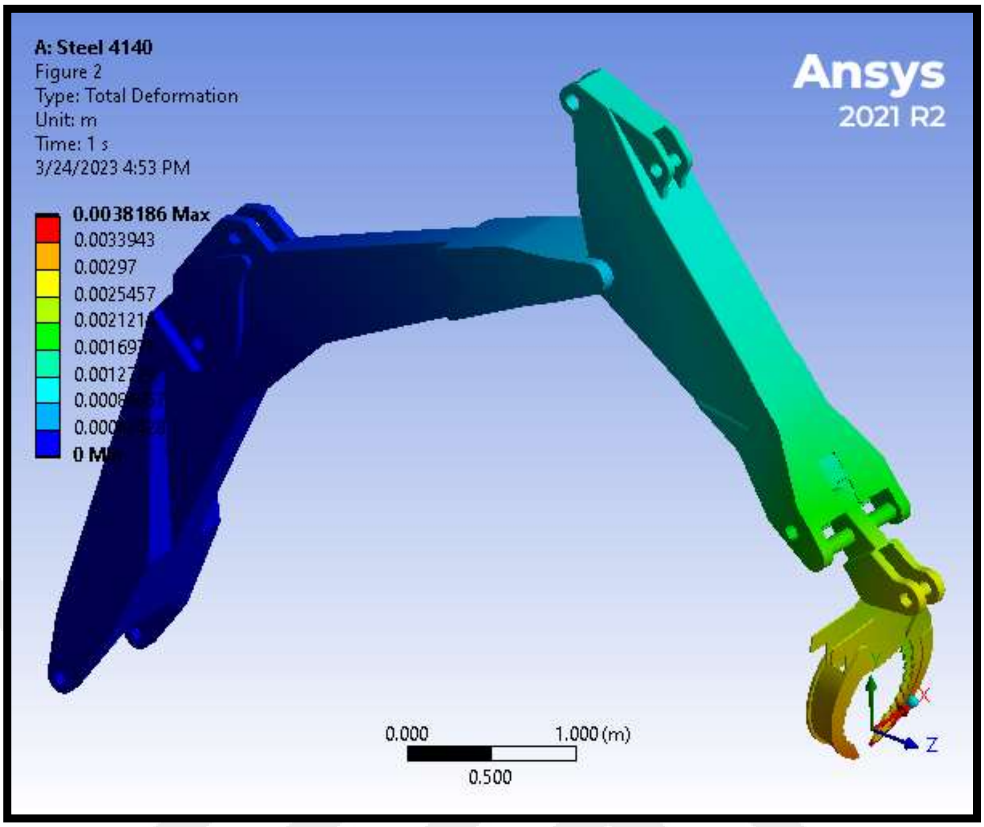

Figure 4.1: Numerical Outcomes of Total Deformations Linked to the Grab Excavator Made of 4140 Steel.

It is concluded from the outputs expressed in this figure that the overall deformations associated with the grab excavator made of 4140 steel that there are some regions at which total deformations are recorded in large quantities. Those regions contain the last arm connected directly with the grab. Also, the grab itself recorded more considerable values of total deformations in the grab excavator. It is vital to note that the maximum total deformations recorded in this case reached roughly 0.00382 m.

4.3 NUMERICAL SIMULATION OUTCOMES OF THE SECOND SCENARIO

In this scenario, another material carbon fiber, is used to manufacture the grab excavator. Nonetheless, this material is more robust compared with 4140 steel. Hence, it is expected that the von Mises, elastic strain, and total deformations register lower values. Figure 4.4 indicates the von Mises linked to the grab excavator when the carbon fiber is used.

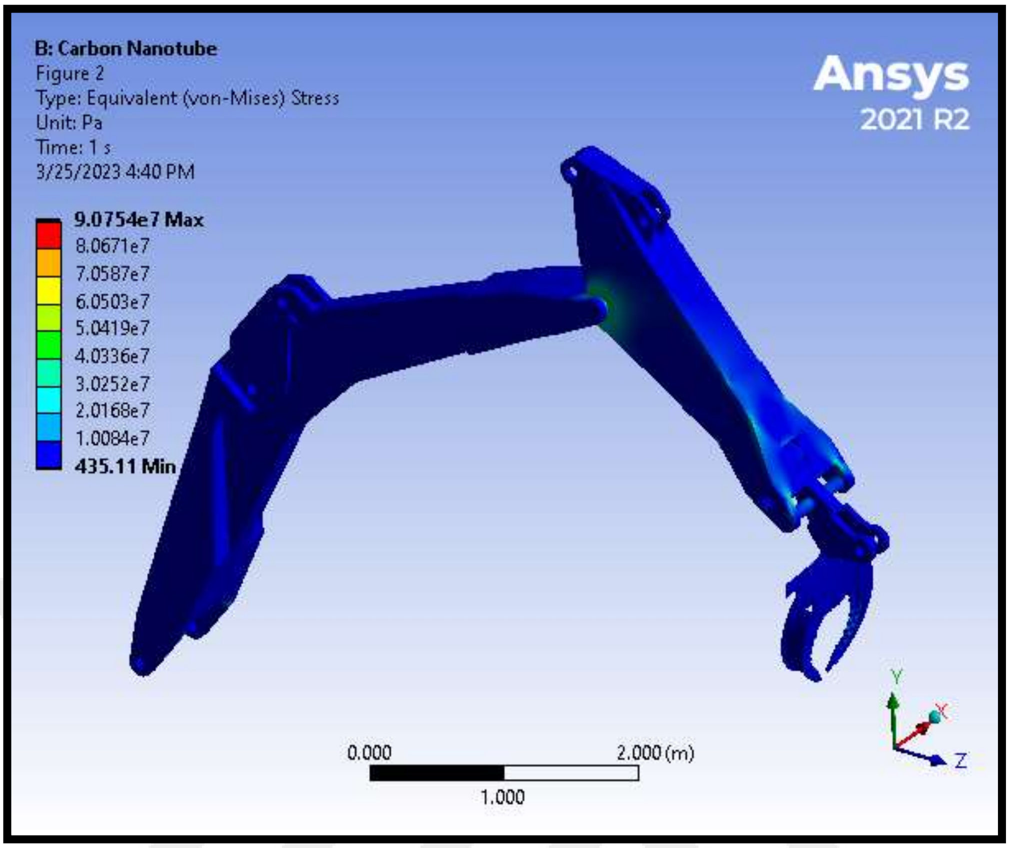

Figure 4.2: Numerical Outcomes of Von Mises Stress Linked to the Grab Excavator Made of Carbon Fiber.

It is deduced from the findings shown in Figure 4.4 that the von Mises approximately registered no large values at the overall structure of the grab excavator. Notwithstanding, large values of this parameter recorded large amounts in very small zones, which are located at the joints and links of the grab connected directly with the grab. Furthermore, the simulation process revealed some findings related to the elastic strain of this robot.

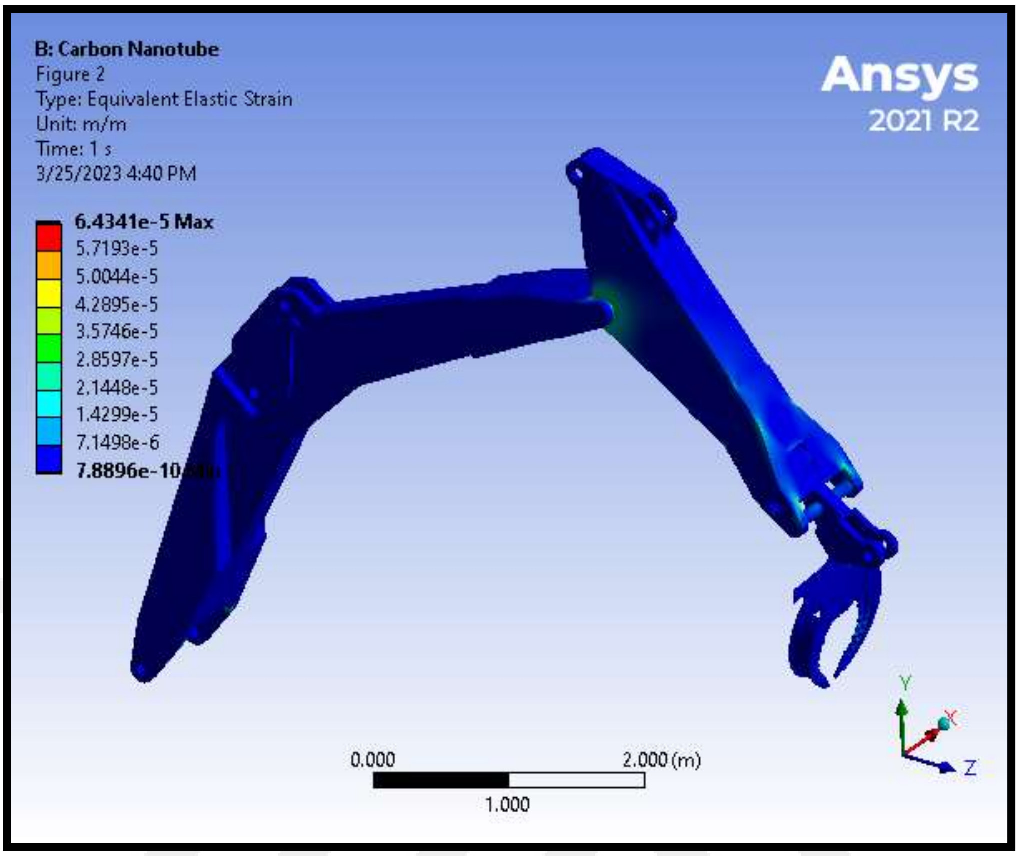

Figure 4.3: Numerical Outcomes of Elastic Strain Linked to the Grab Excavator Made of Carbon Fiber.

It is concluded from the results illustrated in Figure 4.5 that the elastic strain obtained its minimum amounts in various regions of the whole structure of the grab excavator. At the same time, the maximum amounts of elastic strain are about $6.43\times\ 10^{-5}$ m/m. Moreover, the research findings provide some data linked to the total deformations of the grab excavator.

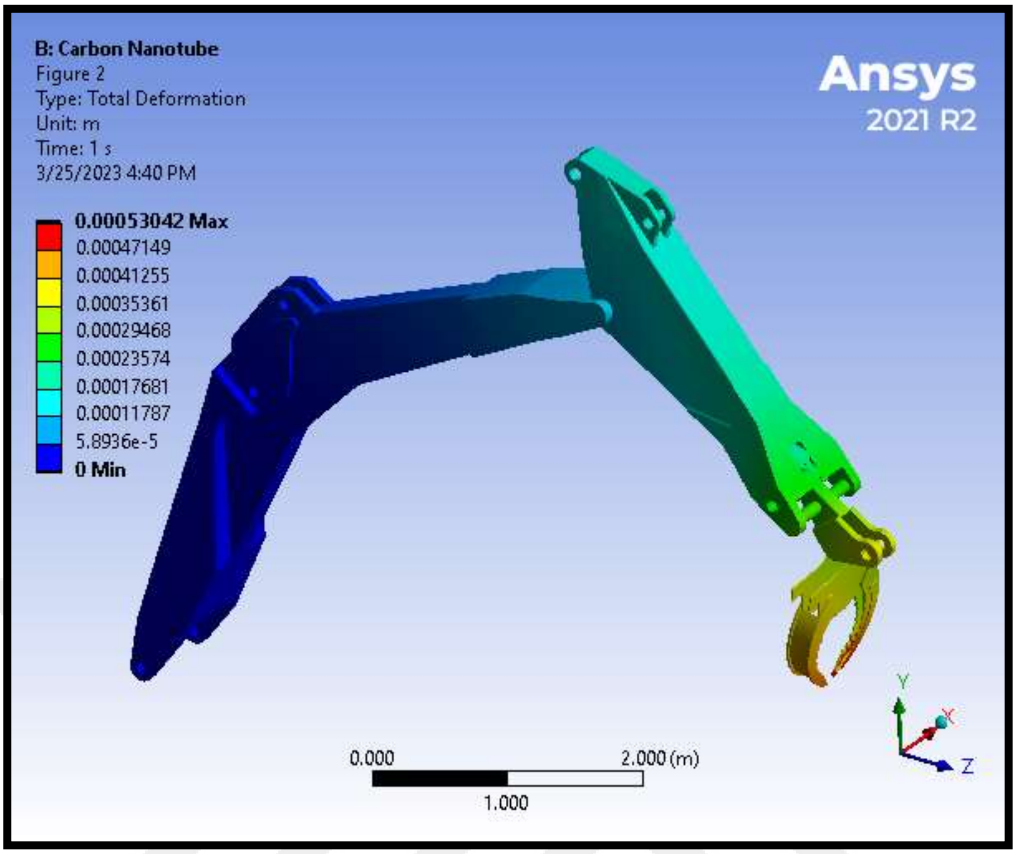

Figure 4.4: Numerical Outcomes of Total Deformations Linked to the Grab Excavator Made of (Carbon Fiber).

It is indicated from the outputs explained in this figure that total deformations are more significant in the last arm connected with the grab and the grab. Green, yellow, and red colours can be noted in those zones. In contrast, the total deformations observed in other areas approach approximately zero. The maximum rate of deformations, in this case, is 0.000530 m.

4.4 COMPARATIVE ANALYSIS BETWEEN THE TWO SCENARIOS

In this section, a summary of the whole numerical results is developed to clearly express the difference and major contributions of carbon fiber compared with 4140 steel. Table 4.1 indicates these results.

Table 4.1: An Illustration of the Comparative Analysis Results Between 4140 Steel and Carbon Fiber.

No.	Category	Maximum values in	
		4140 steel	Carbon Fiber
1	Von Mises	90.54 MPa	90.8 MPa
2	Elastic strain	4.5×10^{-4}	6.4×10^{-5}
3	Total deformations	0.00382 m	0.000530 m

Besides these findings, three graphical illustrations of the von Mises stress, elastic strain, and total deformations are expressed in the following diagrams. Figure 4.7 indicates a graphical representation of the numerical data linked to the von Mises of two scenarios.

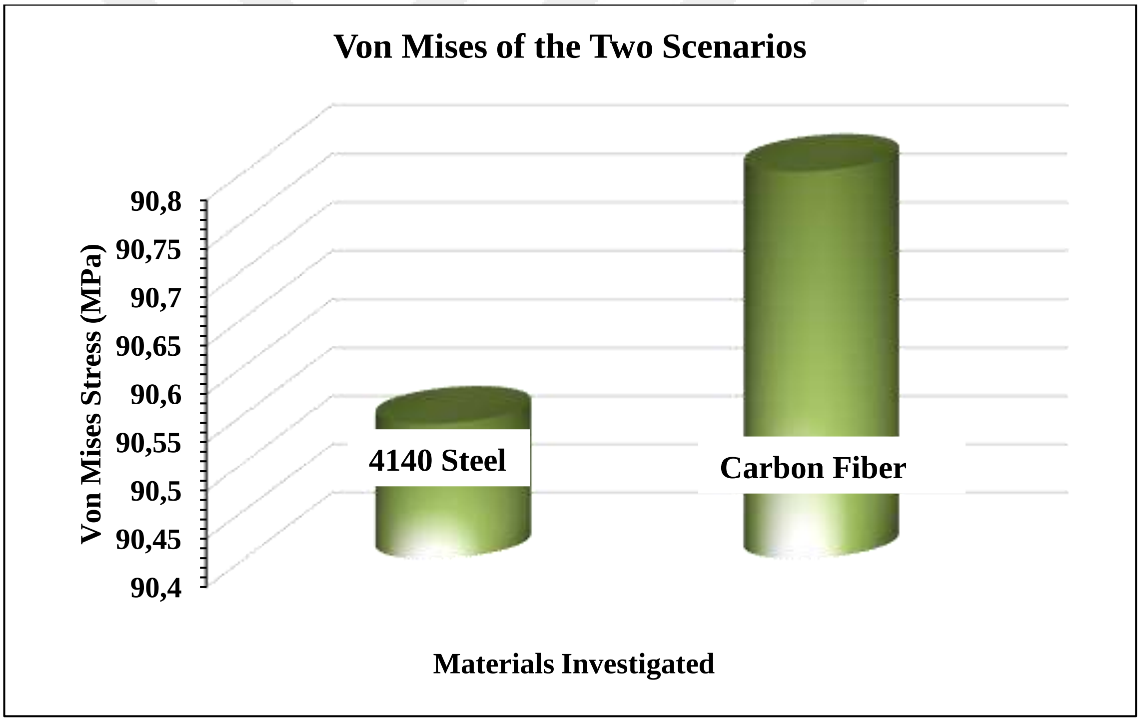

Figure 4.5: A Graphical Representation of The Numerical Data Linked to the Von Mises of Two Scenarios (**4140** Steel, Carbon Fiber).

On the other hand, Figure 4.8 indicates a graphical description of the elastic strain for those two materials.

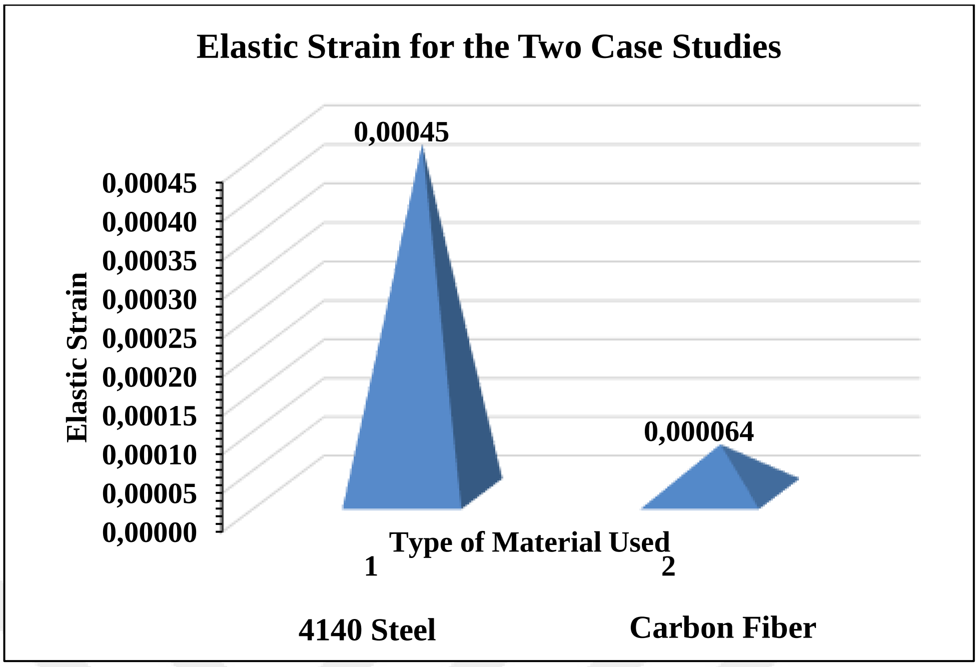

Figure 4.6: A Graphical Description of The Elastic Strain for the Two Materials Used in the Grab Excavator Robot.

Further, Figure 4.9 explains the numerical data described in the previous table regarding the total deformations.

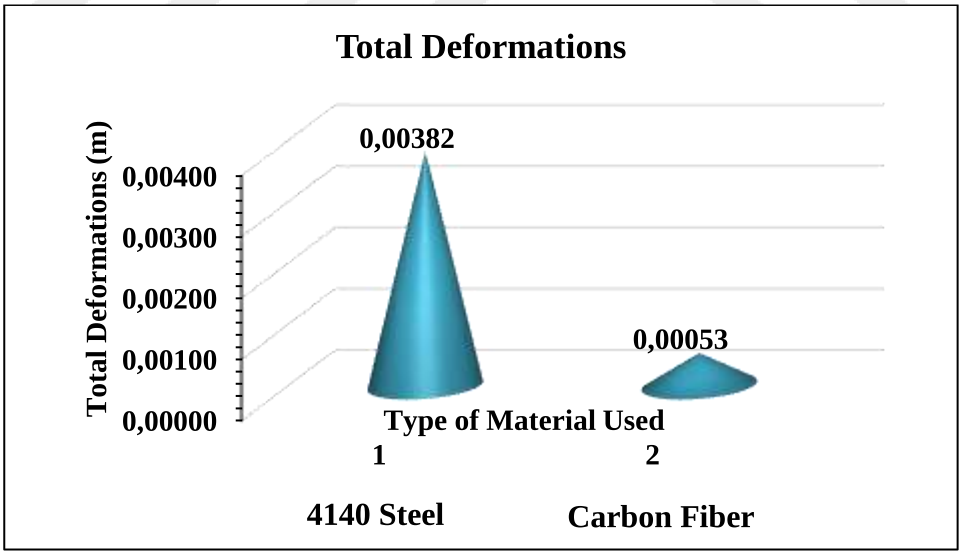

Figure 4.7: A Graphical Description of the Total Deformations for the Two Materials Used in the Grab Excavator Robot.

4.5 DISCUSSIONS

The results of this study indicate that the connecting links and the grabbing arm of the grab excavator record very low rates of von Mises stress, elastic strain, and total deformations according to the numerical simulations conducted for the two scenarios in which (a. 4140 Steel and b. Carbon Fiber) are employed. Also, the research findings reveal that the maximum amounts of von Mises stress noted in those connecting links and grabbing arm are 90.54 MPa and 90.8 MPa for the first scenario (4140 steel) and the second scenario (carbon fiber). Moreover, the elastic strain recorded for 4140 steel and carbon fiber is 4.5×10^{-4} m/m and 6.4×10^{-5} m/m, respectively. Further, total deformations of 4140 steel and carbon fiber are 0.00382 m and 0.00053 m, subsequently. Thus, it can be concluded that using carbon fiber in manufacturing this mechanical tool is beneficial as it mitigates large amounts of von Mises stress, strain, and deformations. These results are consistent with the research outputs of [62]−[76], who conducted an analysis investigating the critical relevance and substantial contributions of carbon fiber employment in different mechanical tools and devices, namely robots, to help enhance the performance of construction activities and building execution by virtue of enhancing robots and tools mechanical durability, efficiency and reliability. Their research outputs revealed that using carbon fiber in those mechanical devices (such as automobiles, aircraft, ships, and bicycles) provided significant improvements and remarkable elaboration of mechanical behaviour and properties of automobiles, aircraft, ships, and bicycles. Thus, their durability, performance, and lifespan can be substantially boosted and fostered. On the other hand, Table 4.2 offers another comparative analysis between the results obtained in this study with the research findings from other studies and engineers.

Table 4.2: Another Comparative Analysis Between the Findings Attained in This Study With the Similar Studies.

No	Type of Variables Investigated	This Research	Chaturvedi et al. (2020) [77]	Kartikejan et al. (2020) [78]
1	Type of analysis	Numerical simulations via ANSYS software	Modeling and simulations via CAD/ CATIA 3 and ANSYS packages	ANSYS software and a step file
2	Aim of the research	To provide mechanically durable and robust robots to help laborers lift heavy equipment in building projects	To offer high quality and effectiveness in performing buildings activities	To provide more significant performance, efficiency, and reliability in achieving tasks of robots by reducing their weights

Table 4.2: Another Comparative Analysis Between the Findings Attained in This Study With the Research Findings from Other Studies "Tables Continued."

3	The kind of application considered	A robotic grab excavator used in the construction	A robotic arm used	A typical robotic manipulator arm used in construction projects
4	Material(s) used	4140 steel and carbon fiber	AISI-1050 Steel, Carbon Fiber, and Kevlar29	Carbon fiber, steel, and aluminum
5	Maximum von Mises values	(4140 Steel, Carbon fiber): (90.54 MPa; 90.8 MPa)	1.12 MPa	290.15 to 371.47 MPa (for carbon fiber)
6	Maximum elastic strain	(4140 Steel, Carbon fiber): ($4.5 \times 10^{-4} \mathrm{m/m}$, $6.4 \times 10^{-5} \mathrm{m/m}$)	0.000017	N/A
7	Total deformation	(4140 Steel; Carbon fiber): (0.00382 m, 0.00053 m)	1.162 mm	7.10 to 17.46 mm (for carbon fiber)

5. CONCLUSIONS AND RECOMMENDAITONS

5.1 CHAPTER GOAL

This section provides a summary of the main numerical results and simulation process obtained from the ANSYS software conducted with the consideration of two scenarios. Also, this chapter indicates some recommendations and vital suggestions that can help mechanical engineers and consultants perform further enhancements on robots that are broadly used in the construction sector.

5.2 CONCLUSIONS

The study is conducted to examine and identify the beneficial contributions and rationale of smart structure materials like carbon fiber that can be used for construction robots to facilitate their operation and improve their efficiency and performance. The two case studies of a grab excavator robot consist of two scenarios: one contains a grab excavator (hydraulic grabs and bucket grabs) that is made of 4140 steel; the second scenario includes the same grab excavator but is made of carbon fiber.

Considered in order to improve the performance of heavy construction equipment. Simulations and numerical modelling are implemented using the ANSYS software package. 4140 Steel and carbon fiber materials are introduced and investigated in this research. Based on the mathematical simulation and modelling results conducted in this study, the following results can be summarised:

a. The links and grabbing arm in the grab excavator recorded very low rates of von Mises stress, elastic strain, and total deformations according to the numerical simulations conducted when the carbon fiber is employed compared with 4140 steel.
b. The efficiency of the carbon fiber grab excavator is improved because it can transfer more heavy objects as it is five times lighter and five times stronger than 4140 steel.
c. The maximum amounts of von Mises stress are 90.54 MPa and 90.8 MPa for the first scenario (4140 steel) and the second scenario (carbon fiber).
d. The elastic strain values recorded for the grab excavator based on 4140 steel and carbon fiber materials are $4.5 \times 10^{-4}\mathrm{m/m}$ and $6.4\times 10^{-5}\mathrm{m/m}$, respectively.
e. Total deformations of the grab excavator that used 4140 steel and carbon fiber are 0.00382 m and 0.00053 m, subsequently.

f. Using carbon fiber in manufacturing, which is measured as a very successful and supportive material for the grab excavator, improves the performance parameters in terms of increasing the strength of materials, reducing weight, and reducing system energy consumption as it mitigates large amounts of von Mises stress, strain, and deformations.

5.3 RECOMMENDATIONS

Depending on the research findings obtained from the mathematical simulations executed in this master’s research, a number of critical recommendations and concrete suggestions can be done that could encourage the adoption of carbon fiber principles in the construction sector and other applications.

The vital recommendation of this study is to apply carbon fiber material in various heavy equipment and mechanical devices that require time and cost-effectiveness besides significant efficiency and performance in performing construction tasks.

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APPENDIX A

THE ANSYS SOFTWARE'S NUMERICAL ANALYSIS PROCESS CONSIDERING BOUNDARY CONDITIONS AND SIMULATION FINDINGS FOR THE FIRST CASE STUDY (4140 STEEL)

Project*

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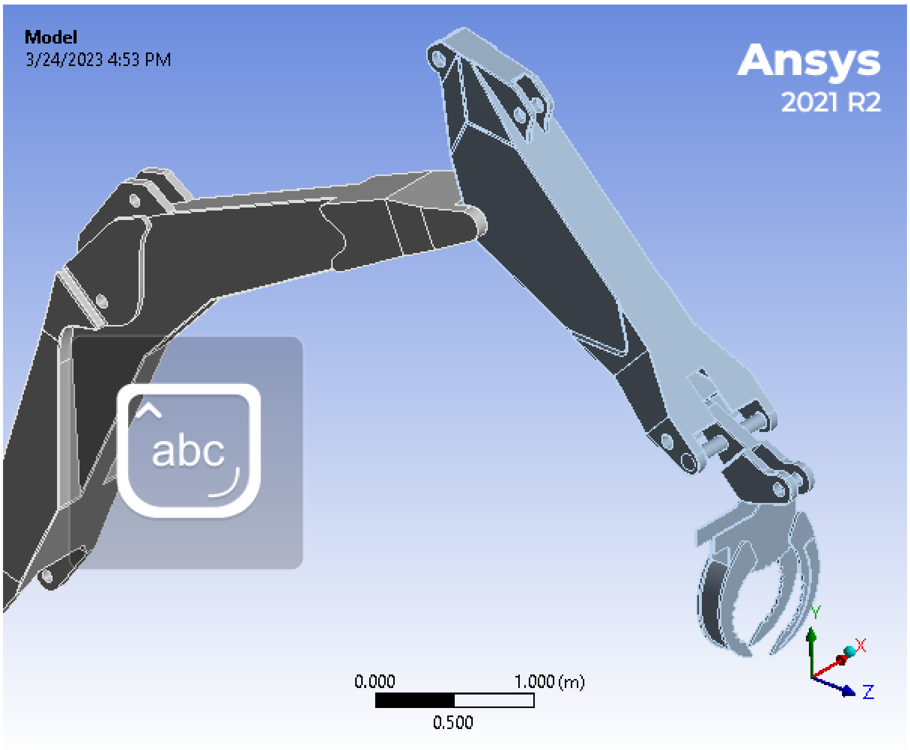
Last Saved	Friday, March 17, 2023
Product Version	2021 R2
Save Project Before Solution	No
Save Project After Solution	No



Contents

Units

TABLE 1

Unit System	Metric (m, kg, N, s, V, A) Degrees rad/s Celsius
Angle	Degrees
Rotational Velocity	rad/s
Temperature	Celsius

Model (A4)

Geometry

TABLE 2
Model (A4) > Geometry

Object Name	*Geometry*
State	Fully Defined
Definition	
Source	D:\Projects\Noor ALordon projects\X ARM\CAD.stp
Type	Step
Length Unit	Millimeters
Element Control	Program Controlled
Display Style	Body Color
Bounding Box	
Length X	4.1135 m
Length Y	5.8922 m

Length Z	8.6742 m
Properties	
Volume	1.2917 m³
Mass	10140 kg
Scale Factor Value	1.
Statistics	
Bodies	2
Active Bodies	2
Nodes	228410
Elements	117514
Mesh Metric	None
Update Options	
Assign Default Material	No
Basic Geometry Options	
Solid Bodies	Yes
Surface Bodies	Yes
Line Bodies	No
Parameters	Independent
Parameter Key	ANS;DS
Attributes	No
Named Selections	No
Material Properties	No
Advanced Geometry Options	
Use Associativity	Yes
Coordinate Systems	No
Reader Mode Saves Updated File	No
Use Instances	Yes
Smart CAD Update	Yes
Compare Parts On Update	No
Analysis Type	3-D
Mixed Import Resolution	None
Import Facet Quality	Source
Clean Bodies On Import	No
Stitch Surfaces On Import	Program Tolerance
Decompose Disjoint Geometry	Yes
Enclosure and Symmetry Processing	Yes

TABLE 3
Model (A4) > Geometry > Parts

Object Name	*Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator*	*Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2*
State	Meshed	
Graphics Properties		
Visible	Yes	
Transparency	1	
Definition		
Suppressed	No	
Stiffness Behavior	Flexible	
Coordinate System	Default Coordinate System	

Reference Temperature	By Environment	
Treatment	None	
Material		
Assignment	Low alloy steel, 4140, normalized	Low alloy steel, 4140, normalized 2
Nonlinear Effects	Yes	
Thermal Strain Effects	Yes	
Bounding Box		
Length X	4.1135 m	2.8534 m
Length Y	5.6087 m	3.9853 m
Length Z	6.0872 m	4.2208 m
Properties		
Volume	1.2115 m^3	8.017e-002 m^3
Mass	9510.3 kg	629.33 kg
Centroid X	5.3932 m	5.3884 m
Centroid Y	5.6325 m	6.5563 m
Centroid Z	-6.8497 m	-2.5439 m
Moment of Inertia Ip1	25122 kg·m^2	70.094 kg·m^2
Moment of Inertia Ip2	1512.7 kg·m^2	745.47 kg·m^2
Moment of Inertia Ip3	26209 kg·m^2	763. kg·m^2
Statistics		
Nodes	63707	164703
Elements	35845	81669
Mesh Metric	None	

FIGURE 1
Model (A4) > Geometry > Figure

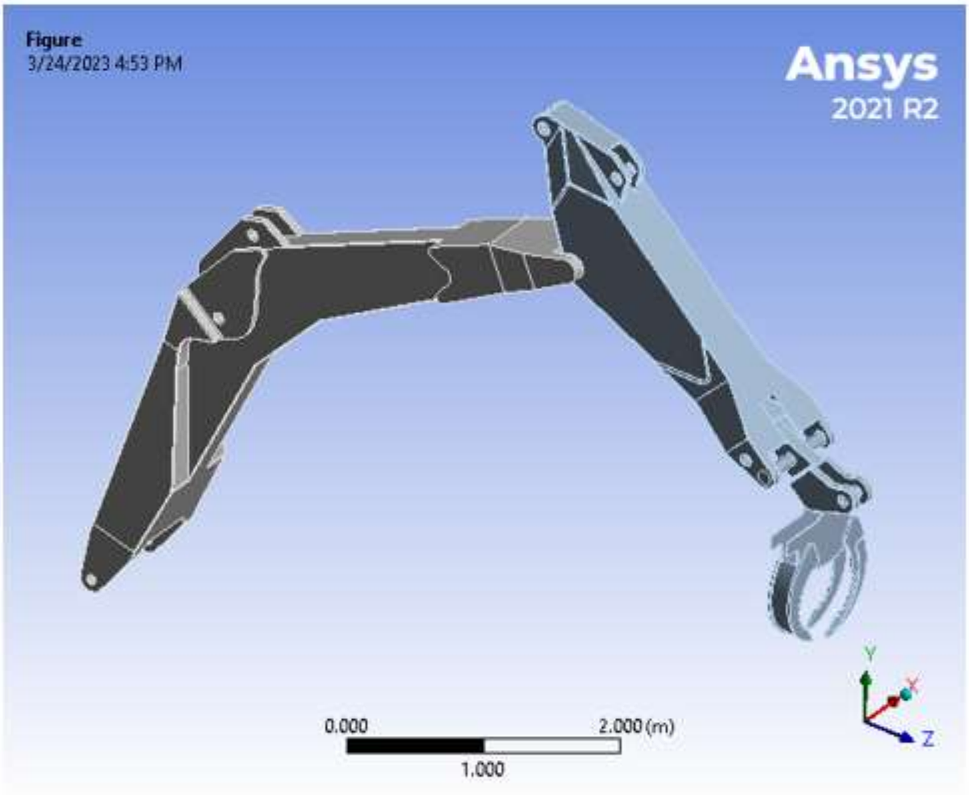


TABLE 4
Model (A4) > Materials

Object Name	*Materials*
State	Fully Defined
Statistics	
Materials	3
Material Assignments	0

Coordinate Systems

TABLE 5
Model (A4) > Coordinate Systems > Coordinate System

Object Name	*Global Coordinate System*
State	Fully Defined
Definition	
Type	Cartesian
Coordinate System ID	0.
Origin	
Origin X	0. m

Origin Y	0. m
Origin Z	0. m
Directional Vectors	
X Axis Data	[1. 0. 0.]
Y Axis Data	[0. 1. 0.]
Z Axis Data	[0. 0. 1.]

Connections

TABLE 6
Model (A4) > Connections

Object Name	*Connections*
State	Fully Defined
Auto Detection	
Generate Automatic Connection On Refresh	Yes
Transparency	
Enabled	Yes

TABLE 7
Model (A4) > Connections > Contacts

Object Name	*Contacts*
State	Fully Defined
Definition	
Connection Type	Contact
Scope	
Scoping Method	Geometry Selection
Geometry	All Bodies
Auto Detection	
Tolerance Type	Slider
Tolerance Slider	0.
Tolerance Value	2.816e-002 m
Use Range	No
Face/Face	Yes
Face-Face Angle Tolerance	75. °
Face Overlap Tolerance	Off
Cylindrical Faces	Include
Face/Edge	No
Edge/Edge	No
Priority	Include All
Group By	Bodies
Search Across	Bodies
Statistics	
Connections	1
Active Connections	1

TABLE 8
Model (A4) > Connections > Contacts > Contact Regions

Object Name	*Contact Region*
State	Fully Defined

Scope	
Scoping Method	Geometry Selection
Contact	5 Faces
Target	7 Faces
Contact Bodies	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator
Target Bodies	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2
Protected	No
Definition	
Type	Bonded
Scope Mode	Automatic
Behavior	Program Controlled
Trim Contact	Program Controlled
Trim Tolerance	2.816e-002 m
Suppressed	No
Advanced	
Formulation	Program Controlled
Small Sliding	Program Controlled
Detection Method	Program Controlled
Penetration Tolerance	Program Controlled
Elastic Slip Tolerance	Program Controlled
Normal Stiffness	Program Controlled
Update Stiffness	Program Controlled
Pinball Region	Program Controlled
Geometric Modification	
Contact Geometry Correction	None
Target Geometry Correction	None

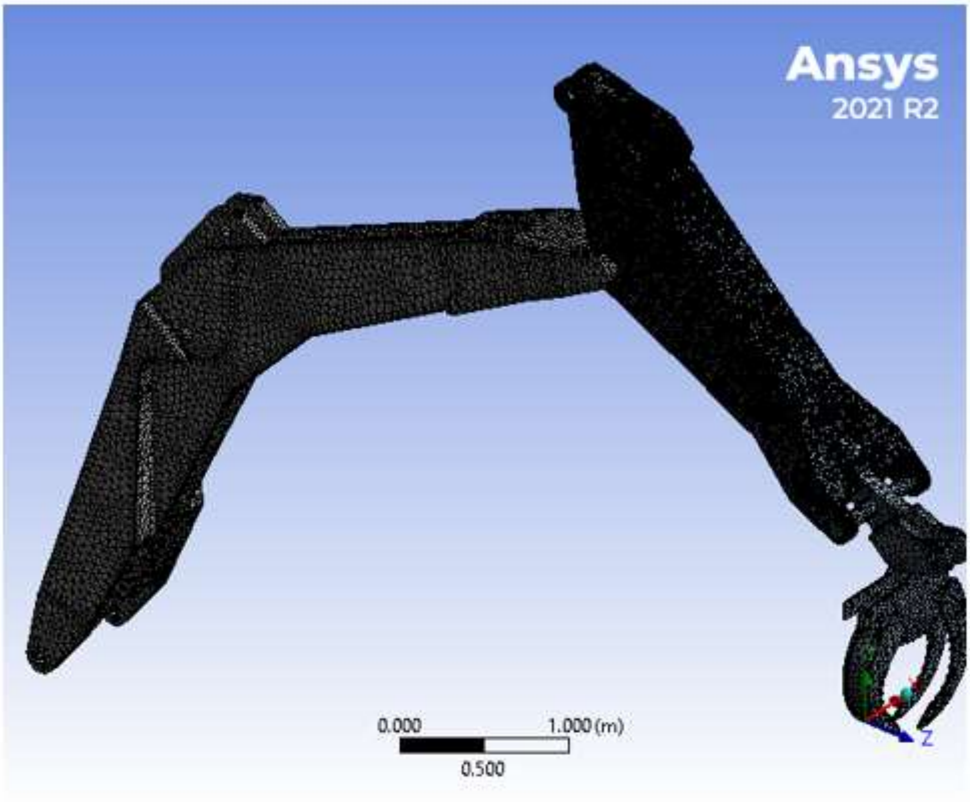
Mesh

TABLE 9
Model (A4) > Mesh

Object Name	*Mesh*
State	Solved
Display	
Display Style	Use Geometry Setting
Defaults	
Physics Preference	Mechanical
Element Order	Program Controlled
Element Size	3.e-002 m
Sizing	
Use Adaptive Sizing	Yes
Resolution	Default (2)
Mesh Defeaturing	Yes
Defeature Size	Default
Transition	Fast
Span Angle Center	Coarse
Initial Size Seed	Assembly
Bounding Box Diagonal	11.264 m

Average Surface Area	3.929e-002 m²
Minimum Edge Length	1.5186e-004 m
Quality	
Check Mesh Quality	Yes, Errors
Error Limits	Aggressive Mechanical
Target Quality	Default (0.050000)
Smoothing	Medium
Mesh Metric	None
Inflation	
Use Automatic Inflation	None
Inflation Option	Smooth Transition
Transition Ratio	0.272
Maximum Layers	5
Growth Rate	1.2
Inflation Algorithm	Pre
View Advanced Options	No
Advanced	
Number of CPUs for Parallel Part Meshing	Program Controlled
Straight Sided Elements	No
Rigid Body Behavior	Dimensionally Reduced
Triangle Surface Mesher	Program Controlled
Topology Checking	Yes
Pinch Tolerance	Please Define
Generate Pinch on Refresh	No
Statistics	
Nodes	228410
Elements	117514

FIGURE 2
Model (A4) > Mesh > Figure



Static Structural (A5)

TABLE 10
Model (A4) > Analysis

Object Name	*Static Structural (A5)*
State	Solved
Definition	
Physics Type	Structural
Analysis Type	Static Structural
Solver Target	Mechanical APDL
Options	
Environment Temperature	22. °C
Generate Input Only	No

TABLE 11
Model (A4) > Static Structural (A5) > Analysis Settings

Object Name	*Analysis Settings*
State	Fully Defined
Step Controls	

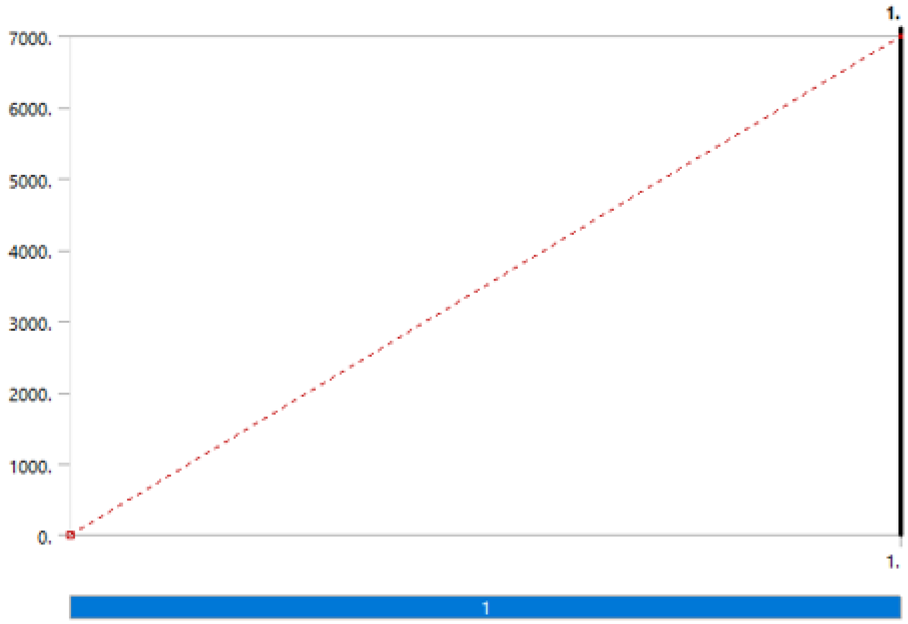
Number Of Steps	1.
Current Step Number	1.
Step End Time	1. s
Auto Time Stepping	Program Controlled
Solver Controls	
Solver Type	Program Controlled
Weak Springs	Off
Solver Pivot Checking	Program Controlled
Large Deflection	Off
Inertia Relief	Off
Quasi-Static Solution	Off
Rotordynamics Controls	
Coriolis Effect	Off
Restart Controls	
Generate Restart Points	Program Controlled
Retain Files After Full Solve	No
Combine Restart Files	Program Controlled
Nonlinear Controls	
Newton-Raphson Option	Program Controlled
Force Convergence	Program Controlled
Moment Convergence	Program Controlled
Displacement Convergence	Program Controlled
Rotation Convergence	Program Controlled
Line Search	Program Controlled
Stabilization	Program Controlled
Advanced	
Inverse Option	No
Contact Split (DMP)	Off
Output Controls	
Stress	Yes
Surface Stress	No
Back Stress	No
Strain	Yes
Contact Data	Yes
Nonlinear Data	No
Nodal Forces	No
Volume and Energy	Yes
Euler Angles	Yes
General Miscellaneous	No
Contact Miscellaneous	No
Store Results At	All Time Points
Result File Compression	Program Controlled
Analysis Data Management	
Solver Files Directory	D:\Projects\Noor ALordon projects\X ARM\sim x arm files\dp0\SYS\MECH\
Future Analysis	None
Scratch Solver Files Directory	
Save MAPDL db	No

Contact Summary	Program Controlled
Delete Unneeded Files	Yes
Nonlinear Solution	No
Solver Units	Active System
Solver Unit System	mks

TABLE 12
Model (A4) > Static Structural (A5) > Loads

Object Name	*Force*	*Fixed Support*
State	Fully Defined	
Scope		
Scoping Method	Geometry Selection	
Geometry	4 Faces	2 Faces
Definition		
Type	Force	Fixed Support
Define By	Vector	
Applied By	Surface Effect	
Magnitude	7000. N (ramped)	
Direction	Defined	
Suppressed	No	

FIGURE 3
Model (A4) > Static Structural (A5) > Force



Solution (A6)

TABLE 13
Model (A4) > Static Structural (A5) > Solution

Object Name	*Solution (A6)*
State	Solved
Adaptive Mesh Refinement	
Max Refinement Loops	1.
Refinement Depth	2.
Information	
Status	Done
MAPDL Elapsed Time	1 m 14 s
MAPDL Memory Used	3.2393 GB
MAPDL Result File Size	76.938 MB
Post Processing	
Beam Section Results	No
On Demand Stress/Strain	No

TABLE 14
Model (A4) > Static Structural (A5) > Solution (A6) > Solution Information

Object Name	*Solution Information*
State	Solved
Solution Information	
Solution Output	Solver Output
Newton-Raphson Residuals	0
Identify Element Violations	0
Update Interval	2.5 s
Display Points	All
FE Connection Visibility	
Activate Visibility	Yes
Display	All FE Connectors
Draw Connections Attached To	All Nodes
Line Color	Connection Type
Visible on Results	No
Line Thickness	Single
Display Type	Lines

TABLE 15
Model (A4) > Static Structural (A5) > Solution (A6) > Results

Object Name	*Total Deformation*	*Equivalent Stress*	*Equivalent Elastic Strain*
State	Solved		
Scope			
Scoping Method	Geometry Selection		
Geometry	All Bodies		
Definition			
Type	Total Deformation	Equivalent (von-Mises) Stress	Equivalent Elastic Strain
By	Time		
Display Time	Last		

<table>
<tr><td>Calculate Time History</td><td colspan="3">Yes</td></tr>
<tr><td>Identifier</td><td colspan="3"></td></tr>
<tr><td>Suppressed</td><td colspan="3">No</td></tr>
<tr><th colspan="4">Results</th></tr>
<tr><td>Minimum</td><td>0. m</td><td>642.19 Pa</td><td>6.74e-009 m/m</td></tr>
<tr><td>Maximum</td><td>3.8186e-003 m</td><td>9.054e+007 Pa</td><td>4.5123e-004 m/m</td></tr>
<tr><td>Average</td><td>1.1233e-003 m</td><td>3.3295e+006 Pa</td><td>1.6836e-005 m/m</td></tr>
<tr><td>Minimum Occurs On</td><td>Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator</td><td colspan="2">Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2</td></tr>
<tr><td>Maximum Occurs On</td><td colspan="3">Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2</td></tr>
<tr><th colspan="4">Information</th></tr>
<tr><td>Time</td><td colspan="3">1. s</td></tr>
<tr><td>Load Step</td><td colspan="3">1</td></tr>
<tr><td>Substep</td><td colspan="3">1</td></tr>
<tr><td>Iteration Number</td><td colspan="3">1</td></tr>
<tr><th colspan="4">Integration Point Results</th></tr>
<tr><td>Display Option</td><td></td><td colspan="2">Averaged</td></tr>
<tr><td>Average Across Bodies</td><td></td><td colspan="2">No</td></tr>
</table>

FIGURE 4
Model (A4) > Static Structural (A5) > Solution (A6) > Total Deformation

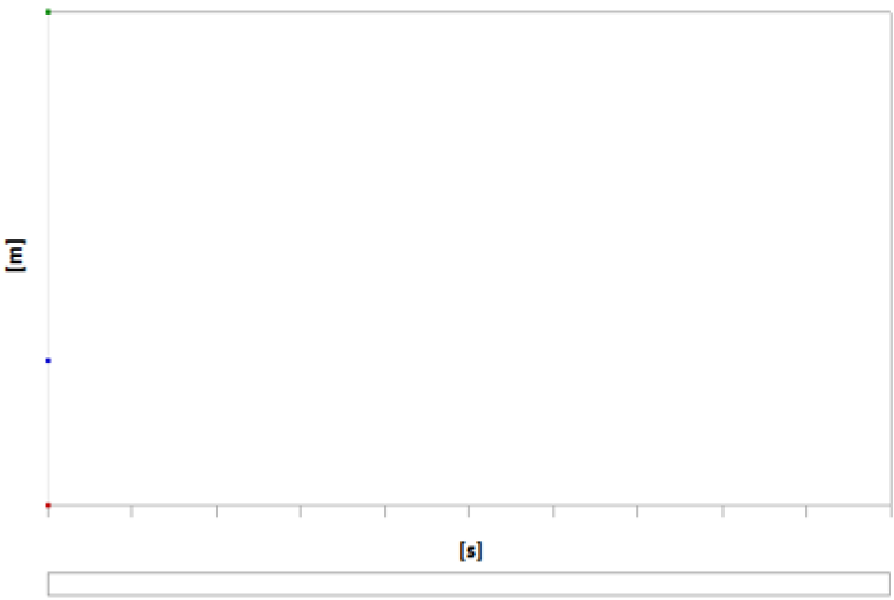


TABLE 16
Model (A4) > Static Structural (A5) > Solution (A6) > Total Deformation

Time [s]	Minimum [m]	Maximum [m]	Average [m]
1.	0.	3.8186e-003	1.1233e-003

FIGURE 5
Model (A4) > Static Structural (A5) > Solution (A6) > Total Deformation > Figure

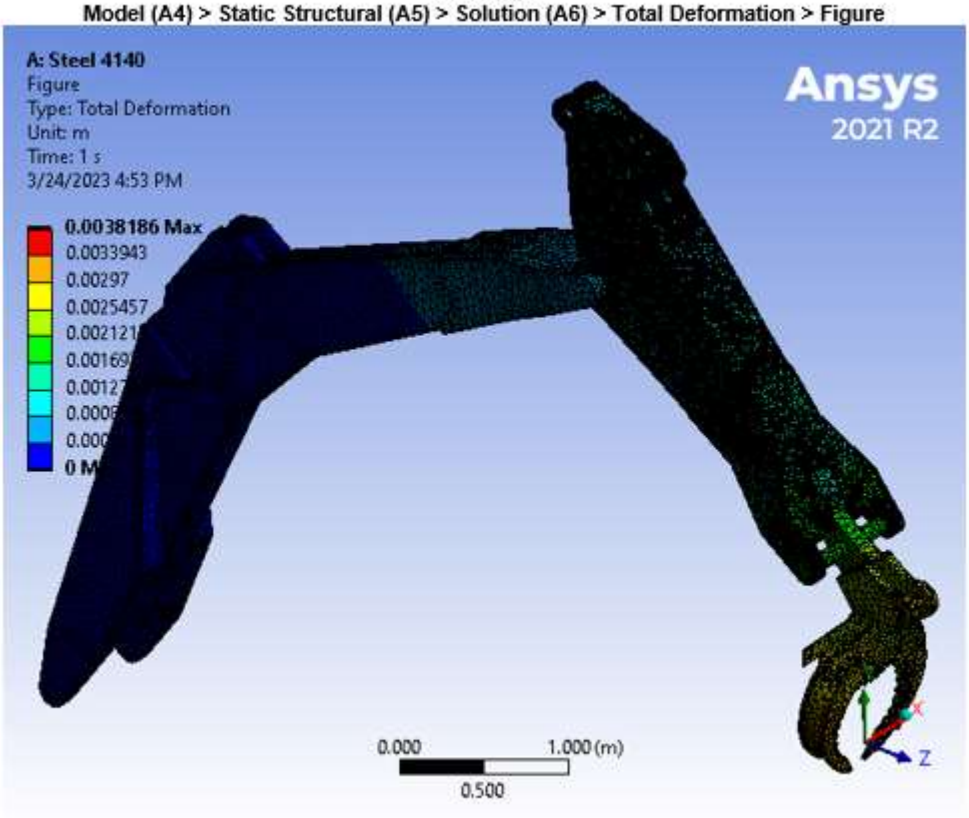


FIGURE 6
Model (A4) > Static Structural (A5) > Solution (A6) > Total Deformation > Figure 2

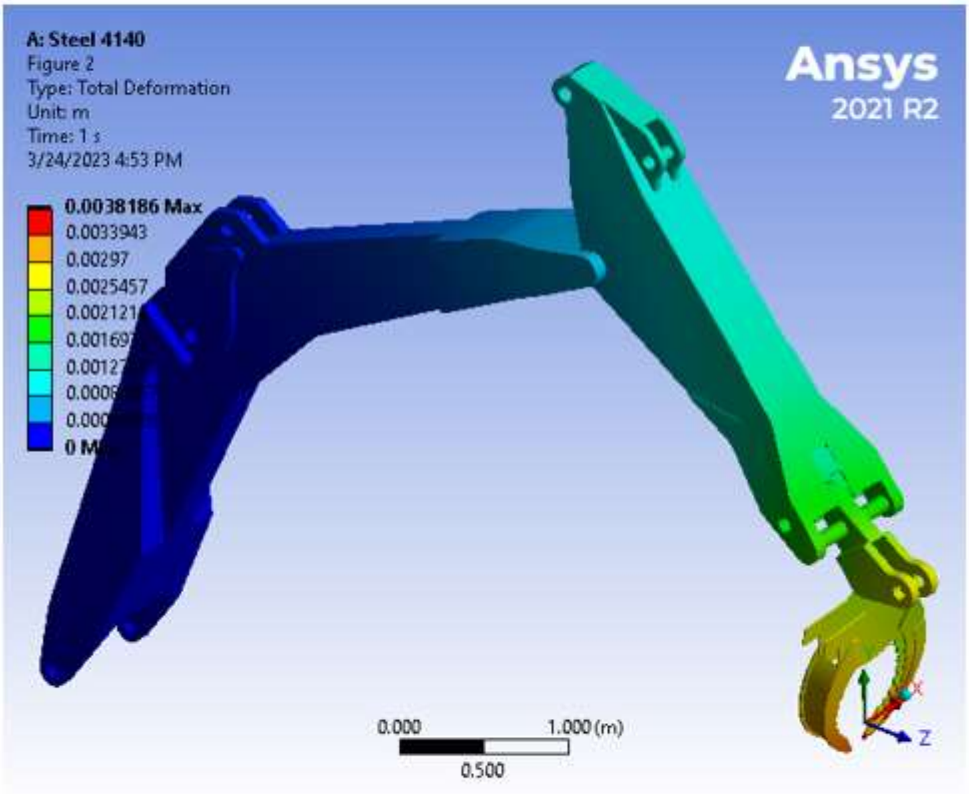


FIGURE 7
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Stress

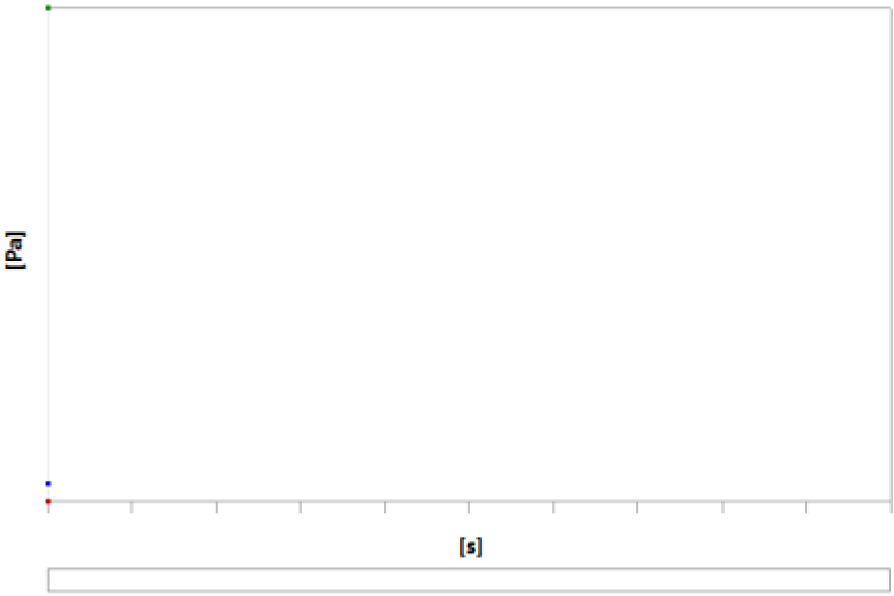


TABLE 17
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Stress

Time [s]	Minimum [Pa]	Maximum [Pa]	Average [Pa]
1.	642.19	9.054e+007	3.3295e+006

FIGURE 8
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Stress > Figure

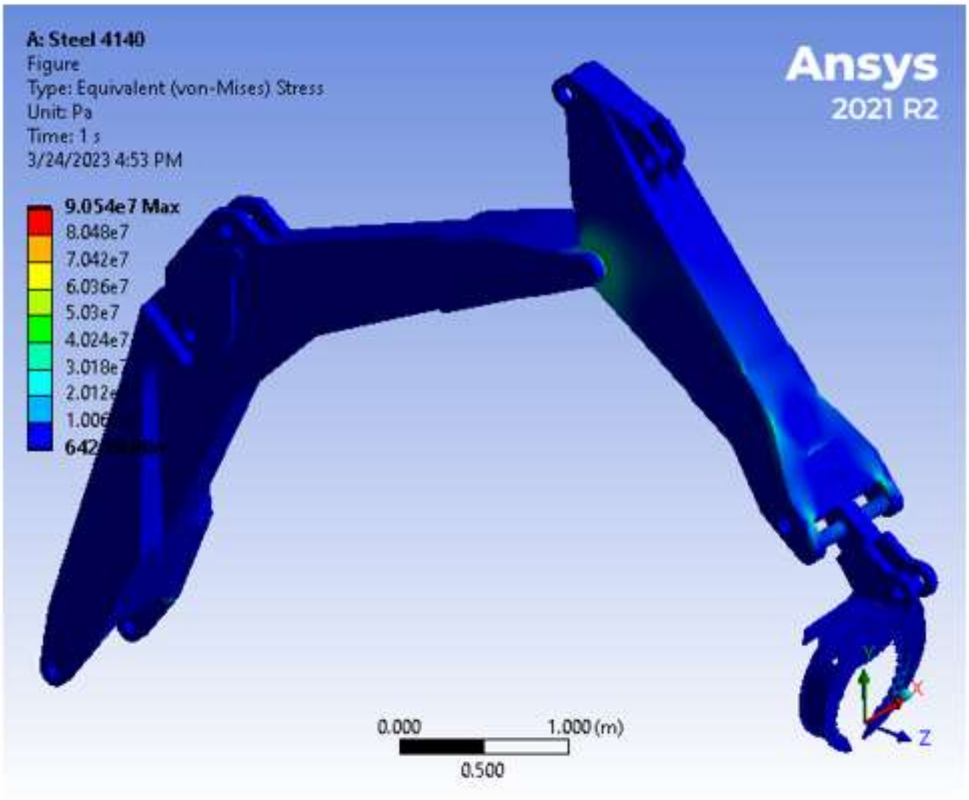


FIGURE 9
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Stress > Figure 2

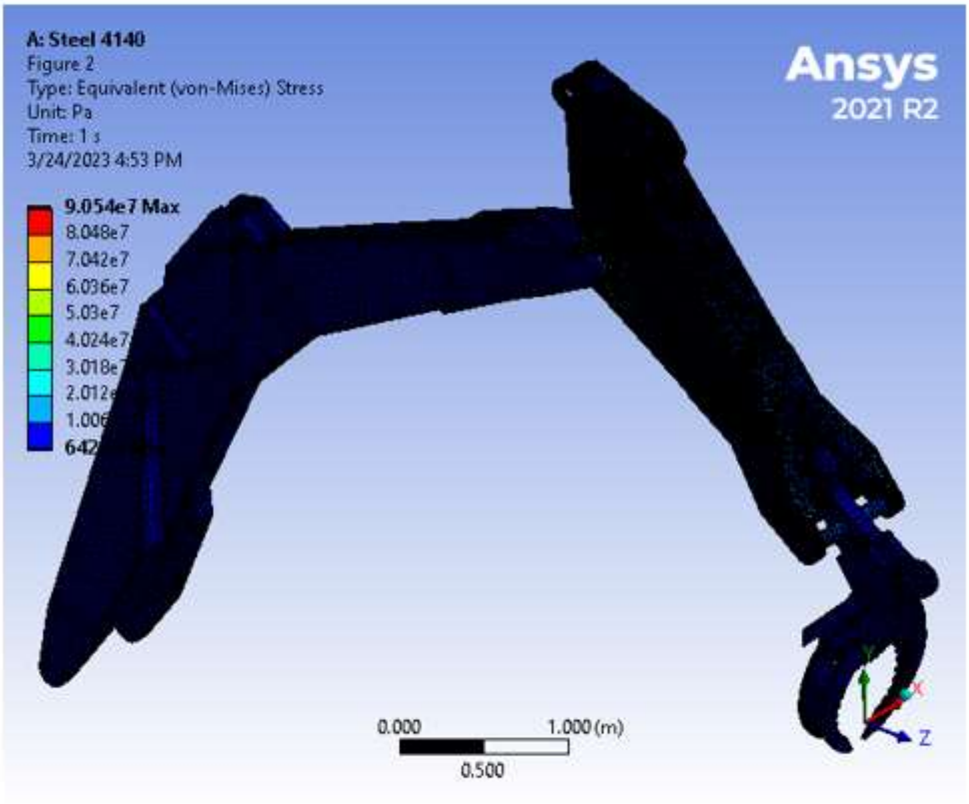


FIGURE 10
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Elastic Strain

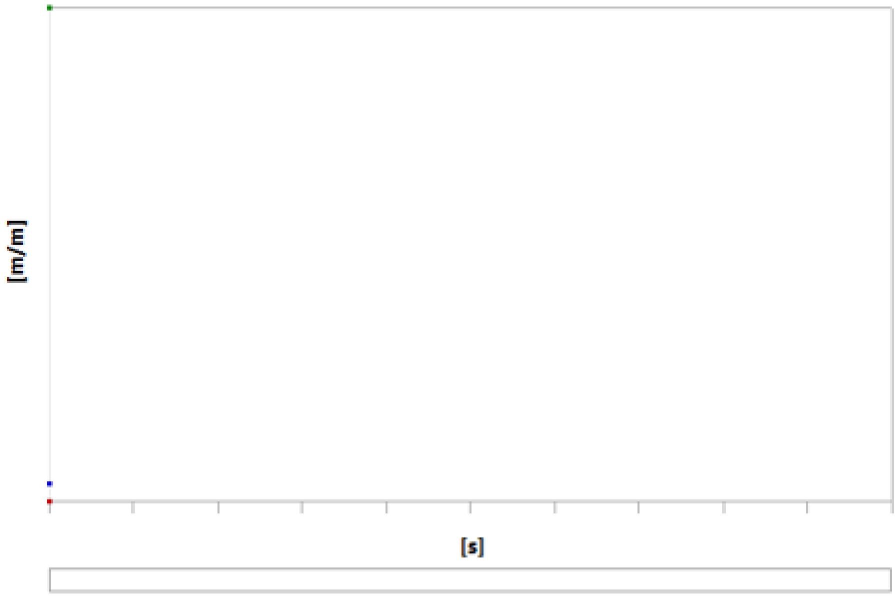


TABLE 18
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Elastic Strain

Time [s]	Minimum [m/m]	Maximum [m/m]	Average [m/m]
1.	6.74e-009	4.5123e-004	1.6836e-005

FIGURE 11
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Elastic Strain > Figure

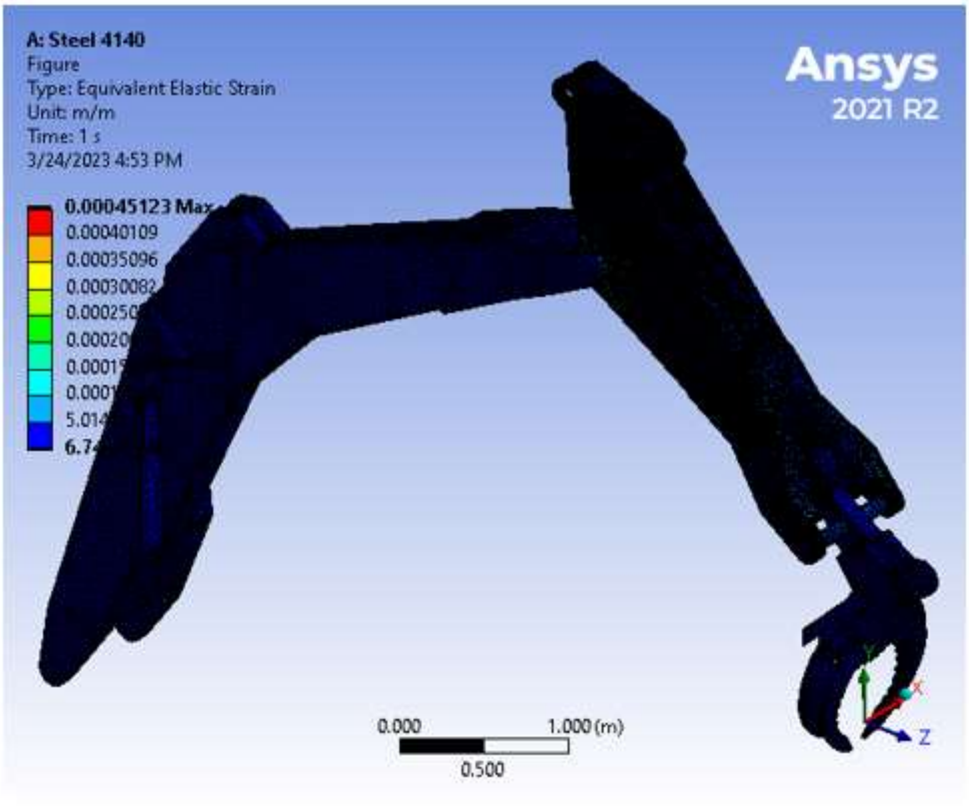
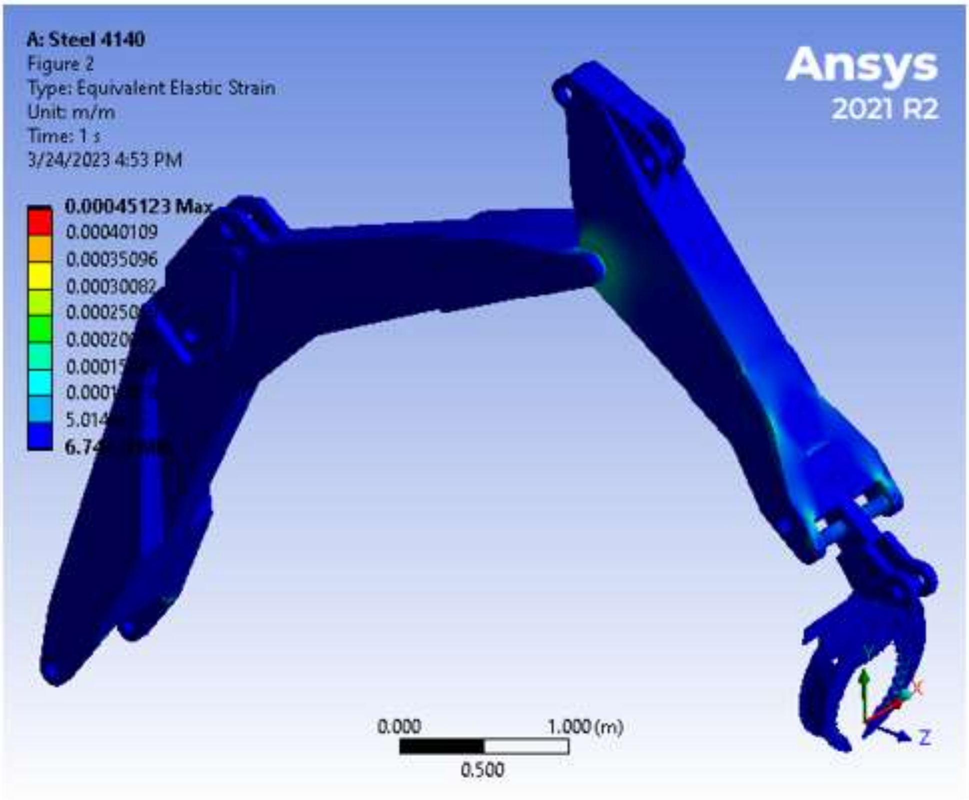


FIGURE 12
Model (A4) > Static Structural (A5) > Solution (A6) > Equivalent Elastic Strain > Figure 2



Material Data

Low alloy steel, 4140, normalized

TABLE 19
Low alloy steel, 4140, normalized > Constants

Density	7850 kg m^-3
Tensile Yield Strength	6.522e+008 Pa
Tensile Ultimate Strength	1.015e+009 Pa
Coefficient of Thermal Expansion	1.172e-005 C^-1
Thermal Conductivity	43.33 W m^-1 C^-1
Specific Heat	435.4 J kg^-1 C^-1

TABLE 20
Low alloy steel, 4140, normalized > Opacity

Red	Green	Blue
204	204	204
Opacity		
1		

Metallic Finish		
1		

TABLE 21
Low alloy steel, 4140, normalized > Isotropic Elasticity

Young's Modulus Pa	Poisson's Ratio	Bulk Modulus Pa	Shear Modulus Pa	Temperature C
2.125e+011	0.29	1.6865e+011	8.2364e+010	23

TABLE 22
Low alloy steel, 4140, normalized > Isotropic Secant Coefficient of Thermal Expansion

Zero-Thermal-Strain Reference Temperature C
20

Low alloy steel, 4140, normalized 2

TABLE 23
Low alloy steel, 4140, normalized 2 > Constants

Density	7850 kg m^-3
Tensile Yield Strength	6.522e+008 Pa
Tensile Ultimate Strength	1.015e+009 Pa
Coefficient of Thermal Expansion	1.172e-005 C^-1
Thermal Conductivity	43.33 W m^-1 C^-1
Specific Heat	435.4 J kg^-1 C^-1

TABLE 24
Low alloy steel, 4140, normalized 2 > Opacity

Red	Green	Blue
204	204	204
Opacity		
1		
Metallic Finish		
1		

TABLE 25
Low alloy steel, 4140, normalized 2 > Isotropic Elasticity

Young's Modulus Pa	Poisson's Ratio	Bulk Modulus Pa	Shear Modulus Pa	Temperature C
2.125e+011	0.29	1.6865e+011	8.2364e+010	23

TABLE 26
Low alloy steel, 4140, normalized 2 > Isotropic Secant Coefficient of Thermal Expansion

Zero-Thermal-Strain Reference Temperature C
20

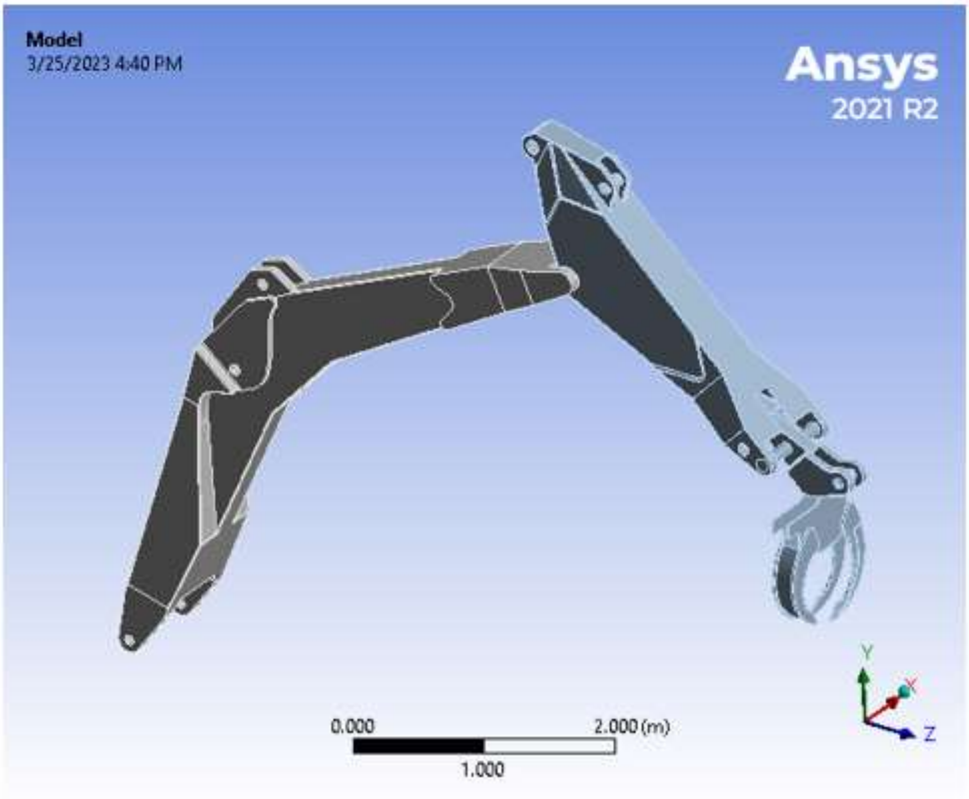
APPENDIX B

THE ANSYS SOFTWARE'S NUMERICAL ANALYSIS PROCESS CONSIDERING BOUNDARY CONDITIONS AND SIMULATION FINDINGS FOR THE SECOND CASE STUDY (CARBON FIBER)

ANSYS

Project*

First Saved	Friday, March 17, 2023
Last Saved	Friday, March 24, 2023
Product Version	2021 R2
Save Project Before Solution	No
Save Project After Solution	No



Contents

Units

TABLE 1

Unit System	Metric (m, kg, N, s, V, A) Degrees rad/s Celsius
Angle	Degrees
Rotational Velocity	rad/s
Temperature	Celsius

Model (B4)

Geometry

TABLE 2
Model (B4) > Geometry

Object Name	*Geometry*
State	Fully Defined
Definition	
Source	D:\Projects\Noor ALordon projects\X ARM\CAD.stp
Type	Step
Length Unit	Millimeters
Element Control	Program Controlled
Display Style	Body Color
Bounding Box	
Length X	4.1135 m
Length Y	5.8922 m
Length Z	8.6742 m

Properties	
Volume	1.2917 m³
Mass	1743.8 kg
Scale Factor Value	1.
Statistics	
Bodies	2
Active Bodies	2
Nodes	228410
Elements	117514
Mesh Metric	None
Update Options	
Assign Default Material	No
Basic Geometry Options	
Solid Bodies	Yes
Surface Bodies	Yes
Line Bodies	No
Parameters	Independent
Parameter Key	ANS;DS
Attributes	No
Named Selections	No
Material Properties	No
Advanced Geometry Options	
Use Associativity	Yes
Coordinate Systems	No
Reader Mode Saves Updated File	No
Use Instances	Yes
Smart CAD Update	Yes
Compare Parts On Update	No
Analysis Type	3-D
Mixed Import Resolution	None
Import Facet Quality	Source
Clean Bodies On Import	No
Stitch Surfaces On Import	Program Tolerance
Decompose Disjoint Geometry	Yes
Enclosure and Symmetry Processing	Yes

TABLE 3
Model (B4) > Geometry > Parts

Object Name	*Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator*	*Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2*
State	Meshed	
Graphics Properties		
Visible	Yes	
Transparency	1	
Definition		
Suppressed	No	
Stiffness Behavior	Flexible	
Coordinate System	Default Coordinate System	

Reference Temperature	By Environment	
Treatment	None	
Material		
Assignment	carbon nanotube	
Nonlinear Effects	Yes	
Thermal Strain Effects	Yes	
Bounding Box		
Length X	4.1135 m	2.8534 m
Length Y	5.6087 m	3.9853 m
Length Z	6.0872 m	4.2208 m
Properties		
Volume	1.2115 m³	8.017e-002 m³
Mass	1635.5 kg	108.23 kg
Centroid X	5.3932 m	5.3884 m
Centroid Y	5.6325 m	6.5563 m
Centroid Z	-6.8497 m	-2.5439 m
Moment of Inertia Ip1	4320.4 kg·m²	12.054 kg·m²
Moment of Inertia Ip2	260.14 kg·m²	128.2 kg·m²
Moment of Inertia Ip3	4507.3 kg·m²	131.22 kg·m²
Statistics		
Nodes	63707	164703
Elements	35845	81669
Mesh Metric	None	

FIGURE 1
Model (B4) > Geometry > Figure

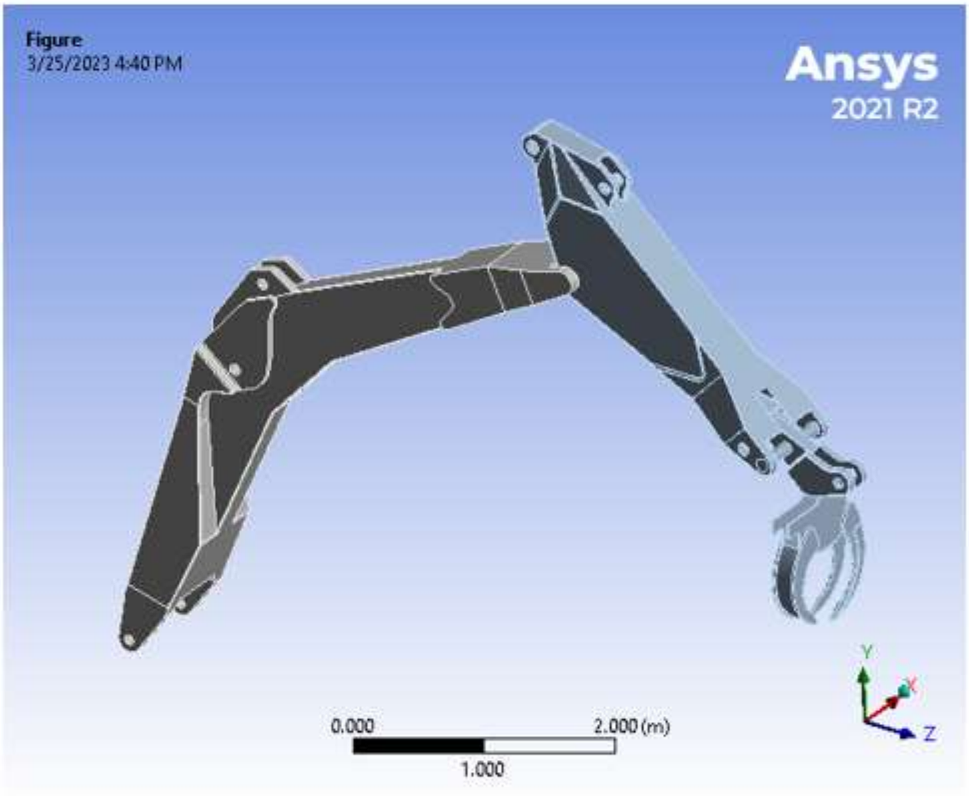


TABLE 4
Model (B4) > Materials

Object Name	*Materials*
State	Fully Defined
Statistics	
Materials	4
Material Assignments	0

Coordinate Systems

TABLE 5
Model (B4) > Coordinate Systems > Coordinate System

Object Name	*Global Coordinate System*
State	Fully Defined
Definition	
Type	Cartesian
Coordinate System ID	0.
Origin	
Origin X	0. m

Origin Y	0. m
Origin Z	0. m
Directional Vectors	
X Axis Data	[1. 0. 0.]
Y Axis Data	[0. 1. 0.]
Z Axis Data	[0. 0. 1.]

Connections

TABLE 6
Model (B4) > Connections

Object Name	*Connections*
State	Fully Defined
Auto Detection	
Generate Automatic Connection On Refresh	Yes
Transparency	
Enabled	Yes

TABLE 7
Model (B4) > Connections > Contacts

Object Name	*Contacts*
State	Fully Defined
Definition	
Connection Type	Contact
Scope	
Scoping Method	Geometry Selection
Geometry	All Bodies
Auto Detection	
Tolerance Type	Slider
Tolerance Slider	0.
Tolerance Value	2.816e-002 m
Use Range	No
Face/Face	Yes
Face-Face Angle Tolerance	75. °
Face Overlap Tolerance	Off
Cylindrical Faces	Include
Face/Edge	No
Edge/Edge	No
Priority	Include All
Group By	Bodies
Search Across	Bodies
Statistics	
Connections	1
Active Connections	1

TABLE 8
Model (B4) > Connections > Contacts > Contact Regions

Object Name	*Contact Region*
State	Fully Defined

Scope	
Scoping Method	Geometry Selection
Contact	5 Faces
Target	7 Faces
Contact Bodies	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator
Target Bodies	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2
Protected	No
Definition	
Type	Bonded
Scope Mode	Automatic
Behavior	Program Controlled
Trim Contact	Program Controlled
Trim Tolerance	2.816e-002 m
Suppressed	No
Advanced	
Formulation	Program Controlled
Small Sliding	Program Controlled
Detection Method	Program Controlled
Penetration Tolerance	Program Controlled
Elastic Slip Tolerance	Program Controlled
Normal Stiffness	Program Controlled
Update Stiffness	Program Controlled
Pinball Region	Program Controlled
Geometric Modification	
Contact Geometry Correction	None
Target Geometry Correction	None

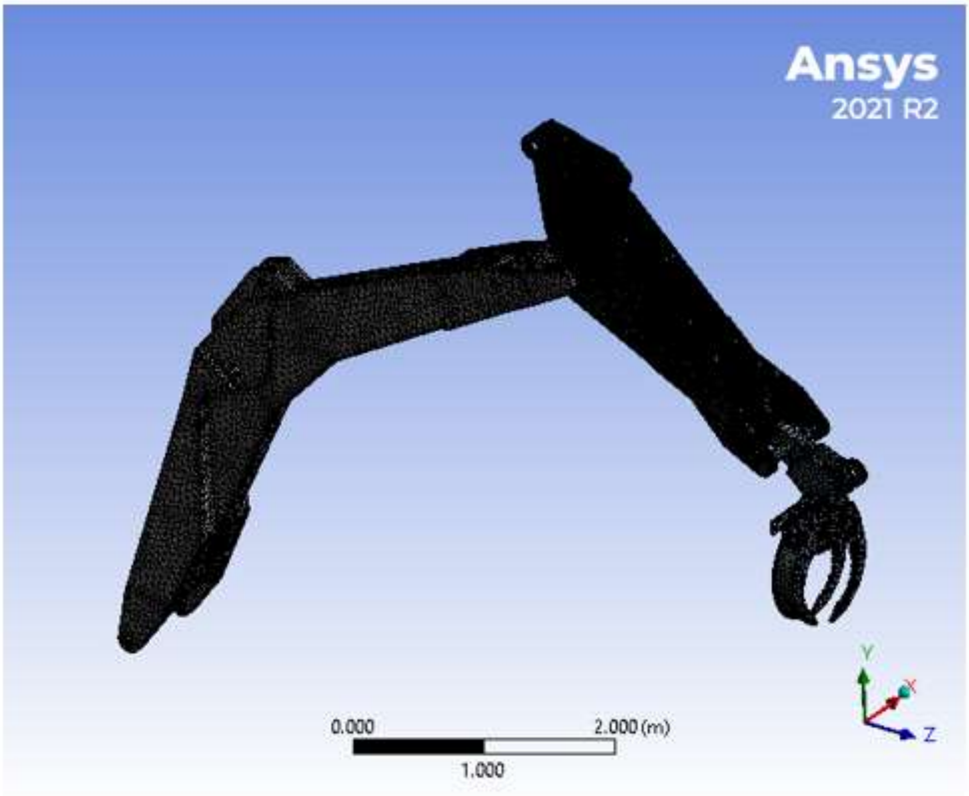
Mesh

TABLE 9
Model (B4) > Mesh

Object Name	*Mesh*
State	Solved
Display	
Display Style	Use Geometry Setting
Defaults	
Physics Preference	Mechanical
Element Order	Program Controlled
Element Size	3.e-002 m
Sizing	
Use Adaptive Sizing	Yes
Resolution	Default (2)
Mesh Defeaturing	Yes
Defeature Size	Default
Transition	Fast
Span Angle Center	Coarse
Initial Size Seed	Assembly
Bounding Box Diagonal	11.264 m

Average Surface Area	3.929e-002 m²
Minimum Edge Length	1.5186e-004 m
Quality	
Check Mesh Quality	Yes, Errors
Error Limits	Aggressive Mechanical
Target Quality	Default (0.050000)
Smoothing	Medium
Mesh Metric	None
Inflation	
Use Automatic Inflation	None
Inflation Option	Smooth Transition
Transition Ratio	0.272
Maximum Layers	5
Growth Rate	1.2
Inflation Algorithm	Pre
View Advanced Options	No
Advanced	
Number of CPUs for Parallel Part Meshing	Program Controlled
Straight Sided Elements	No
Rigid Body Behavior	Dimensionally Reduced
Triangle Surface Mesher	Program Controlled
Topology Checking	Yes
Pinch Tolerance	Please Define
Generate Pinch on Refresh	No
Statistics	
Nodes	228410
Elements	117514

FIGURE 2
Model (B4) > Mesh > Figure



Static Structural (B5)

TABLE 10
Model (B4) > Analysis

Object Name	*Static Structural (B5)*
State	Solved
Definition	
Physics Type	Structural
Analysis Type	Static Structural
Solver Target	Mechanical APDL
Options	
Environment Temperature	22. °C
Generate Input Only	No

TABLE 11
Model (B4) > Static Structural (B5) > Analysis Settings

Object Name	*Analysis Settings*
State	Fully Defined
Step Controls	

Number Of Steps	1.
Current Step Number	1.
Step End Time	1. s
Auto Time Stepping	Program Controlled
Solver Controls	
Solver Type	Program Controlled
Weak Springs	Off
Solver Pivot Checking	Program Controlled
Large Deflection	Off
Inertia Relief	Off
Quasi-Static Solution	Off
Rotordynamics Controls	
Coriolis Effect	Off
Restart Controls	
Generate Restart Points	Program Controlled
Retain Files After Full Solve	No
Combine Restart Files	Program Controlled
Nonlinear Controls	
Newton-Raphson Option	Program Controlled
Force Convergence	Program Controlled
Moment Convergence	Program Controlled
Displacement Convergence	Program Controlled
Rotation Convergence	Program Controlled
Line Search	Program Controlled
Stabilization	Program Controlled
Advanced	
Inverse Option	No
Contact Split (DMP)	Off
Output Controls	
Stress	Yes
Surface Stress	No
Back Stress	No
Strain	Yes
Contact Data	Yes
Nonlinear Data	No
Nodal Forces	No
Volume and Energy	Yes
Euler Angles	Yes
General Miscellaneous	No
Contact Miscellaneous	No
Store Results At	All Time Points
Result File Compression	Program Controlled
Analysis Data Management	
Solver Files Directory	D:\Projects\Noor ALordon projects\X ARM\sim x arm_files\dp0\SYS-1\MECH\
Future Analysis	None
Scratch Solver Files Directory	
Save MAPDL db	No

Contact Summary	Program Controlled
Delete Unneeded Files	Yes
Nonlinear Solution	No
Solver Units	Active System
Solver Unit System	mks

FIGURE 3
Model (B4) > Static Structural (B5) > Figure

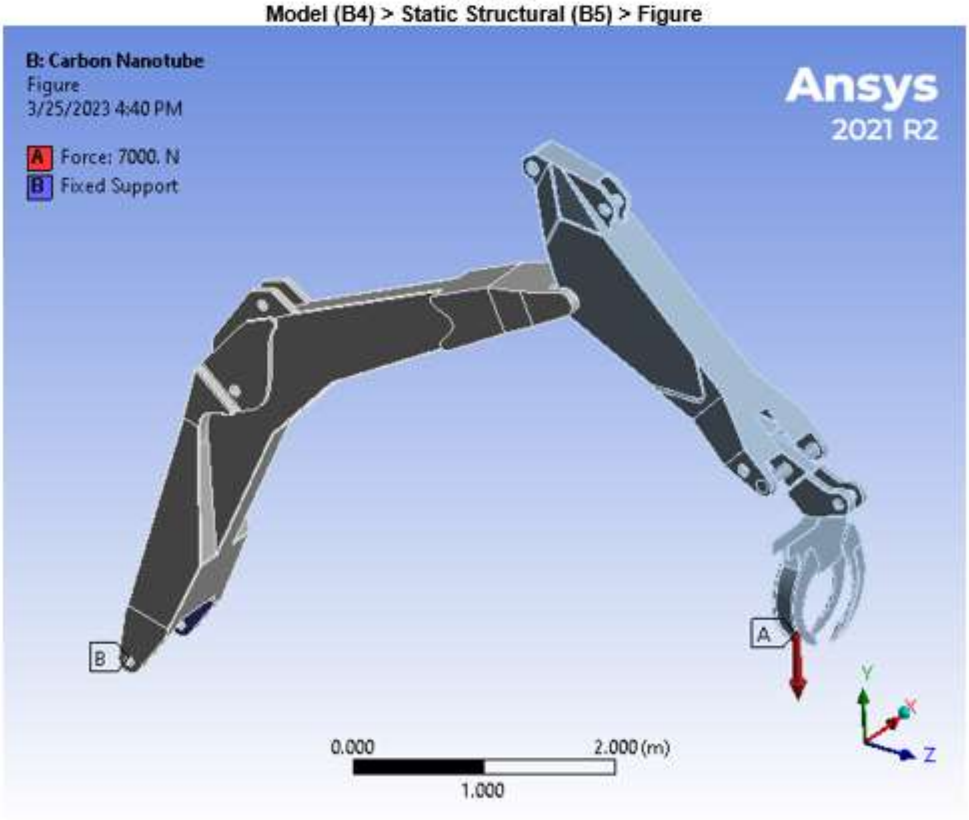
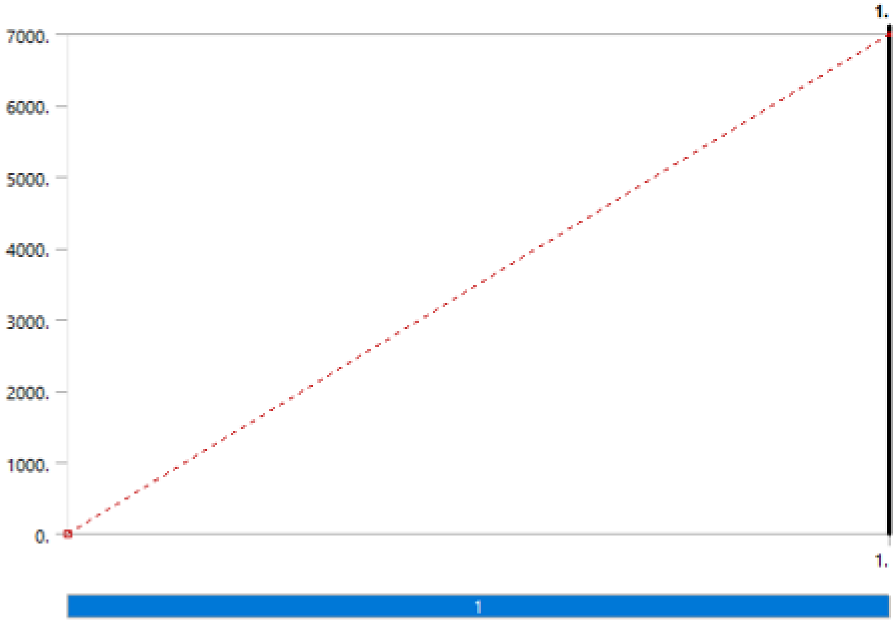


TABLE 12
Model (B4) > Static Structural (B5) > Loads

Object Name	*Force*	*Fixed Support*
State	Fully Defined	
Scope		
Scoping Method	Geometry Selection	
Geometry	4 Faces	2 Faces
Definition		
Type	Force	Fixed Support
Define By	Vector	
Applied By	Surface Effect	

Magnitude	7000. N (ramped)	
Direction	Defined	
Suppressed	No	

FIGURE 4
Model (B4) > Static Structural (B5) > Force



Solution (B6)

TABLE 13
Model (B4) > Static Structural (B5) > Solution

Object Name	*Solution (B6)*
State	Solved
Adaptive Mesh Refinement	
Max Refinement Loops	1.
Refinement Depth	2.
Information	
Status	Done
MAPDL Elapsed Time	1 m 14 s
MAPDL Memory Used	3.2393 GB
MAPDL Result File Size	76.938 MB
Post Processing	
Beam Section Results	No
On Demand Stress/Strain	No

TABLE 14

Model (B4) > Static Structural (B5) > Solution (B6) > Solution Information

Object Name	*Solution Information*
State	Solved
Solution Information	
Solution Output	Solver Output
Newton-Raphson Residuals	0
Identify Element Violations	0
Update Interval	2.5 s
Display Points	All
FE Connection Visibility	
Activate Visibility	Yes
Display	All FE Connectors
Draw Connections Attached To	All Nodes
Line Color	Connection Type
Visible on Results	No
Line Thickness	Single
Display Type	Lines

TABLE 15

Model (B4) > Static Structural (B5) > Solution (B6) > Results

Object Name	*Total Deformation*	*Equivalent Stress*	*Equivalent Elastic Strain*
State	Solved		
Scope			
Scoping Method	Geometry Selection		
Geometry	All Bodies		
Definition			
Type	Total Deformation	Equivalent (von-Mises) Stress	Equivalent Elastic Strain
By	Time		
Display Time	Last		
Calculate Time History	Yes		
Identifier			
Suppressed	No		
Results			
Minimum	0. m	435.11 Pa	7.8896e-010 m/m
Maximum	5.3042e-004 m	9.0754e+007 Pa	6.4341e-005 m/m
Average	1.5751e-004 m	3.3428e+006 Pa	2.404e-006 m/m
Minimum Occurs On	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2	
Maximum Occurs On	Model|Excavator ZeroTwo|Boom Excavator|Boom Excavator.2		
Information			
Time	1. s		
Load Step	1		
Substep	1		
Iteration Number	1		

Integration Point Results		
Display Option		Averaged
Average Across Bodies		No

FIGURE 5
Model (B4) > Static Structural (B5) > Solution (B6) > Total Deformation

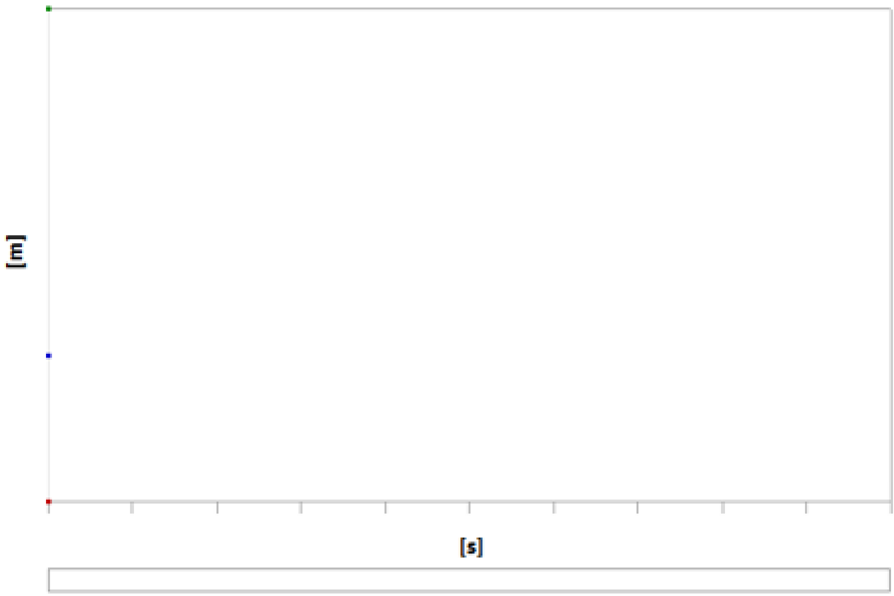


TABLE 16
Model (B4) > Static Structural (B5) > Solution (B6) > Total Deformation

Time [s]	Minimum [m]	Maximum [m]	Average [m]
1.	0.	5.3042e-004	1.5751e-004

FIGURE 6
Model (B4) > Static Structural (B5) > Solution (B6) > Total Deformation > Figure

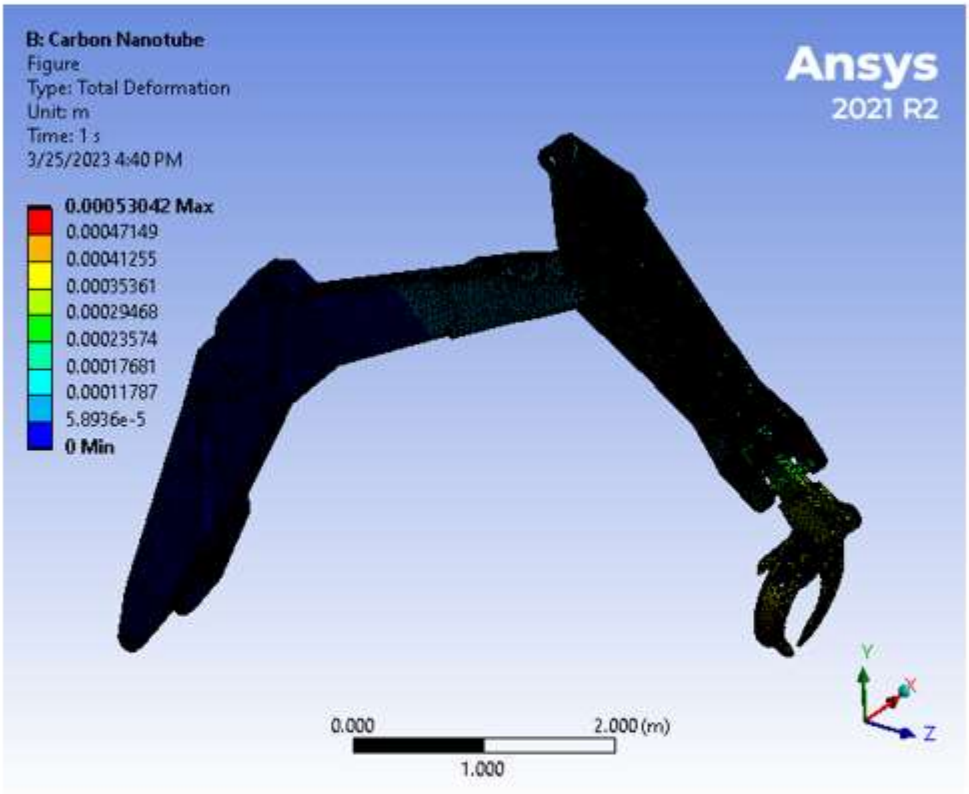


FIGURE 7
Model (B4) > Static Structural (B5) > Solution (B6) > Total Deformation > Figure 2

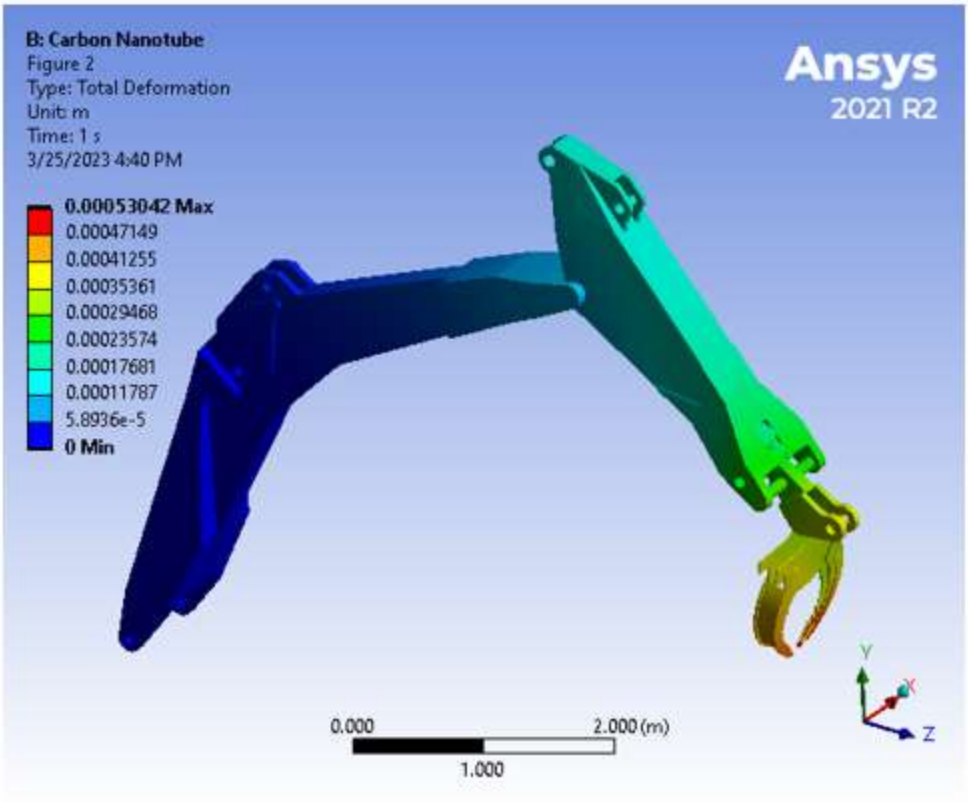


FIGURE 8
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Stress

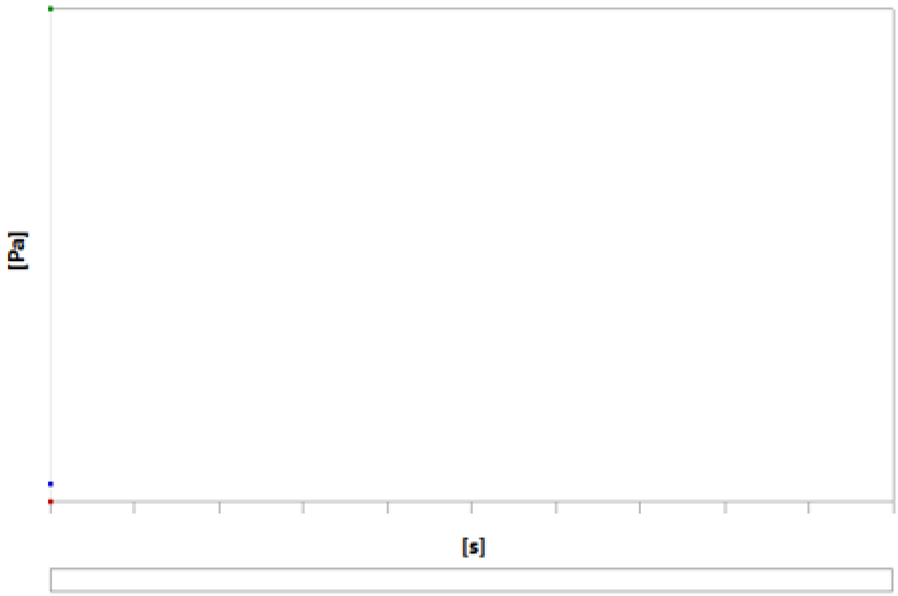


TABLE 17
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Stress

Time [s]	Minimum [Pa]	Maximum [Pa]	Average [Pa]
1.	435.11	9.0754e+007	3.3428e+006

FIGURE 9
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Stress > Figure

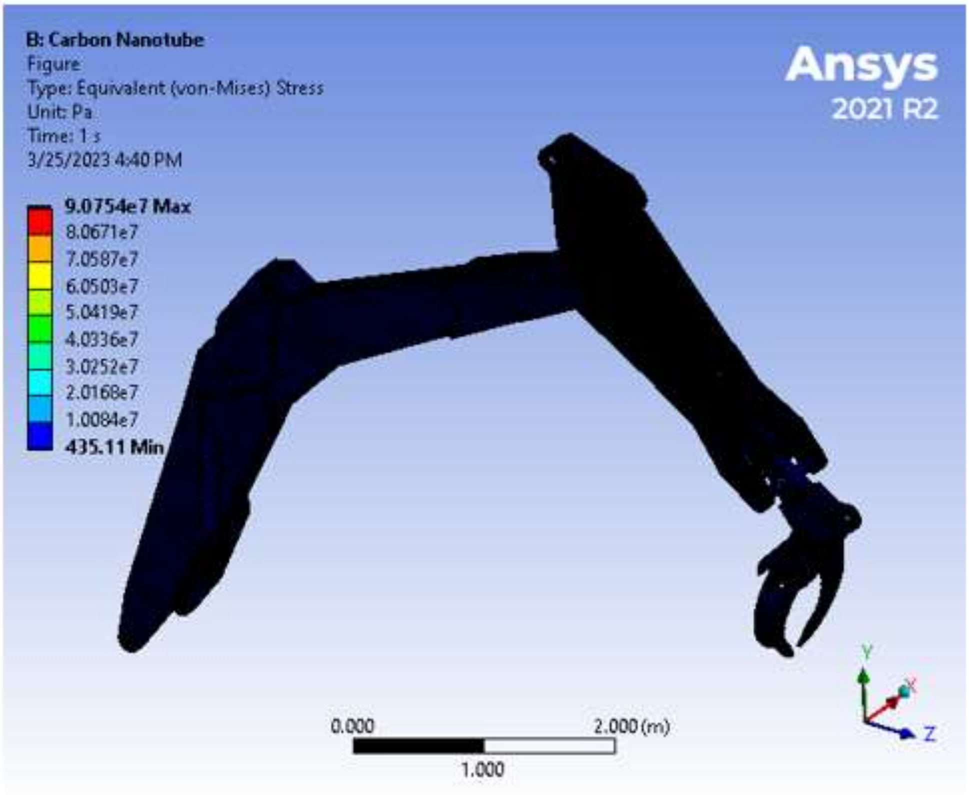


FIGURE 10
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Stress > Figure 2

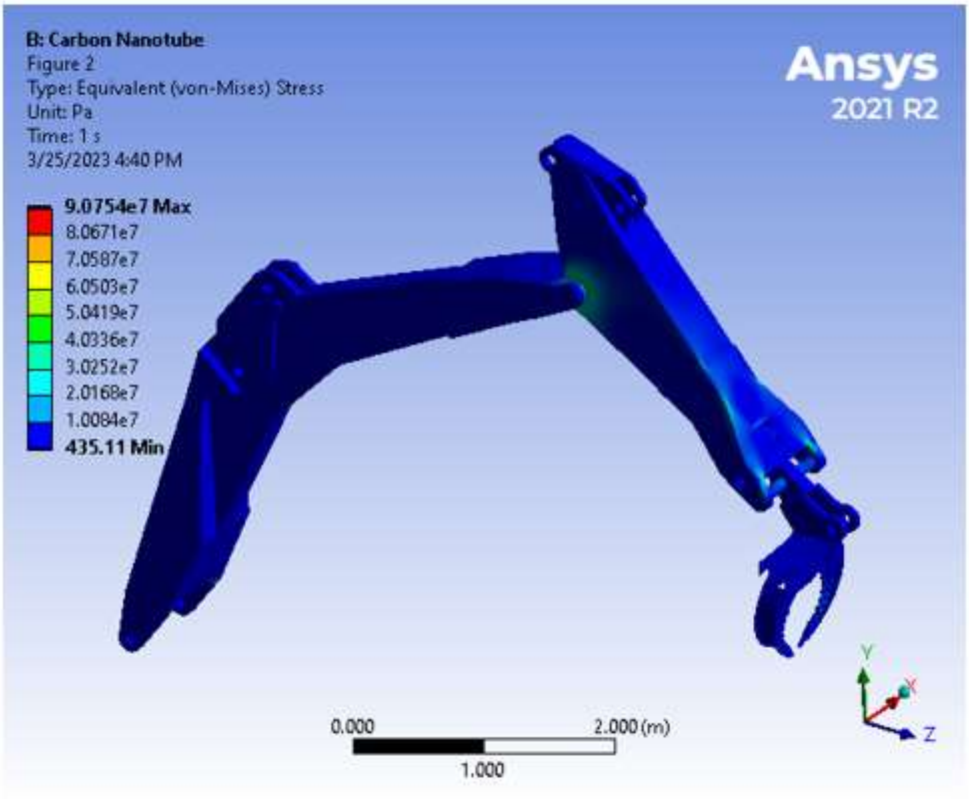


FIGURE 11
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Elastic Strain

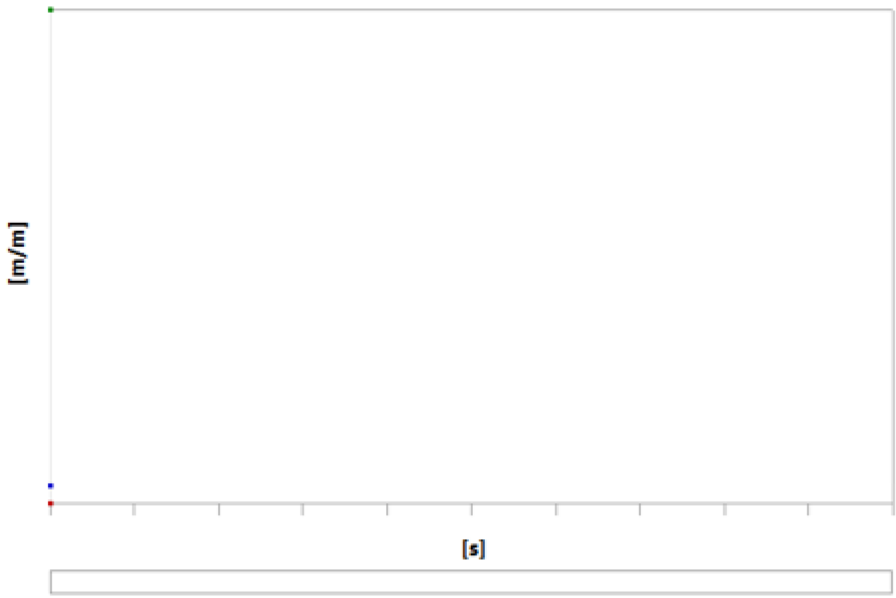


TABLE 18
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Elastic Strain

Time [s]	Minimum [m/m]	Maximum [m/m]	Average [m/m]
1.	7.8896e-010	6.4341e-005	2.404e-006

FIGURE 12
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Elastic Strain > Figure

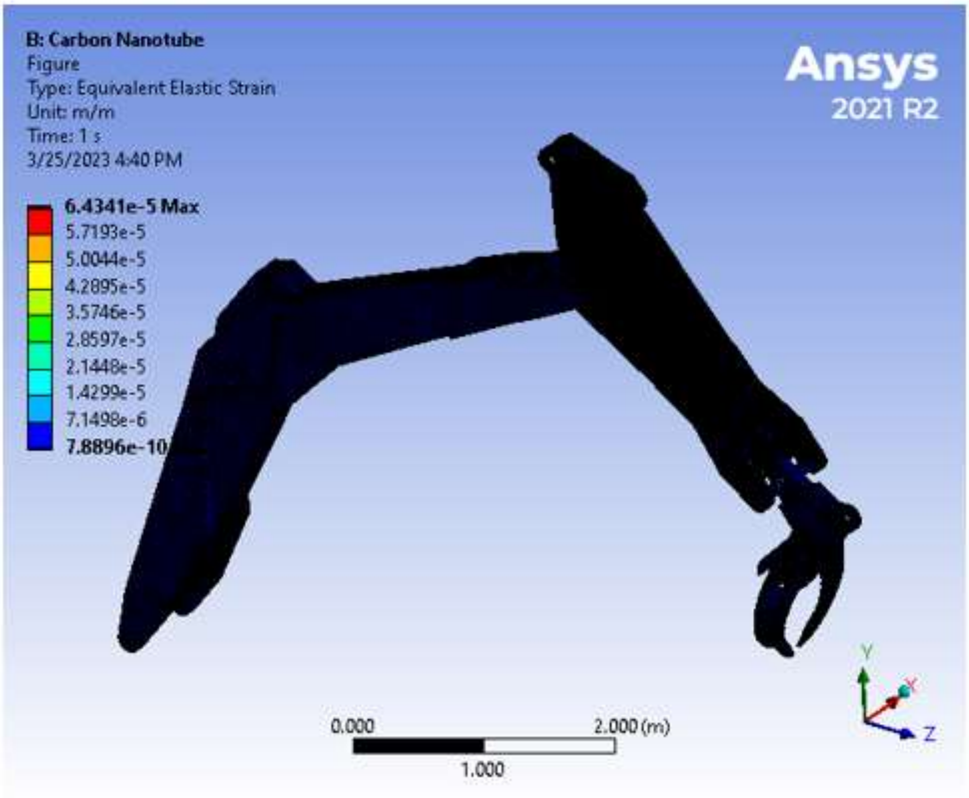
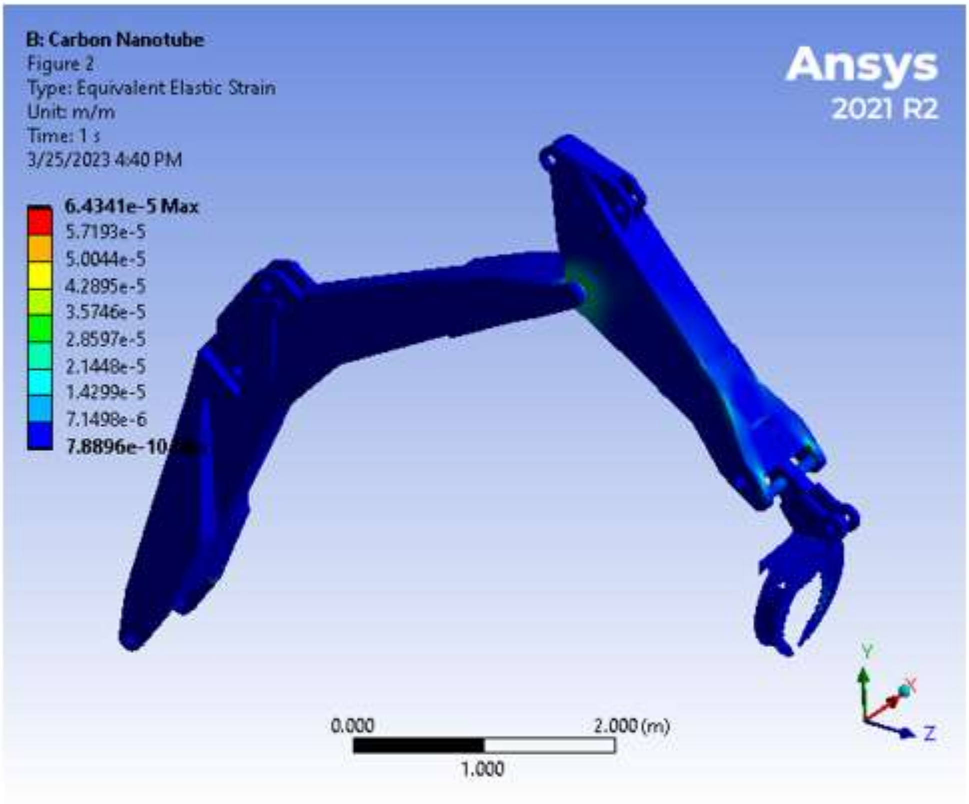


FIGURE 13
Model (B4) > Static Structural (B5) > Solution (B6) > Equivalent Elastic Strain > Figure 2



Material Data

carbon nanotube

TABLE 19
carbon nanotube > Constants

Density	1350 kg m^-3

TABLE 20
carbon nanotube > Color

Red	Green	Blue
235	209	184

TABLE 21
carbon nanotube > Isotropic Elasticity

Young's Modulus Pa	Poisson's Ratio	Bulk Modulus Pa	Shear Modulus Pa	Temperature C
1.5e+012	0.2	8.3333e+011	6.25e+011	