GÖKHAN BÜRGE

OPTIMIZATION OF A SOCCER ROBOT COMPONENTS USING ENGINEERING GENERATIVE DESIGN APPROACH

Ph.D. THESIS

2025

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June, 2025

Approval

We certify that we have read the thesis submitted by GÖKHAN BÜRGE titled "**Optimization of a Soccer Robot Components Using Engineering Generative Design Approach**" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Mechanical Engineering.

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Declaration of Ethical Principles

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Gökhan Bürge

10/06/2025

Acknowledgments

I am grateful to Prof. Dr. Hüseyin Çamur and Prof. Dr. Mahmut A. Savaş, who contributed to the emergence of this research and shaped my research with their academic guidance and encouragement. I would like to thank the Near East University Robotics Laboratory and Günsel Electric Vehicle Factory for the infrastructure, facilities and valuable technical information they have provided. I would also like to express my gratitude to the Chairman of the Board of Trustees of our university, Prof. Dr. İrfan S. Günsel, who has always supported me throughout my research and has been a source of inspiration with his support for scientific development. My most sincere thanks are directed to my wife Damla Önder, who has always been by my side with her patience, love and understanding throughout this process, and to my family, who have supported me unconditionally. Their support has formed one of the most solid foundations of this study.

This study hopes not only to provide an academic contribution but also to contribute to the scientific, technological, and industrial development of the Island of Cyprus. I hope that this study, dedicated to these lands, will inspire future projects.

Gökhan Bürge

Abstract

Optimization of a Soccer Robot Components Using Engineering Generative Design Approach

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PhD, Department of Mechanical Engineering
June 2025, 87 Pages

The object of the present study is to design and develop the chassis parts of a soccer robot, including the main chassis and electronic assembly member (EAM) using innovative design techniques. Generative design (GD) is an iterative process that leverages software algorithms to create and evaluate numerous design options based on defined parameters and constraints. In this study, Autodesk Fusion 360 software was utilized, incorporating inputs such as preserve and observe geometry, starting shape, load cases, and manufacturing methods. These techniques were influenced by factors including product capacity, cost, and material choices. It is particularly beneficial in additive or conventional manufacturing, enabling the creation of complex geometries with ease. This approach allows designers to explore new possibilities, reduce material waste, and enhance the overall manufacturing process. The study here was aimed to minimize material usage, improve the robot's stability, weight reduction and innovate thereby reducing production costs while maintaining structural integrity. Also, various engineering materials with previous methods and materials throughout this approach. The Innovative design process application method begins with the definition of the problem. After that three-dimensional(3D) modelling was performed and appropriate materials were defined and selected. Accordingly, design optimization was achieved by applying generative design methods. At the end of the process, production was carried out using 3D printing technology, to obtain prototypes that were produced, tested and evaluated. The optimal conditions were obtained up to 38 and %45 weight reduction leading to a revised and improved version of the robot. This research highlights the efficiency of processes in optimizing material utilization, improving product stability, and minimizing waste.

***Key Words**:* generative design, 3D printing, optimization, weight reduction

Özet

Üretken Tasarım Mühendislik Yaklaşımı Kullanılarak Bir Futbol Robotu Bileşenlerinin Optimize Edilmesi

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Doktora, Makine Mühendisliği Bilim Dalı

Haziran, 2025, 87 Sayfa

Mevcut çalışmanın amacı, ana şasi ve elektronik montaj elemanı dahil olmak üzere bir futbol robotunun şasi parçalarını yenilikçi tasarım teknikleri kullanarak tasarlamak ve geliştirmektir. Üretken tasarım, tanımlanmış parametrelere ve kısıtlamalara dayalı olarak çok sayıda tasarım seçeneği oluşturmak ve değerlendirmek için yazılım algoritmalarından yararlanan yinelemeli bir süreçtir. Bu çalışmada, geometriyi koruma ve gözlemleme, başlangıç şekli, yük durumları ve üretim yöntemleri gibi girdileri içeren Autodesk Fusion 360 yazılımı kullanılmıştır. Bu teknikler, ürün kapasitesi, maliyet ve malzeme seçimleri gibi faktörlerden etkilenmiştir. Özellikle eklemeli veya geleneksel üretimde faydalıdır ve karmaşık geometrilerin kolaylıkla oluşturulmasını sağlar. Bu yaklaşım, tasarımcıların yeni olasılıkları keşfetmelerine, malzeme israfını azaltmalarına ve genel üretim sürecini geliştirmelerine olanak tanır. Buradaki çalışma farklı malzeme ve yöntemlerle, malzeme kullanımını, robotun kararlılığını, ağırlık azaltılması ve iyileştirmeyi ile yapısal bütünlüğü korunarak üretim maliyetlerini düşürerek yenilik yapmayı amaçlamaktadır.Yenilikçi tasarım süreci uygulama yöntemi, sorunun tanımlanmasıyla başlar. Daha sonra üç boyutlu (3B) modelleme yapıldı ve uygun malzemeler tanımlandı ve seçildi. Buna göre, üretken tasarım yöntemleri uygulanarak tasarım optimizasyonu sağlandı. Sürecin sonunda değerlendirilen modellemeler 3B baskı teknolojisi kullanılarak üretimi gerçekleştirildi. Robotun revize edilen komponentlerinde 38 ve %45'e kadar ağırlık tasarrufuna kadar optimum koşullar elde edildi. Bu araştırma, malzeme kullanımını optimize etmede, ürün kararlılığını iyileştirme ve çevresel atığı en aza indirme süreçlerinde verimliliği vurgulamaktadır.

Anahtar kelimeler: üretken tasarım, 3 boyutlu yazıcı, optimizasyon, ağırlık azaltma

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List of Abbreviations

3D: Three-Dimensional

ABS: Acrylonitrile Butadiene Styrene

AI: Artificial Intelligence

AL: Aluminum

ASA: Acrylonitrile Styrene Acrylate

ASTM: American Society for Testing and Materials

CAD: Computer Aided Design

CAM: Computer Aided Manufacturing

DfAM: Design for Additive Manufacturing

EAM: Electronic Assembly Member

FDM: Fused Deposition Manufacturing

FFF: Fused Filament Manufacturing

GD: Generative Design

Gen AI: Generative Artificial Intelligence

Kg: Kilogram

MNE: Ministry of National Education

NEU: Near East University

Nm: Newton Meter

ML: Machine Learning

PETG: Polyethylene Terephthalate Glycol

PLA: Polylactic Acid

RP: Rapid Prototyping

SLA: Stereolithography

SLS: Selective Lazer Sintering

TRNC: Turkish Republic of North Cyprus

mm: Millimeter

CHAPTER I

Introduction

Generative design (GD) can have the potential to change the manufacturing environment which allows the creation of optimized complex shapes and internal structures (Buonamici et.al 2020; Gromat et.al., 2023). It can benefit companies from all sectors in terms of the production process. It is a design and research process (Dean & Loy 2020). Designers or engineers enter design goals, as well as parameters such as performance requirements, materials, manufacturing methods, and cost constraints, into the design software (Buonamici et.al 2020). The software quickly generates design alternatives by exploring all possible permutations of a solution. It tests and learns what works and what doesn't each time (Shrestha et al., 2021). The method can be used in fields such as automotive, aviation, robotics, construction and architecture, and industrial machinery (Kumaran & Senthilkumar 2021; Kazancı, 2018). With this method, some of the optimizations of the designs can be produced by traditional methods and some by additive manufacturing methods (Kumaran & Senthilkumar 2021). In a study conducted in 2021, a weight reduction of approximately 36% was achieved using the generative design method without compromising the structural function of the part (Zaimis et al., 2021). In another remarkable study in 2021, the authors compared three different materials and modelled the mechanical part on the robot by examining and redesigning it using this method, showing that the weight was significantly reduced by approximately 85-90 percent, allowing the robot part to be designed more economically (Walia et al., 2021). The studies examined have inspired the emergence of this study. Therefore, it is important to carry the developing methods further by supporting them with scientific studies. Accordingly, the aim here is to redevelop and improve the Near East University (NEU) Islanders football robots improved by NEU. Teams make innovations in their robots every year to implement new developing technologies and provide the opportunity to test them in competitions. NEU Islanders football robots which were participated in one of the world’s most prestigious robot competition RoboCup and became the world champion in 2018, Canada (Kazancı, 2018; Near East University. 2016). Consequently, new robots are improving and developing each year for these competitions. Industry 4.0 enhances this by enabling Computer Numerical Control (CNC) machines to utilize data for production processes. Additive manufacturing (AM) technology plays a crucial role (Buonamici et al., 2020; Ntintakis et al., 2022). It's offering greater flexibility and precision in production, reducing the need for extensive prototyping, molds, and processes (Shahrubudin et al., 2019). The main objective of the study here is to modify a soccer robot using generative design methods and also to compare manufacturing techniques such as AM and CNC machining and different materials to evaluate an optimal range of parameters such as production cost, usability, and manufacturability to develop and reproduce robot components more effectively (eSUN, 2024).

Background and Review

Additive manufacturing (AM), also known as 3D printing, involves building objects layer by layer from digital designs. It revolutionizes traditional manufacturing methods by enabling the creation of complex geometries with reduced material waste and increased design flexibility. The process starts with a digital model, which is sliced into thin layers. Then, the printer deposits material layer by layer, fusing or solidifying each layer to form the final object. Additive manufacturing has found applications in various industries, including aerospace, automotive, healthcare, and consumer goods. There are many advantages of these methods in descending order; design flexibility, material efficiency, and prototyping customization. Subtractive manufacturing involves removing material from a solid block or workpiece to create the desired shape. It encompasses various techniques such as milling, turning, drilling, and grinding. Subtractive manufacturing has been widely used for centuries and remains a cornerstone of modern manufacturing processes. It is suitable for producing high-precision parts with excellent surface finish and mechanical properties. There are many advantages of these methods descending order; wide range of materials, precision, and scalability (Veronneau et al., 2017; Gibson et al., 2021).

Aim of the Research

Near East University (NEU) Robotics Football Team competes with the world's leading universities in the International RoboCup football tournaments held every year with autonomous robot football players of its own design. Achieving success in these global competitions requires a research and development(R&D) process supported by continuous improvement and technological innovations. Therefore, every new season is spent with systematic studies to optimize the hardware and software components of existing robots, to provide new functions and to increase the overall system performance. This study aims to integrate innovative engineering approaches in the design and development process of robots. In particular, in order to make the mechanical structures of the robots lighter, more durable and more manufacturable, advanced production technologies are used as well as contemporary design techniques. This analysis aims to contribute to the adoption of sustainable and innovative production approaches not only in robotic system design but also in engineering disciplines in general.

Significance of the Research

This research can be beneficial, significantly impacting both the field of robotics and broader engineering applications. The Robotics Football Team's aim for success at the international level every year necessitates a constantly developing R&D process, and the knowledge gained in this process contributes to the development of innovative approaches in engineering disciplines. In particular, providing lighter, more durable and more manufacturable solutions in the mechanical structures of robots not only provides increased performance but also serves sustainable production goals. In this respect, the study is both an example of the integration of advanced production technologies in robotic system design and contributes to the spread of creative and efficient design understanding in engineering.

Statement of the Problem

In order for autonomous robotic systems to function effectively, especially in competitive international platforms such as RoboCup, continuous innovation and improvement are required in both hardware and software components. When evaluated specifically in Northern Cyprus, the limited technological infrastructure and research and development resources make the need for innovative solutions in engineering design and production processes even more critical. Integrating advanced additive manufacturing techniques and rapid prototyping processes into robotic system design offers an important opportunity to fill this gap. However, structuring these technologies by local conditions and systematic application still stands out as an important problem area. This study aims to produce a solution to this problem; it aims to contribute to regional technology production by proposing a design and development process supported by contemporary engineering tools.

Limitations of the Research

Since it is a new technology, there are not many widespread studies available in the literature. Giant companies in the industry are conducting trial studies, but it will develop further and become more widespread in the coming years, especially with 3D production technology. The material range is expected to expand. Not all materials are suitable for use in 3D production. In addition, production costs, especially the high prices of machine technologies used in metal printing.

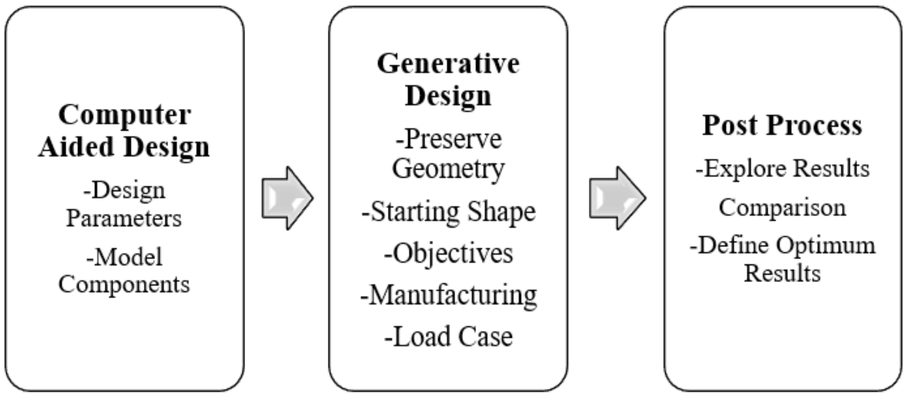
CHAPTER II

Literature Review

Generative design (GD), Computer Aided Design (CAD), and Computer-Aided Manufacturing (CAM) are interconnected in modern design and manufacturing, with generative design aiding in the early-stage exploration of multiple design alternatives (Ntintakis et al., 2022). CAD software integrates generative design algorithms for visualization and refinement, while CAM transforms the finalized designs into machine instructions for manufacturing. This integration improves efficiency, optimizes designs for materials and performance, and ensures manufacturability (Kumaran & Senthilkumar, 2021; Aman, 2020). Designing complex products or special projects requires designers to explore multiple alternatives CAD can assist in the early design stages, helping designers explore possibilities. Figure 1, illustrates CAD and GD relations (Aman, 2020).

Figure 2.1

Exploring of Generative Design and Computer-Aided Design (Aman, B. 2020)



Generative Design (GD) in Literature

Generative Design (GD) is an iterative and data-driven process that produces multiple design outputs that comply with certain constraints (Dean & Loy, 2020; Armstrong et al., 2022). In this process, designers or engineers define data such as parameters, constraints, targeted performance criteria, requirements, materials to be used and manufacturing methods in the software (Buonamici et.al 2020; Kumaran and Senthilkumar, 2021). Software such as Autodesk Fusion 360 analyses all possible solution scenarios and permutations in line with this data, thus producing many alternative designs (Schwaar, 2023). This approach allows the creation of innovative and efficient structures that are optimized in terms of functionality (Aman, 2020). Generative design is an effective method, especially in the development of lighter and more durable parts. In addition, a final design is not required at the beginning to complete the process. The software produces the most suitable solutions itself. It allows to explore the design space of material possibilities from an existing file with only basic information and requirements and optimizes the strength and weight of the product (Shrestha et al., 2021; Ntintakis et al., 2022). The cabin compartment in the Airbus A320 model was redesigned and manufactured using generative design techniques. The new part produced is half the weight of the original part and provides a fuel saving of 3,180 kg each component. This may lead to a decrease in co_2 emissions of 166 metric tons per aircraft per year. Also, the new design was originally designed for the metal additive manufacturing process (Sampson, Ben. 2025; Deplazes, 2019). In addition, in a study conducted in the aircraft industry in 2021, it was aimed to emphasize environmental factors by conducting experiments to reduce the weight of the Aircraft Seat Structure part (Noronha et al., 2021). There are many important scientific studies on this subject in the literature. Some of them are the study published in Bayburt University Science Journal and the studies conducted by Nottingham Trent University; here, experimental studies were carried out in robot application using additive manufacturing technology with the design of Humanoid Robot Arm Part (Walia et al., 2021; Walia et al., 2021). Technical University of Cluj-Napoca, Cluj-Napoca in Romania, gear optimization was performed using GD with AM technology in a study (Cristian et al., 2022). In literature, optimization was performed using generative design tools for the design of a racing car crankshaft. This optimization was performed on an industrial case to investigate the extent to which these tools are suitable for use in the early design stages and what the main differences are between them (Vlah et al., 2020).

Figure 2.2

Comparison of Different Manufacturing Techniques (Zaimis et al., 2021)

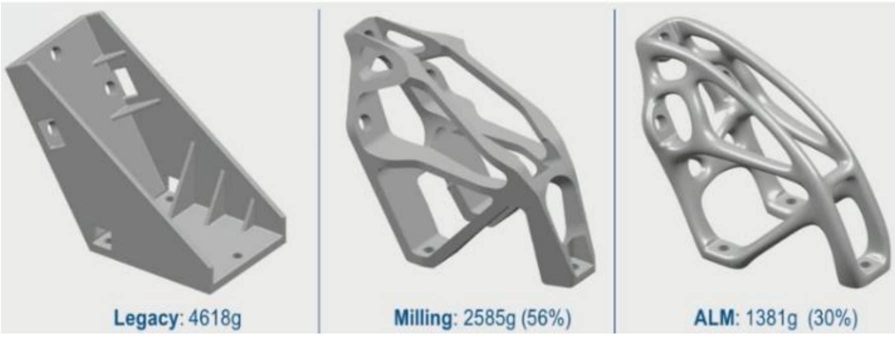
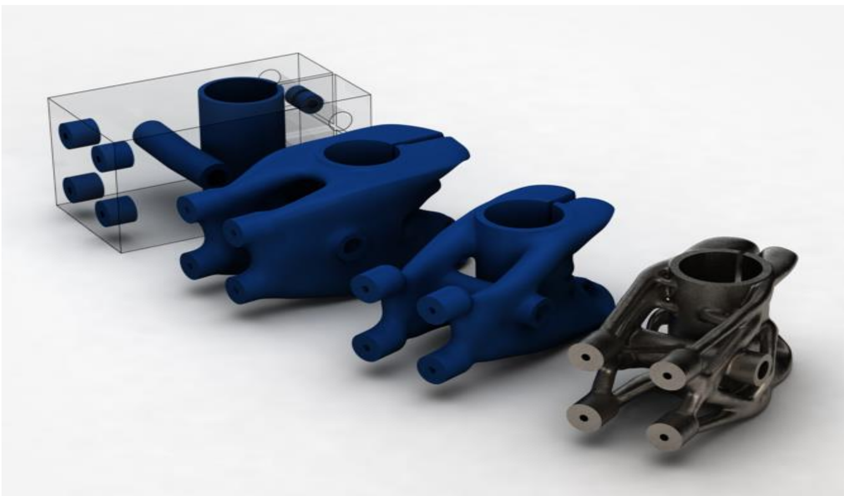


Figure 2, is divided into three distinct shapes which illustrate different manufacturing processes. The first part is designed and represents conventional manufacturing methods, the second part show cases production through CNC machining and the third part is for additive layer manufacturing (ALM). In the normal design of 4618g, a %56 weight reduction was achieved by using the generative design method and the traditional production method. In the third part, ALM was used as production with the generative design method and a total weight reduction of %86 percent was achieved (Kaladhar, 2020).

Figure 2.3

Generative Design Process Achieved (Nathan, 2022).



Generative Design vs Topology Optimization

Topology Optimization and Generative Design (GD) are gaining more and more attention in CAD design. However, there is a common misconception that these two concepts are the same. Topology optimization is actually a long-standing method and is included in many CAD software. The process begins with the engineer defining the loads and boundary conditions according to the project requirements. Based on these inputs, the software provides a single optimized mesh structure by removing unnecessary materials (Eschenauer & Olhoff, 2001). In other words, topology optimization requires a human-created starting model. Therefore, it keeps the design process, scope and outputs within certain limits. (Madeline, 2024).

GD software may include built-in testing and simulation. It may deliver opportunities for part consolidation and lightweight. Some products feature several of these attributes but don't use the label generative design, which makes comparing software in this rapidly evolving category a bit of a challenge (Eschenauer & Olhoff, 2001; Madeline P. 2024).

There are some differences between topology optimization and generative design. The main differences in these approaches are as follows;

- In the topology optimization approach, the initial geometry is set in the current design stages. Therefore, this approach provides a more controlled design space when creating new shapes (Eschenauer & Olhoff, 2001; Madeline P. 2024). Hinge Bracket for an Airbus A320 optimized by topology optimization using metal 3D printing technology as shown in Figure 2.4 (Madigana et all., 2023)
- The GD approach can be harnessed in the early stages of design, even in the absence of a current model, offering designers invaluable feedback on initial possibilities. This makes GD not just a method, but a vibrant and groundbreaking realm of design innovation (Eschenauer & Olhoff, 2001; Madeline P. 2024).

Figure 2.4

Hinge Bracket for an Airbus A320 (Madigana et all., 2023)

How Does Generative Design Truly Work?

Engineers and designers must take into account a variety of technical and functional requirements when developing their projects. Instead of creating a design from scratch using traditional methods, the goal is simply defined in the software through the generative design process. In this process, design goals are determined and all possible parameters, such as load conditions, material type, manufacturing method and constraints, are entered into the software. No specific geometry is needed at the beginning. The software generates hundreds or even thousands of possible design alternatives based on this data. Artificial intelligence-supported analyses can evaluate these alternatives according to performance criteria and determine the most efficient options. This method is extremely effective for systematically exploring design possibilities and reaching the optimum part solution (McKnight, 2017). Generative design software uses cloud computing and machine learning (ML) technologies to discover new solution sets. These systems continuously learn by analyzing which designs work and which do not through all the iterations they perform. Generative design software, which is based on AI algorithms, focuses on finding the most suitable design in line with the defined constraints. Basic information is sufficient to start the process; a detailed design is not required for the system to work. The first step in the design process is to define various inputs and information about the required structure for the software. This data should include elements such as load conditions, material selection, production method, and especially physical constraints. Physical constraints provide the basic technical data required to create a design and form the skeleton of the process (Stackpole, B. 2025). The basic information that should be provided to the software during the design process includes the weight and size limitations of the part. In addition, geometric restrictions such as which areas the part should not cover or which areas it should avoid should be defined. Force, pressure and load information help the algorithm determine which areas of the part need to be reinforced and which areas are exposed to high stress. This technical data is critical to the functionality of the part. However, information about the available material options should also be included in the process. In this way, the software can understand which materials the design can be produced with, and use more durable materials in high-stress areas, while minimizing the use of material in low-stress areas. This contributes to the design being both durable and lightweight. The manufacturing method is also an important parameter. Each manufacturing method has its limitations and possibilities. Therefore, information about the manufacturing process is critical for the software to produce manufacturable designs. Once all these criteria are defined, the software can create hundreds of possible design alternatives. At the end of the process, the engineer or designer chooses the most suitable one among these alternatives according to their experience and project requirements (Madigana et all., 2023). This approach provides the opportunity to compare different possibilities and makes it easier to reach the optimum solution. Generative design software uses AI and ML algorithms to mimic nature's evolutionary design process (McKnight, 2017).

Use of Algorithmic Models to Achieve Lightweight Designs

Computer-aided design and modelling methods are constantly evolving, and advanced manufacturing techniques such as 3D printing are becoming increasingly common. In line with these developments, designers and engineers are developing new approaches to create more complex models more easily. The topology optimization algorithm is effectively used to maximize design efficiency and push existing boundaries. (Shrestha et all., 2021). A topology optimization problem can be written in the general form of an optimization problem as (Sigmund & Kurt, 2013): The problem statement includes the following:

$$\text{Minimize } (\rho) = \mathrm{F} = F(\mathrm{u}(\rho), \rho) = \int_{\Omega} f\ (\mathrm{u}(\rho), \rho)\ \mathrm{d}V$$

$$\text{Subjected to} \quad \mathrm{G}_0\ (\rho) = \int_{\Omega} \rho\ \rho \mathrm{d}V - \mathrm{V}_0 \leq 0$$

$$Gj(u(\rho), \rho) \leq 0 \text{ with } j = 1,\ldots,$$

- $F(u(\rho), \rho)$: This function represents the quantity to be minimized for best performance.
- This is described by the density of the material at each location ρ
- $\mathbf{u} = \mathbf{u}(\rho)$ is a state field that satisfies a linear or nonlinear state equation depending on ρ
- The design space is identified with Ω
- All analyses are performed within a defined geometry region Ω.
- m constraints $Gj(u(\rho), \rho)$ a characteristic that the solution must satisfy. m constraints. These constraints include engineering criteria such as volume, displacement or stress limits. Evaluating $\mathbf{u}$ (ρ) often includes solving a differential equation The relationship between density and Young's modulus is interpolated as follows: $E(\rho)=E_0+\rho^p(E_1-E_0)$

This approach allows determining the optimal material distribution using a continuous density field.

What Are the Benefits of Generative Design?

The generative design process has a wide range of applications in many sectors and provides significant advantages. Innovation-oriented sectors such as automotive, aviation, industrial machinery, architecture and consumer goods in particular benefit greatly from the design discovery potential offered by this technique. Generative design allows the emergence of unique and complex geometries that are difficult to imagine with traditional methods by exceeding the mental limits of human creativity (Stackpole, B. 2025). This method offers great advantages, especially for industries such as automotive and aviation, where lightweight and high-performance parts are critical. By using only, the necessary materials in the design process, both structural efficiency and weight are reduced. At the same time, generative design also provides significant contributions in terms of part consolidation. Thanks to a single strong part that can replace multiple components, both production processes are simplified, and overall maintenance and production costs are reduced. The high level of design freedom offered by these production techniques eliminates traditional assemblies and enables simpler, more durable and more efficient solutions to be offered (Madeline P. 2024; Massobrio, A., 2024)

Possibilities of Generative Design and Additive Manufacturing

If 3D printing (additive manufacturing) is desired for components to be produced in a project, generative design is an extremely interesting approach to consider. Especially in advanced and technical projects, the possibilities offered by generative design provide significant advantages. Design for Additive Manufacturing (DfAM) is a process that requires special knowledge and training, unlike traditional methods. This method allows for the development of innovative solutions by offering greater design freedom and flexibility. Using DfAM, it becomes possible to produce sophisticated and functional designs, such as lattice geometries used in the internal structure of a product to optimize its weight. Such structures not only increase production efficiency but also improve the performance of the product. The design process for additive manufacturing technology is independent of the geometric limitations imposed by traditional manufacturing techniques (Ntintakis et al., 2022).

Generative Design Application in Additive Manufacturing

Seat bracket General Motors: General Motors is one of the world's largest automotive companies, created the seat bracket design to which seat belts are attached in its vehicles using generative design technology. The new bracket as shown in the Figure 2.5 is lighter and stronger (Briard et all., 2020).

Figure 2.5

GM Generative Design Iterations for Seat Bracket (Briard et all., 2020).

Crankshaft made by HONDA: Japanese auto giant Honda aims to reduce the environmental impact of cars by using innovative design and advanced manufacturing processes. For this reason, its R&D department teamed up with software company Autodesk to redesign a crankshaft component and use 3D printing technology to lighten the components and thus save fuel. Honda has developed a 50% lighter crankshaft component (Boissonneault, T. 2020).

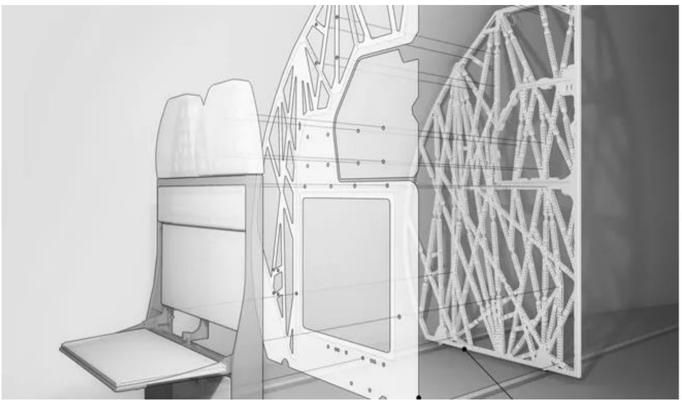
Figure 2.6

3D printed Crankshaft using Generative Design (Boissonneault, T. 2020).

Airbus and the cabin partition: In the A 320 model belonging to Airbus, as a result of innovative design model research, 3,180 kg of fuel savings per piece has been achieved thanks to the reduced weight of the components in the cabin compartments. This reduction can contribute to a reduction of 166 metric tons of CO_2 emissions per aircraft per year (Airbus, 2022).

Figure 2.7

Airbus and the cabin partition (Airbus, 2022)



Generative Desing Tools and Software in the Industry

- Fusion 360
- Ansys
- nTop
- Creo Generative Design
- Altair
- NX & Solid Edge by Siemens (Briard et all., 2020)

Autodesk Fusion 360 Generative Design: In the FUSION 360 program, it is a great advantage to be able to make designs with both a student license login and full access to the program, and to discover the benefits and advantages of generative design, including improved product performance, increased productivity and reduced production costs, Fusion 360 and Generative Design Extension are provided by Autodesk to enable users to discover the benefits and advantages of generative design, all transactions made via the cloud are recorded and can be logged in from different devices and worked on 24/7 (Autodesk. 2020**;** Autodesk. 2019).

Use of Autodesk Fusion 360 CAD Software in the Present Study: Fusion 360 is a 3D-based integrated CAD/CAM/CAE software that combines modeling, simulation, and documentation functions. Developed by Autodesk in 2013, this software adopts a top-down design approach with its cloud-based structure. This approach allows users to first design complex structures and then details them by breaking them down into smaller components. Being cloud-based facilitates collaboration between teams, enables synchronized management of data, and provides access from various devices (Autodesk, 2019).

The possibilities of using the program are listed below parametric modelling;

- Mesh Modelling
- Surface Modelling
- CAD and CAM integration
- Extremely realistic renders
- Printed Circuit Board (PCB) layout, planning and manufacturing
- Cooling of electronics
- Topology and shape optimization

Figure 2.8

Fusion 360 Logo (Autodesk, 2019).

Advantages of Using Autodesk Fusion 360

Affordability: Fusion 360 comes at a variety of price ranges for large scale corporations, boutique firms, small scale businesses, start-ups, hobbyists and students (Anandita, 2025).

Streamlined Workflow: Fusion 360 is completely cloud integrated, and so it is possible to collaborate with multiple stakeholders such as co-designers and work on the same project together (Anandita, 2025).

Integrated and Real-Life Simulation: Fusion 360 allows a user to accurately test how their design holds up to real life stresses (Anandita, 2025).

Realistic Rendering: Fusion 360 has extremely powerful built-in tools that allow for hyper-realistic rendering. In fact, it has an entire workstation dedicated just to rendering (Anandita, 2025).

Cloud System: With Fusion, data is always centralized, accessible, and secure. Cloud collaboration: Connect with teams and suppliers anywhere, anytime, on any device. Fusion's cloud-based design and manufacturing solution increases operational efficiency and agility by providing centralized data across the installation. (Anandita, 2025).

Disadvantages of Using Autodesk Fusion 360

Malware Risks: Many users have found that despite its vast range of uses, Fusion 360 can be prone to frequent crashes (Anandita, 2025).

Keyboard Incompatibility: Most CAD based software allows the user to customize their keyboard controls. However, Fusion 360 does not allow for this (Anandita, 2025).

Frequently Updating Features: Fusion 360 users report that the software comes with very frequent feature updates and patches, which can be irritating to the users (Anandita, 2025).

No Web-Based Version: Fusion 360 cannot be operated without a high-speed internet connection, and data and files can often be lost if the connection is interrupted. This is a disadvantage of most cloud-based software. (Anandita, 2025).

Using Autodesk Fusion Generative Design in Industrial Designs

Bicycle manufacturer SRAM partnered with Autodesk to test additive manufacturing for a new mountain bike crank arm using the generative design module in Fusion 360 as shown in the Figure 2.9. SRAM explored multiple design iterations and selected two designs to prototype based on manufacturing methods. The selected designs resulted in a titanium mountain bike crank arm that is twice as strong and 20% lighter (Miller, 2024).

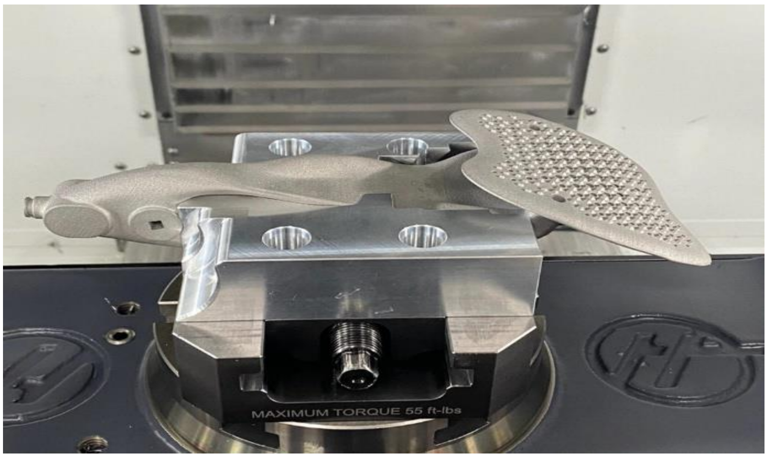
Figure 2.9

SRAM Product of Bicycle Crank -Arm Using GD Technique (Miller, 2024).

Stewart-Haas Racing, a NASCAR team, has won championships in two top national touring series. The team used generative design in Fusion 360 to lighten the brake pedal and used traditional manufacturing methods to design the existing brake pedal as shown in Figure 2.10. Using Autodesk Fusion 360, the team used generative design to explore multiple new designs with weight and safety in mind. They decided on their best bet for simulation testing and fabricated it using Renishaw's Ren 500Q quad laser powder bed metal printing 3D system. They achieved a 32% weight reduction and a 50% increase in stiffness for the new brake pedal (Miller, 2024).

Figure 2.10

Stewart-Haas Racing New Brake Pedal (Miller, 2021).



NASA and the European Space Agency (ESA) were planning an ambitious feat to safely return rocks and soil from Mars to Earth for the first time with the Mars Sample Return Mission. The team identified a part illustrated Figure 2.11 that connects the lid to the rotating hinge that could be mass-optimized to achieve a greater torque margin for movement. Maintaining stiffness in the part was crucial. Using Fusion 360 generative design, the team reduced the weight of the lid by 30% while maintaining the required stiffness. Materials were also a consideration for optimization (Miller, 2024).

Figure 2.11

Image courtesy of Newton | Engineering and Product Development (Miller, 2024).

The team compared Aluminum 6061, Aluminum 7075 steel, and titanium in the study. Aluminum provided the lightest solution that met the requirements. Aluminum 6061 was selected over 7075 due to its better manufacturability and lower cost, while still meeting the requirements with more than adequate safety margins. Fusion 360 generative design allowed for efficient and rapid analysis of different results and how different material options compared to each other and to determine optimum material stability (Miller, 2024).

Artificial Intelligence in Design and Manufacturing

AI is improving and transforming the manufacturing sector by increasing efficiency, precision and adaptability in manufacturing processes in the context of Industry 4.0 (Finio & Downie, 2025). The application of AI technologies such as ML, computer vision and natural language processing (NLP) improves various aspects of manufacturing processes. AI can analyze data from equipment and production lines through sensors to optimize efficiency, improve quality and reduce downtime. Using algorithms, it can identify patterns in data and predict potential problems, suggesting improvements and adapting processes to become autonomous in real-time. One of the most effective applications of AI is predictive maintenance (Adekoya et al., 2022).

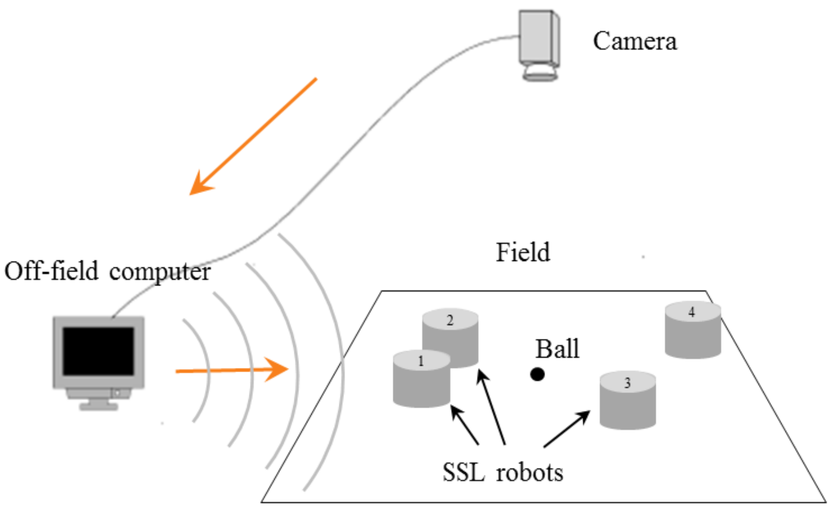
Generative AI has the capacity to generate new content through artificial neural networks, such as language models and visual models, by training on large data sets. These systems can generate outputs such as text, images, and software code by learning patterns in inputs. Industrial application areas include semantic product search to optimize information access, document summarization based on natural language processing, automated customer interaction, and digitization of call center processes. In application design and prototyping, AI-powered tools enable engineers to quickly evaluate alternative design solutions and adapt to dynamic manufacturing requirements. In supply chain management, generative artificial intelligence (Gen AI) increases flexibility, predictability, and communication efficiency in supply networks through content generation, scenario modelling, and advanced automation. In manufacturing, AI not only optimizes automation but also improves operational agility through autonomous decision-making supported by real-time data analytics (Finio & Downie, 2025). This area of responsibility is a component of advanced manufacturing approaches, often described as “smart factories” or “smart manufacturing systems” and identified with Industry 4.0. It aims to build manufacturing infrastructures with high flexibility, efficiency and autonomy through the integration of real-time data analytics and AI technologies. AI algorithms continuously monitor manufacturing processes, make instant decisions and optimize system parameters without the need for human intervention. This autonomous adaptation capability allows for minimizing energy consumption and material waste while maximizing manufacturing efficiency. These systems provide a structural transformation across the entire value chain, from product lifecycle management to distribution processes (Adekoya et al., 2022).

AI is at the heart of human-robot collaboration, making manufacturing smarter, more flexible, and more sustainable. Unlike traditional robots, new-generation AI-powered robots can work safely with humans, making AI a valuable tool in modern manufacturing (Adekoya et al., 2022).

Robocup Organization

Figure 2.12

Robot's Communication System in the field (Weitzenfeld et al., 2015)



The year 1997 was an important year for robotics and artificial intelligence (AI) to take a new form. In May of that year, IBM's Deep Blue, controlled by AI, defeated the world chess champion. On July 4, 1997, NASA's Mars Pathfinder mission successfully landed, deploying the first autonomous robotics system, Sojourner, on the surface of Mars. RoboCup took its first steps toward developing robotic soccer players capable of defeating a human World Cup champion team, alongside these achievements. The concept of robots playing soccer was initially introduced by Professor Alan Mackworth from the University of British Columbia, Canada, in a paper titled "On Seeing Robots," presented at VI-92 in 1992. Before the match, the robots are programmed with artificial intelligence and communicate with this software using a computer, camera, and Frequency modulation (FM) transmitter. The control system of the robots is shown in Figure 2.12 (Weitzenfeld et al., 2015)

Figure 2.13

RoboCup Organization Logo (Weitzenfeld et al., 2015)

A group of researchers including Minoru Asada, Yasuo Kuniyoshi and Hiroaki Kitano decided to organize a robotics competition tentatively called Robot J-League in June 1993. However, they soon received requests from researchers in different countries to expand the organization into an international collaborative project. Thus, they renamed the project the Robot World Cup Initiative, "RoboCup" for short. Since 2018 the Small Size League is divided into two divisions with separate tournaments: Division A and division B. Division A is aimed at advanced teams whereas new and/or less competitive teams can play in division B. Each team will only play in one of those two divisions (Weitzenfeld et al., 2015). The different robot league categories of the Robocup organization are listed below.

Small Size League (SSL)

Teams of 11 robots (6 in Division B) play 11 versus 11 matches on a 12x9 meter field using an orange golf ball. Robots are no taller than 15 cm, and their positions are tracked by overhead cameras. The league emphasizes intelligent multi-agent coordination and control in a dynamic environment (Weitzenfeld et al., 2015).

Middle Size League (MSL)

Teams of five fully autonomous robots play 2x15 minute matches with a regular FIFA soccer ball. Teams can design their own robots, but all sensors must be onboard, and there are size and weight limitations. The focus is on mechatronics design, control, and multi-agent cooperation (Weitzenfeld et al., 2015).

Standard Platform League (SPL)

All teams use the same robot, the NAO robot from United Robotics Group. This league emphasizes software development, as all robots are identical hardware-wise. Teams must develop intelligent strategies and communication protocols to outperform others (Weitzenfeld et al., 2015).

Humanoid League (HL)

Robots with human-like bodies (two legs, two arms, and a head) play soccer against each other. This league promotes research in hardware, perception, decision-making, and execution processes of autonomous robots that can interact with humans in a socially acceptable way (Weitzenfeld et al., 2015).

***Simulation League* (Ssim)**

This league focuses on artificial intelligence and team strategy. Independently moving software players (agents) play soccer on a virtual field inside a computer. There are two sub leagues: Two Dimensional(2D) and Three Dimensional(3D) (Weitzenfeld et al., 2015).

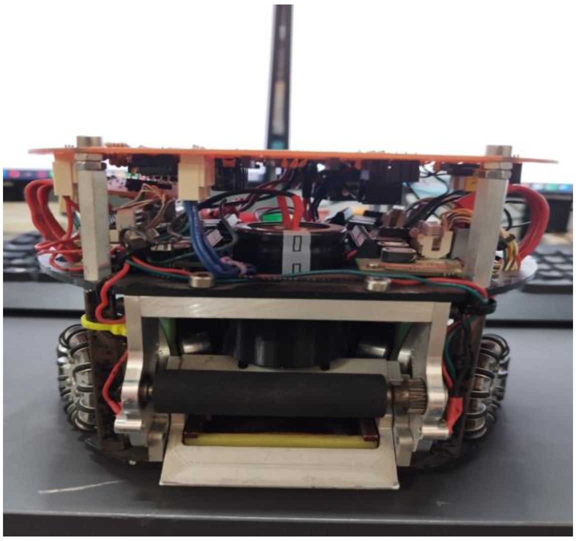
RoboCup robot soccer aims to advance artificial intelligence (AI) and robotics research. It is an annual international robotics competition. The expected goal is for a team of fully autonomous humanoid robots to compete alongside humans and win a FIFA World Cup match by the mid-21st century (Stone, 2024).

NEU Islanders

NEU Islanders is an interdisciplinary team consisting of NEU students and experienced engineers. The team has been participating in RoboCup events since 2012 (Near East University, 2016). Every year, there are significant developments in the teams of autonomous football-playing robots. The NEU Islanders robot system consists of three main components: robot mechanical hardware, electronics and control software (Kazancı, 2018). NEU Islanders competes in the Small Size League. The team has been attending to RoboCup events since 2012, and currently seeking qualification for RoboCup 2016. Since last year, significant developments had been made on the team of autonomous soccer playing robots. This paper is going to outline the progress in implementation of the current model of robots. The NEU Islanders robot system consists of three main components: robot hardware, electronics, and control software. These components are shown in Figure 2.14.

Figure 2.14

NEU Islander Robot Assembly.

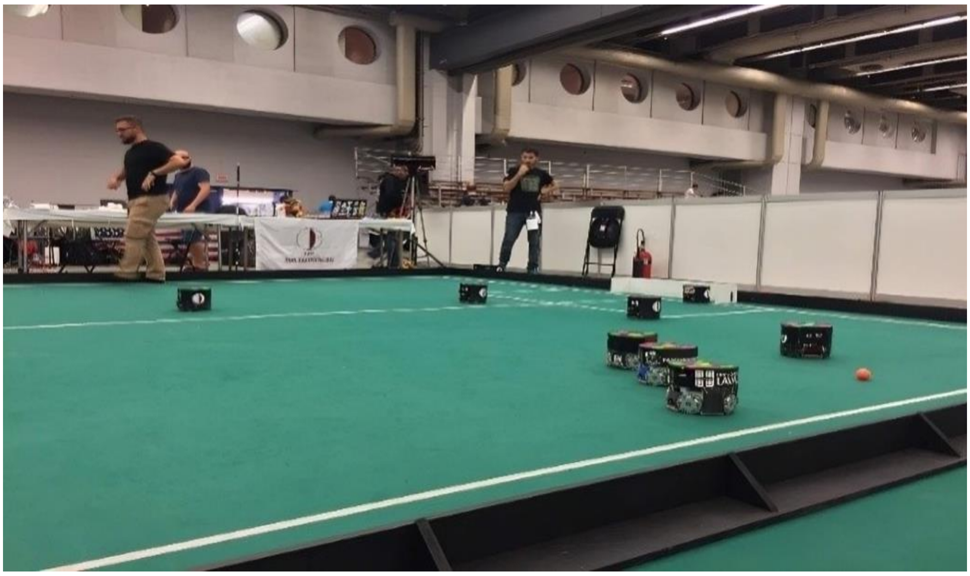


First of all, hardware of the robots is going to be examined here in this work. Mechanical parts of robots are going to be illustrated, and basic mechanical components of the robots are going to be described in detail. Electronics section is going to follow the hardware section. Electronic design of the robots is going to be illustrated in details, and basic information on the working principles of the electrical parts is going to be narrating. Finally, implementation details of control software are going to take place in the software section. Software for decision-making system, path finding and motion control is going to be illustrated in this section (Weitzenfeld et al., 2015).

The Small Size League, also known as the F180 League, is one of the earliest divisions in RoboCup Soccer. It focuses on the challenges of intelligent cooperation and control among multiple robots/agents in a fast-paced environment, utilizing a hybrid centralized/distributed system. Each match involves two teams of six robots. The robots must comply with F180 rules, fitting within a 180 mm diameter and standing no taller than 150 mm. They play soccer with an orange golf ball on a 9m by 6m green carpeted field. A standardized vision system, known as SSL-Vision, tracks all field objects using data from four overhead cameras mounted 4m above the field. The system is open-source and community-maintained. Off-field computers handle the coordination and control of the robots, with wireless communication via commercial radio transmitter/receiver units. Figure 2.15, shows the view of players from our robot football team on the field (Weitzenfeld et al., 2015).

Figure 2.15

During Soccer Robot Competition in Canada (Kazancı, 2018).



Competition History of Neu Islanders

Since its establishment, NEU Islanders has earned the right to participate in the World Robot Football Championship in Mexico in 2012, the Netherlands in 2013, Brazil in 2014, China in 2015, Germany in 2016, and Japan in 2017. In these tournaments, the football robots ranked 3rd in Europe in 2016, 9th in the world in 2017, and became World Champions in 2018. Near East University Robot Football

Team NEU Islanders defeated the Robojackets team from the United States of America, Georgia Institute of Technology University, 1-0, the “Thunderbots” team from the University of British Columbia from Canada, 2-0, the “Ultron” team from the University of Laval, 2-0, and the “AIS” team from Chile, 7-0 in the RoboCup 2018 held in Canada. NEU Islanders tied 0-0 with Brazil's Military Engineering Institution University and AMC in the tournament. NEU Islanders finished the tournament undefeated with 4 wins and 2 draws. All mechanical and electronic designs and artificial intelligence coding of the Near East University Robot Football Team NEU Islanders, consisting of 8 robots, were 100% of the Near East University's own production and were designed and produced by engineers working in research laboratories. Each of the football robots, which are handmade with a special technology, are managed with a three-dimensional coordination and communication system. With the joint work of electrical and electronics engineers and computer engineers, this year, the artificial intelligence that manages the team was written from scratch and a more offensive robotic football team was created (Stone, 2024).

Figure 2.16

NEU Islander Robot

Engineering Manufacturing Methods

Manufacturing is the process of transforming raw materials into products. It consists of processes such as product design, raw material selection and material processing. There are many traditional manufacturing processes. However, manufacturing engineering is a dynamic field marked by continuous advances in traditional approaches and the incorporation of new approaches for the production of advanced products. Manufacturing processes cannot produce the product to be manufactured with equal ease, quality and economy. Each manufacturing process usually has some advantages and disadvantages over other processes (Dahotre & Harimkar 2008; Khan et al., 2011)

Traditional Manufacturing Technology

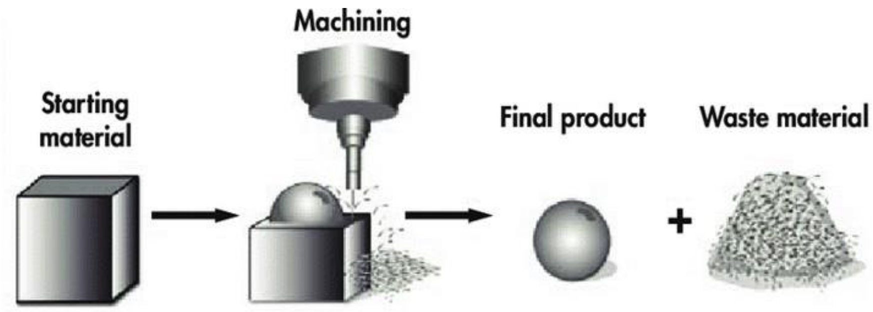
Traditional manufacturing methods are also known as Subtractive Manufacturing. These methods refer to manufacturing and processing to create high-volume products. Common applications in traditional manufacturing include extrusion, injection, molding, CNC machining and sand casting. Many production lines use a mold to produce high volumes of a single product. In this way, it is an efficient and cost-effective application model that allows mass production (Khan et al., 2011). Subtractive manufacturing is a general term for a variety of controlled machining and material removal processes that begin with solid blocks, rods, or bars made of plastic, metal, or other materials that are shaped by removing material through cutting, drilling, boring, and grinding. These processes are either performed manually or, more commonly, are managed by CNC. In CNC, a model designed in CAD software serves as input for the manufacturing tool. Software simulation is combined with user input to create tool paths that guide the cutting tool through the part geometry, aided by CAM. Instructions given in the CAM program prior to production tell the machine how to make the necessary cuts, channels, holes, and other features that require material removal, taking into account the speed of the cutting tool and the feed rate of the material. CNC tools can produce parts based on computer-aided manufacturing (CAM) data with little or no human assistance or interaction (Khan et al., 2011).

Subtractive Manufacturing Processes

The advantages of using CNC are that the machine provides smoother touches and more strength to objects than additive manufacturing. Another feature of additive manufacturing is that three-dimensional products are made by injecting a thermoplastic material into molds. Molds are usually made of aluminum, wax or sand, which speed up the injection material process. These technologies are the most common methods used for mold manufacturing. The Figure below shows how subtractive manufacturing stages are formed (Khan et al., 2011).

Figure 2.17

Stages of subtractive manufacturing process (Veronneau et al., 2017)



There are various production methods for subtractive manufacturing technologies (Veronneau et al., 2017). These are listed below;

- Turning
- Drilling
- Boring
- Milling
- Reaming
- Laser cutting
- Water jet cutting

Additive Manufacturing Technology

Additive manufacturing is referred to in industry and literature as rapid prototyping or 3D printing. The term rapid prototyping (RP) is used in various industries to describe the process of rapidly creating a product system or parts of a system before final release or commercialization. In other words, it is used to quickly create or prototype a part or system. It is used to describe the development process of manufacturing in parts, allowing designers to test ideas and provide feedback before reaching the final product. In the context of product development, the term rapid prototyping has been widely used to describe technologies that create physical prototypes directly from computer-aided design data (Gibson et al., 2021).

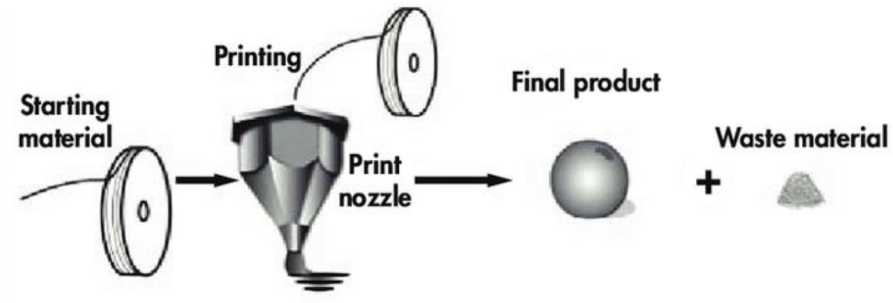
Figure 2.18

CAD Image of a Tea-Cup with Further Images Showing the Effects of Building Using Different Layer Thicknesses (Gibson et al., 2021)

Significant improvements in the quality of production output from these machines have increased the structural and functional similarity of manufactured parts to the final product. Accordingly, the fact that many components can be produced directly for end-use purposes by these systems makes it difficult to classify these products as mere “prototypes. A Technical Committee was established at American Society for Testing and Materials International (ASTM) to define a standardized set of terminologies. As a result of this widespread situation, the manufacturer's ASTM consensus standards for cut material acceptance are used. Referred to in short as AM, the basic principle of this technology is that a model, initially generated using a three-dimensional Computer Aided Design (3D CAD) system, can be fabricated directly without the need for process planning. Although this is not in reality as simple as it first sounds, AM technology certainly significantly simplifies the process of producing complex 3D objects directly from CAD data. Other manufacturing processes require a careful and detailed analysis of the part geometry to determine things like the order in which different features can be fabricated, what tools and processes must be used, and what additional fixtures may be required to complete the part. In contrast, AM needs only some basic dimensional details and a small amount of understanding as to how the AM machine works and the materials that are used. The key to how AM works is that parts are made by adding material in layers; each layer is a thin cross-section of the part derived from the original CAD data. All commercialized AM machines to date use a layer-based approach, and the major ways that they differ are in the materials that can be used, how the layers are created, and how the layers are bonded to each other. Such differences will determine factors like the accuracy of the final part, plus its material properties and mechanical properties. They will also determine factors like how quickly the part can be made, how much postprocessing is required, the size of the AM machine used, and the overall cost of the machine and process (Gibson et al., 2021).

Figure 2.19

Additive Manufacturing Process (Veronneau et al., 2017)

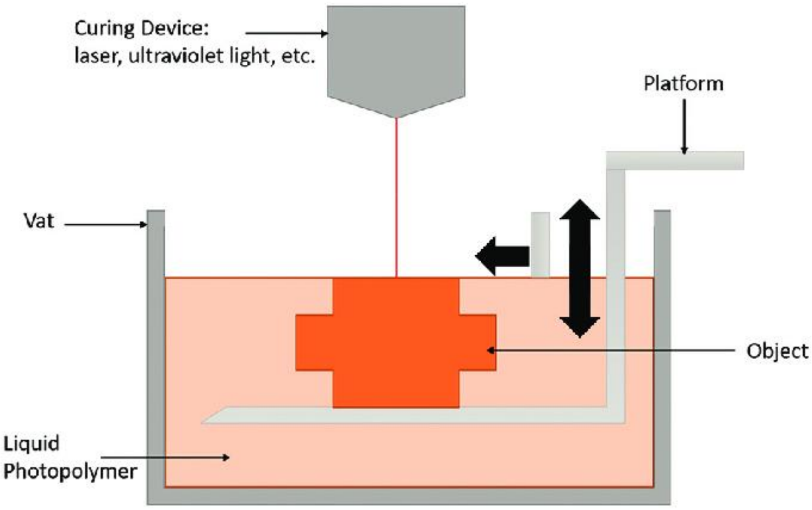


Typres of Additive Manufacturing Technology

Vat Photopolymerization: A 3D printer based on Vat Photopolymerization has a chamber filled with photopolymer resin, which is solidified using a UV light source (Pagac et al., 2021). This technology is especially preferred in applications requiring high precision and surface quality, and includes sub-technologies such as Stereolithography (SLA) and Digital Light Processing (DLP). While the SLA method hardens individual layers with a laser beam, DLP offers faster production by curing the entire layer simultaneously with a digital light projector (Pagac et al., 2021).

Figure 2.20

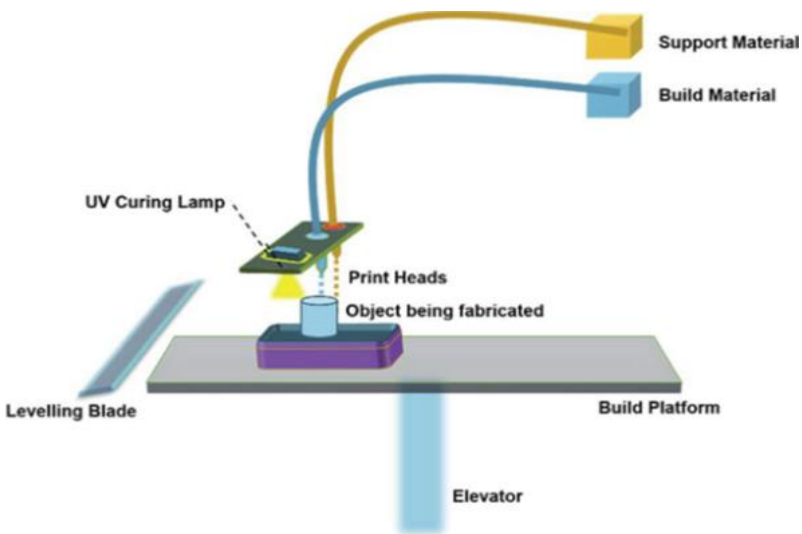
Stereolithography (Mancilla et all., 2022)



***Material Jetting*: ** In this process, material is applied in droplets through a small diameter nozzle, similar to the way a common inkjet paper printer works, but it is applied layer-by-layer to a build platform and then hardened by UV light (Alexandra P. 2024). Material jetting (MJ) technology is an additive manufacturing method that selectively cures liquid photopolymer to build functional parts (Gülcan et al., 2021).

Figure 2.21

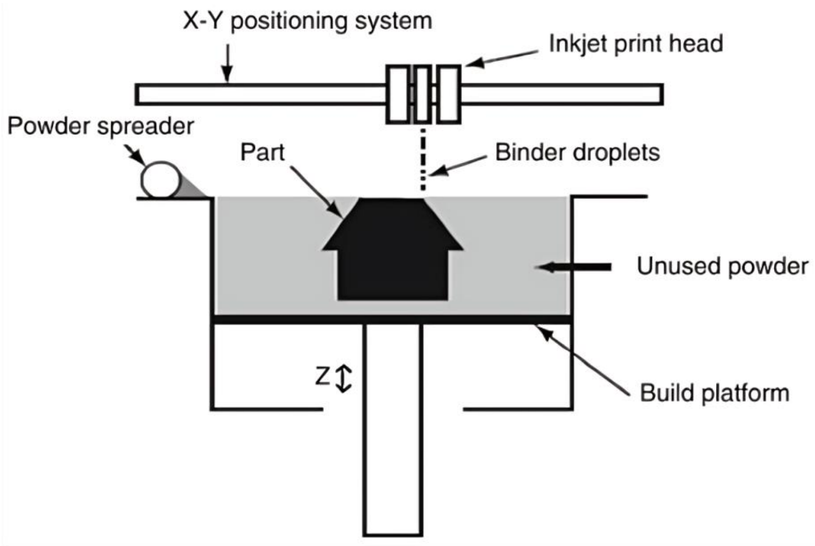
Material Jetting Technology (Gülcan et al., 2021).



Binder Jetting: With Binder Jetting two materials are used: powder base material and a liquid binder. In the build chamber, powder is spread in equal layers and binder is applied through jet nozzles that "glue" the powder particles in the required shape. After the print is finished, the remaining powder is cleaned off which often can be re-used printing the next object. This technology was first developed at the Massachusetts Institute of Technology in 1993 (Alexandra, 2024).

Figure 2.22

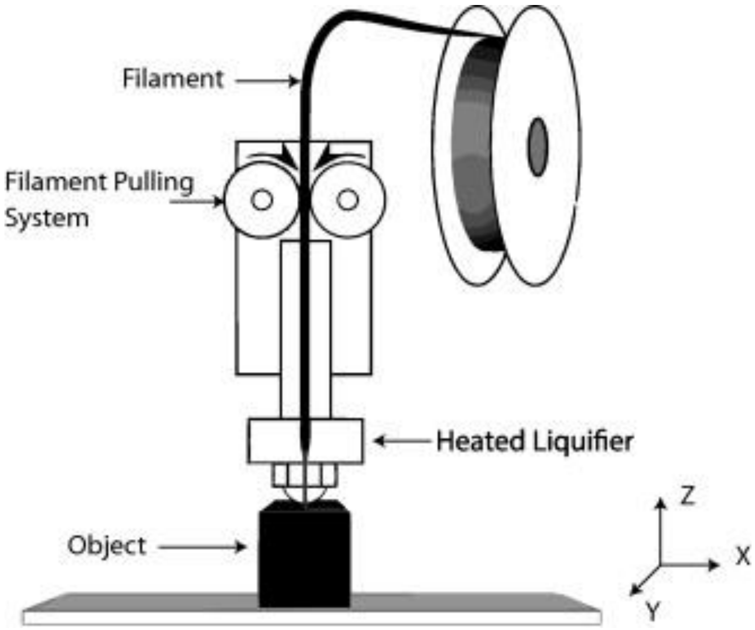
Binder Jetting Technology (Chiririwa, 2021)



Fused deposition modeling (FDM): FDM is a 3D printing technique performed by modeling and extrusion. As with all other additive manufacturing technologies, after the computer modeling is completed, cross-sectional slicing is performed to determine the cross-sectional area to be deposited. This technology processes the melted material layer by layer by transferring the thermoplastic material from the feeder to the heated head and nozzle (Sfetsas et al., 2021).

Figure 2.23

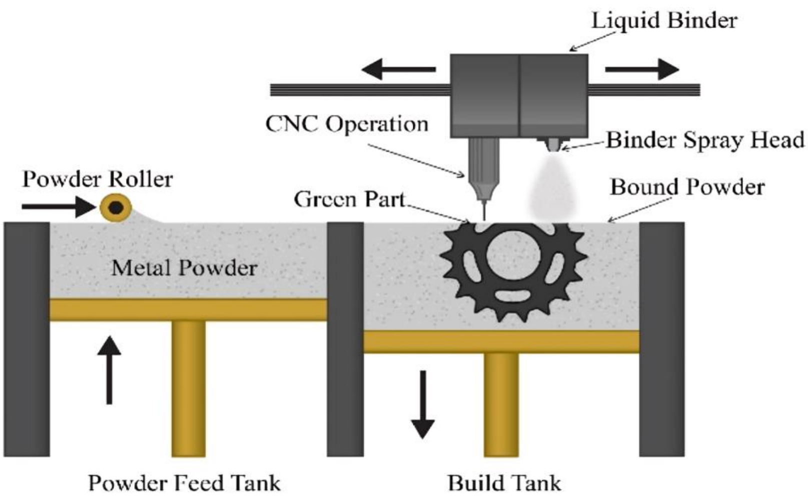
Fused Deposition Modelling (FDM) (Mahmood, 2021)



Powder Bed Fusion: Selective Laser Sintering (SLS), Multi Jet Fusion (MJF), and Direct Metal Laser Sintering (DMLS) powder bed fusion technology are divided into 3 groups. Logically, these 3 different technologies have different features that distinguish them from each other, depending on the same working principle. To beginning the printing process, an inert atmosphere is created in the 3D printer chamber and the system is heated to the optimum printing temperature (3DPrinting.com, 2024)

Figure 2.24

Powder Bed Fusion technology working Principle (Amfg, 2021)



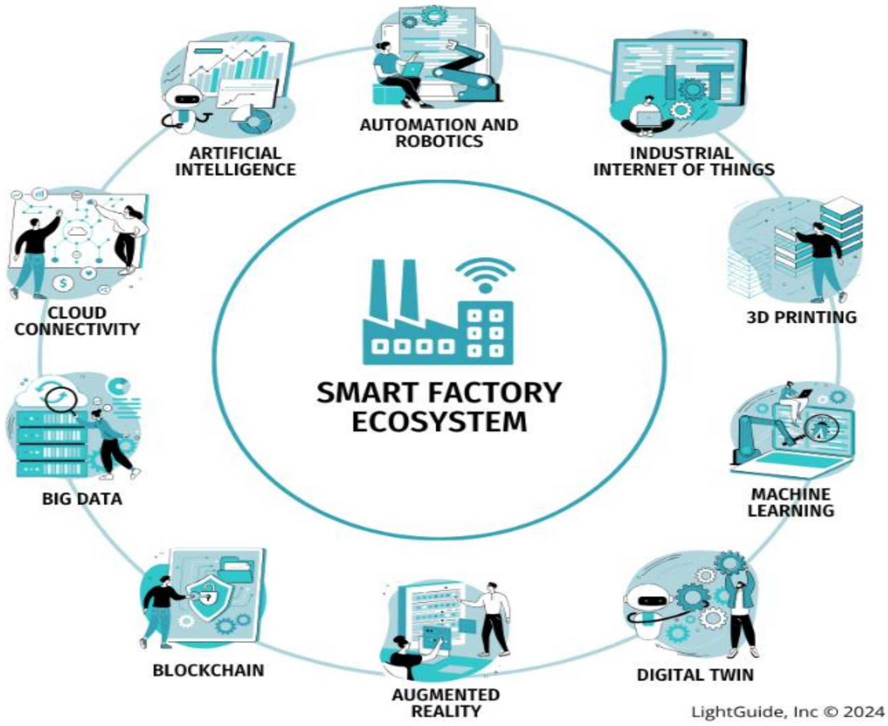
Then, a thin layer of metal powder, usually 20 to 60 microns thick, is laid down on the build platform. This layer is scanned by a fiber optic laser to melt and solidify the metal powder to match the cross-section of the part. As each layer is completed, the build platform moves down and a new layer of powder is added on top. This process is repeated layer by layer until the final part is created (3DPrinting.com, 2024).

Relations of Additive Manufacturing with Industry 4.0

3D printing, also known as additive manufacturing, has been identified as an important component of Industry 4.0, the fourth phase of industrial change defined by the merging of digital technologies and production mechanization. Additive manufacturing enables the creation of highly customized and complicated shapes with less waste and quicker development periods, thereby enabling the digitalization and automation concepts of Industry 4.0 (Stone, 2024). Furthermore, the use of additive manufacturing in Industry 4.0 can result in new business models and income sources, as well as improved supply chain adaptability and speed. Integrating additive manufacturing into Industry 4.0, on the other hand, poses difficulties, such as the need for more advanced materials and processes, as well as more complex software and hardware overall, additive manufacturing has the ability to greatly change the manufacturing industry while also playing an important part in the current Industry 4.0 transformation (Prashar et al., 2023; Howell, C. 2024)

Figure 2.25

Smart Manufacturing of Industry 4.0 (Howell, 2024).



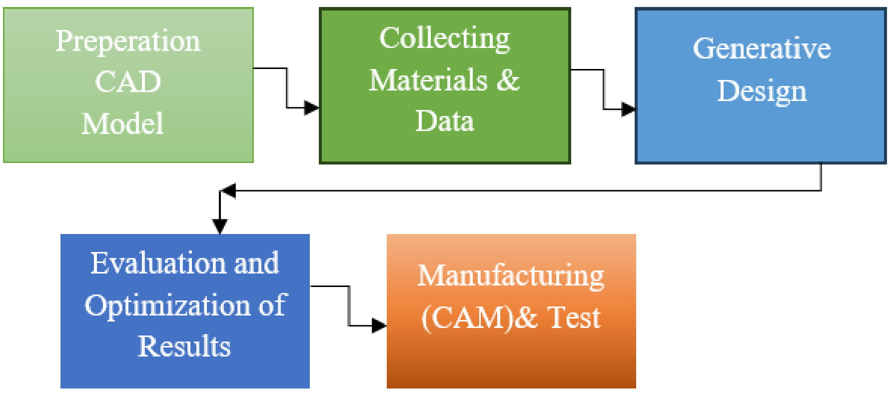
CHAPTER III

Methodology

The development and analysis process of a product is typically conducted to determine which inputs have an impact on the outputs and to try to optimize those inputs to achieve the desired performance. Experiments can be planned to collect various combinations of elements. An effective method of experimental planning is to obtain meaningful data at the least possible cost and to achieve the required strong and lightweight structure, the materials to be selected and the production processes are important factors for optimum outputs. These inputs and outputs can be obtained on a platform, with the generative design method of the Autodesk Fusion 360 program, which provides the opportunity to design optimization and analysis (Trautmann, 2021). In this work, the road map for improving product stability and robustness, minimizing material waste and reducing the cost of building an agile robot's parts such as the main chassis and electronic assembly member, is given in Figure 3.1 (Toptas, E. 2020; Danon, B. 2018)

Figure 3.1

The Flowchart for Improvement of the Product (Bürge et all., 2025)



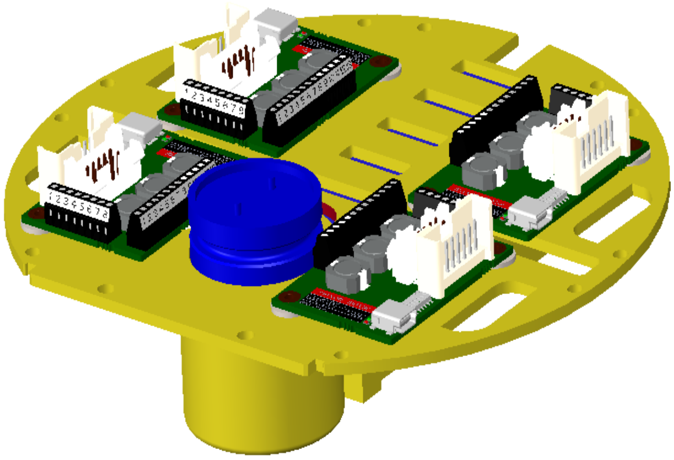
Production methods before performing the generative design process can be analyzed according to four different ways. The program shapes the optimum design according to these production processes namely, Unrestricted, Additive, Milling, Casting (Toptas, E. 2020; Danon, B. 2018).

Development of CAD Model.

A robot must fit inside a cylinder that is 0.18 meters wide and 0.15 meters high at any point in time. Additionally, the top of the robot must adhere to the standard pattern size and surface constraints. In the earlier version, the robot had a speed of approximately 3.5 meters per second and a weight of about 2.46 kg (excluding cover and battery). Figure 3.2, belongs to electronic assembly member that is earlier version. The comparative evaluation criteria include costs, lead time, rigidity, material usability, and weight.

Figure 3.2

Earlier Version of Electronic Assembly Member (EAM).



Tables 3.1 and 3.2 show in detail the material properties of four different thermoplastic materials, Polylactic Acid (PLA+), Acrylonitrile Butadiene Styrene (ABS), Polyethylene Terephthalate Glycol (PETG) and Acrylonitrile Styrene Acrylate (ASA), for the part to be redesigned with the generative design method.

Materials Selection

Thermoplastic Materials for Electronic Assembly Member

The materials above, offer cost, manufacturability and performance-focused solutions that can address a wide range of uses for FDM 3D printers. Which filament you choose depends on which features your project prioritizes, such as durability, heat resistance, UV resistance, aesthetics and ease of printing.

Table 3.1

Observations of Thermoplastic Material (Khaled, 2025; All3DP, 2023)

Materials	Durability	Performance /Application	Advantages	Disadvantages
PLA+	Medium, Brittle	Easy To Print	Biodegradable	Thermal Resistant
ABS	High Impact Resistance	Need Enclosure	UV Resistant	Particularly Water-Resistant
PETG	Good Balance, Durable and Flexible	Ease Of Printing	Less Brittle	Susceptible To Moisture
ASA	Good Adhesion, And Durability.	Need Enclosure	Strong UV, Chemical, And Water Resistance	High Extruder and Bed Temperature Required

The materials listed in Table 3.1 are thermoplastic materials selected for the electronic assembly member. These materials were evaluated based on their characteristics, including usage conditions, as well as their advantages and disadvantages.

Metal Materials Observation for Main Chassis

- **Al 6061 T651:** It is a versatile material known for its combination of strong strength values, corrosion resistance and weldability. These properties make this material suitable for different applications. T designation indicates Tempered (Ribeiro et al., 2011).
- **Al 5083 H111:** Aluminum 5083 material is known for its exceptional performance in extreme environments. This material is highly resistant to corrosion from both seawater and industrial chemical environments. H designation indicates hardened (AZoM., 2020).

- **Al Si10Mg:** Aluminium alloy (AlSi10Mg), composed of silicon, magnesium, and Aluminium. Today's advanced manufacturing range stands out as a leading choice for metal additive manufacturing technology due to its strength and versatility (Dughi,2024).
- **Ti-6Al-4V:** Titanium alloy, which contains 6% Aluminium and 4% vanadium, offers a combination of high strength, low density, excellent corrosion resistance, and good formability, making it suitable for a wide range of applications such as metal 3D printing (Rajan et all., 2022).
- **SS 316L:** AISI 316L stainless steel, also known as 316L, is a type of austenitic stainless steel recognized for its outstanding corrosion resistance, particularly in environments containing chlorides. It is one of the most widely used materials in metal additive manufacturing technology (D'Andrea, 2023).

Table 3.2

Materials Properties of Electronic Assembly Member (eSUN, 2024)

Material	Yield Strength (MPa)	Flexural Strength (MPa)	Tensile Strength (MPa)	Flexural Modulus (MPa)	Elongation at Break (%)	Density (g/cm^3)
ABS	66	66	43	2348	22	1.04
PLA+	74	75	63	2108	12	1.25
ASA	35	35	50	4300	30	1
PETG	58.1	68	52.2	1800	225	1.23

This analysis is used to compare parts produced using the traditional design method without utilizing generative design. The comparison encompasses production cost, component weight, and production time. Also, the materials of the previous version of the part are compared with the earlier design. In this study, the comparisons of the new design made according to generative design are also shown in the results section (eSUN, 2024).

Table 3.3

Materials List of Main Chassis (MatWeb, 2024).

Material	Yield Strength (MPa)	Modulus of Elasticity (GPa)	Tensile Strength (MPa)	Elongation at Break (%)	Density (g/cm3)
Al6061 T651	276	270	310	17	2.70
Al 5083 H111	115	70	270	16	2.66
Al Si10Mg	300	7.9	450	5	2.68
Ti Ti-6Al-4V	1100	114	1170	10	4.43
SS 316L	205	193	515	60	8.00

Figure 3.3

Comparison of Price, Weight, and Printing Time.

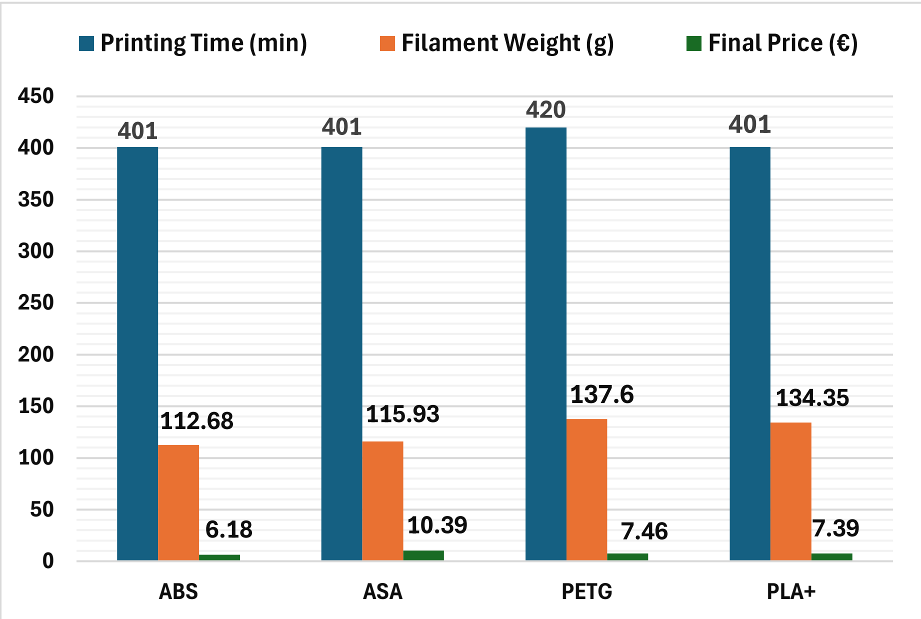
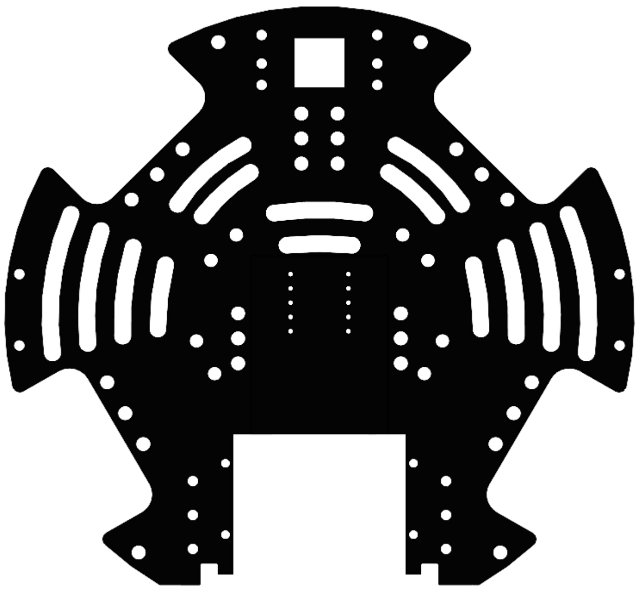


Figure 3.3, compares the workpieces produced with different materials and in different combinations according to the earlier design in terms of time, weight, and production costs, and the results show the production cost and production time of each part. The metal housing for the earlier robot's main body needs improvement. It was produced using the 3-axis CNC method with a previous design of 344 g. The goal is to utilize generative design to develop a lighter version without compromising durability. This will involve re-manufacturing it using advanced technology and comparing it with production methods to achieve the desired outcome.

Figure 3.4:

The Earlier Version Robot Main Chassis Soccer Robot.



The previous generation robot's main chassis, presented in Figure 3.4. Material selection is a determining factor in production planning and prototyping processes, and has a direct impact on the performance, production efficiency and cost effectiveness of the final product. In this context, it is of great importance to meticulously analyses the physical, mechanical and workability properties of each material and to ensure its structural and functional compatibility with the preferred production technologies. Otherwise, it is likely to encounter negativities such as delays, waste of resources and high production costs in the design process. Figure 3.4 represents the main chassis architecture of a previous generation football robot. Material selection for the new generation chassis design was carried out by taking into account criteria such as availability, workability and integration with existing production technologies. In this context, within the scope of the comparative analysis, five different engineering materials were evaluated: Aluminium 6061-T651, Aluminium 5083-H111, Aluminium Si10Mg, Titanium Ti-6Al-4V (3.7164/3.7165) and Stainless Steel 316L.

Table 3.3 compares the materials according to their mechanical properties. These materials are compared according to different manufacturing methods such as CNC machining, additive manufacturing (3D printing) and limited production, and analyzes each material in terms of manufacturability, technical capability and aims to make the optimum material selection for the final design (MatWeb, 2024).

Mechanical Behavior and Failure Theories of Materials

The mechanical behavior of materials refers to the stress, strain and deformation responses they exhibit under external loading. Understanding this behavior is of great importance in predicting how materials will perform in real applications. In this context, mathematical models and formulas based on various theoretical approaches are used to analyze the mechanical behavior of materials and their possible damage. These formulas play a critical role in the evaluation of structural reliability in both theoretical analyses and computer-aided engineering software. Figure 3.5 illustrated stress vs strain diagram and the formulas are given below.

Formulation of Force:

$\vec{F} = m\vec{a}$ = Newton (N) $\vec{a}$: Acceleration, ($\frac{m}{s}$)

m: Mass, (kg)

Formulation of Stress:

$\sigma = \frac{F}{A} = {}^{N}/_{m^2}$ = Pascal (Pa) F: Applied Force: Newton(N)

A: Cross Sectional Area. (In meter per square: m^2)

Strain Formula

$\varepsilon = (\Delta L/L)$

Young's Modulus

$E = \frac{\sigma}{\epsilon}$ = (Pa) or N/m^2

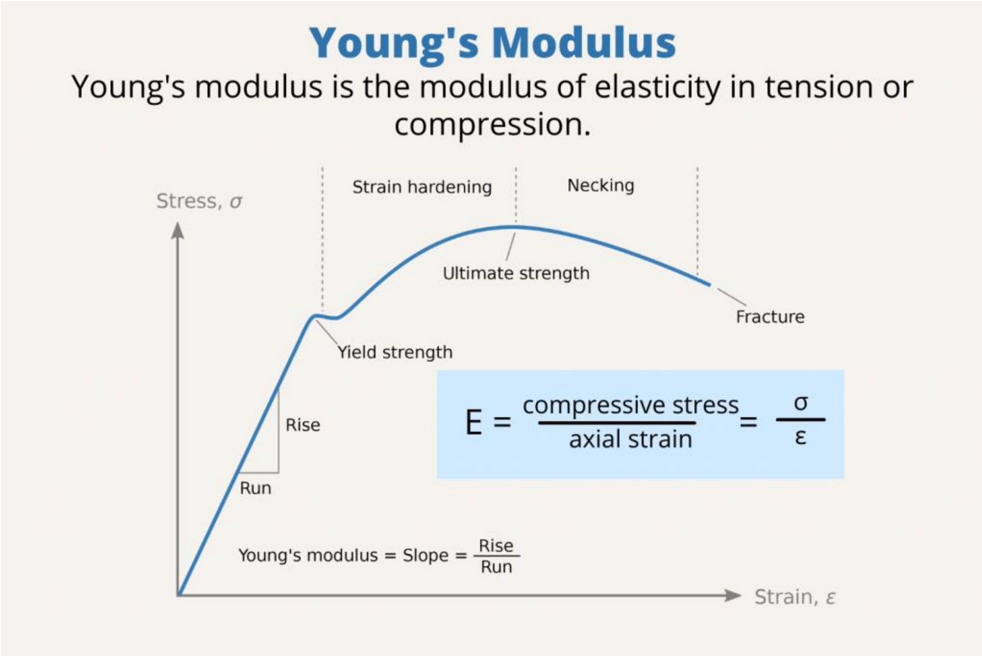
Elongation

ΔL: Final Length in (mm)

L: Initial Length in (mm)

Figure 3.5

Stress vs Strain Diagram (Helmenstine, 2022).



Shear Modulus Formula

$G = \tau xy \,/\, \gamma xy = \frac{F}{A} \,/\, \frac{\Delta x}{l} = Fl \,/\, \frac{Fl}{A\Delta x}$

G is the shear modulus or modulus of rigidity

τxy= Shear Strain

γxy= or F/A is the shear stress

A low Young's modulus value means a solid is elastic. A high Young's modulus value means a solid is inelastic or stiff (Helmenstine A., 2022). At the behind of the software using these formulas as shown up while calculation of input and output data.

Algorithm of Generative Design

Generative Design approach takes help from some algorithms to achieve design goals. These algorithms are mentioned below.

- **Topology Optimization:** Topology optimization aims to increase structural efficiency by optimizing material distribution within a given design space. It's working with generative design approach. This method focuses on achieving the optimal design by iteratively removing unnecessary material in accordance with performance constraints such as weight, stress, and stiffness (Massobrio, 2024).

- **Genetic Algorithm:** It evaluates the suitability of the design solutions based on constraints, which aims to increase the number of design solutions and to express the design goals by applying genetic operators, which are mutation and crossover techniques, to design alternatives (Massobrio, 2024).

- **Machine Learning**
  In generative design, artificial AI and ML algorithms are an important tool for analyzing design constraints, goals, and historical data. These algorithms learn from existing designs, materials, manufacturing methods, and performance data to create innovative and optimized design solutions (Massobrio, 2024).

- **Cloud-Based Computing**
  Parametric design integrated with cloud computing provides designers and engineers with advanced computational power, real-time collaboration, and more efficient design processes. This integration enables complex calculations to be performed quickly and flexible work environments to be created, independent of location, thanks to cloud-based resources (Massobrio, 2024).

Model Preparation to Generative Design Process

At the beginning of the generative design process, the fusion 360 generative design process is started on the prepared CAD file as indicated in Figure 3.4. These processes follow each other in order. If, all inputs are not correct then the generative design result will not be as desired and correct results cannot be obtained. The path followed for the two workpieces is indicated in detail in Figure 3.4. The robots weight approximately 2.5 kg. Therefore, during the match, the robots apply forces of certain intensities to each other according to their collision speeds. Using the equations 3.1 and 3.2 below, the average collision force of the robots against each other during the match was assumed as 5, 15, and 25 Newtons(N) respectively.

The force distribution acting on the parts were determined during the generative design load case inputs, and the results were concluded according to the study.

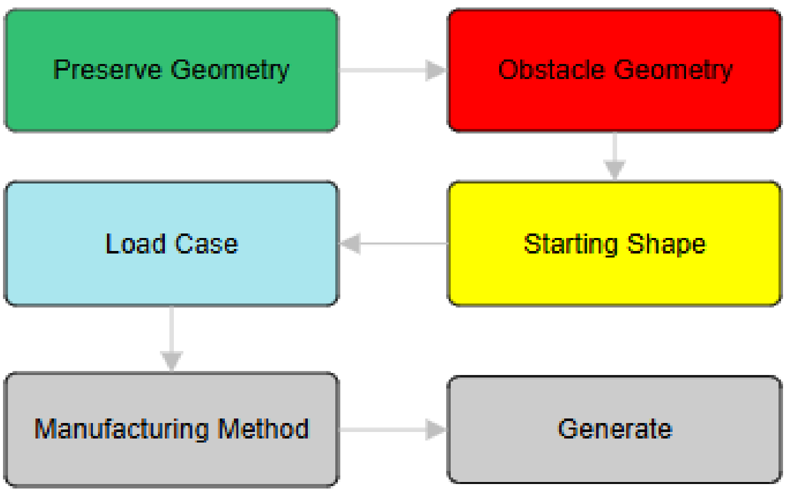
$$a)\ F_{avg} = \left(\frac{0.5.\text{m}.v^2}{\text{d}}\right) = kg\frac{\text{m}}{s^2} \qquad (\text{N}) \qquad (3.1)$$

$$b)\ F_{avg} = \left(\frac{\text{m.v}}{\text{t}}\right) == kg\frac{\text{m}}{s^2} \qquad (\text{N}) \qquad (3.2)$$

The formula for impact force in expressed in terms of the body's velocity (speed) in $\frac{\text{m}}{\text{s}}$ on impact (**v**), it's mass (**m**) in kg, collision distance (**d**)in meter, and the (**t**) is time in second.

Figure 3.5

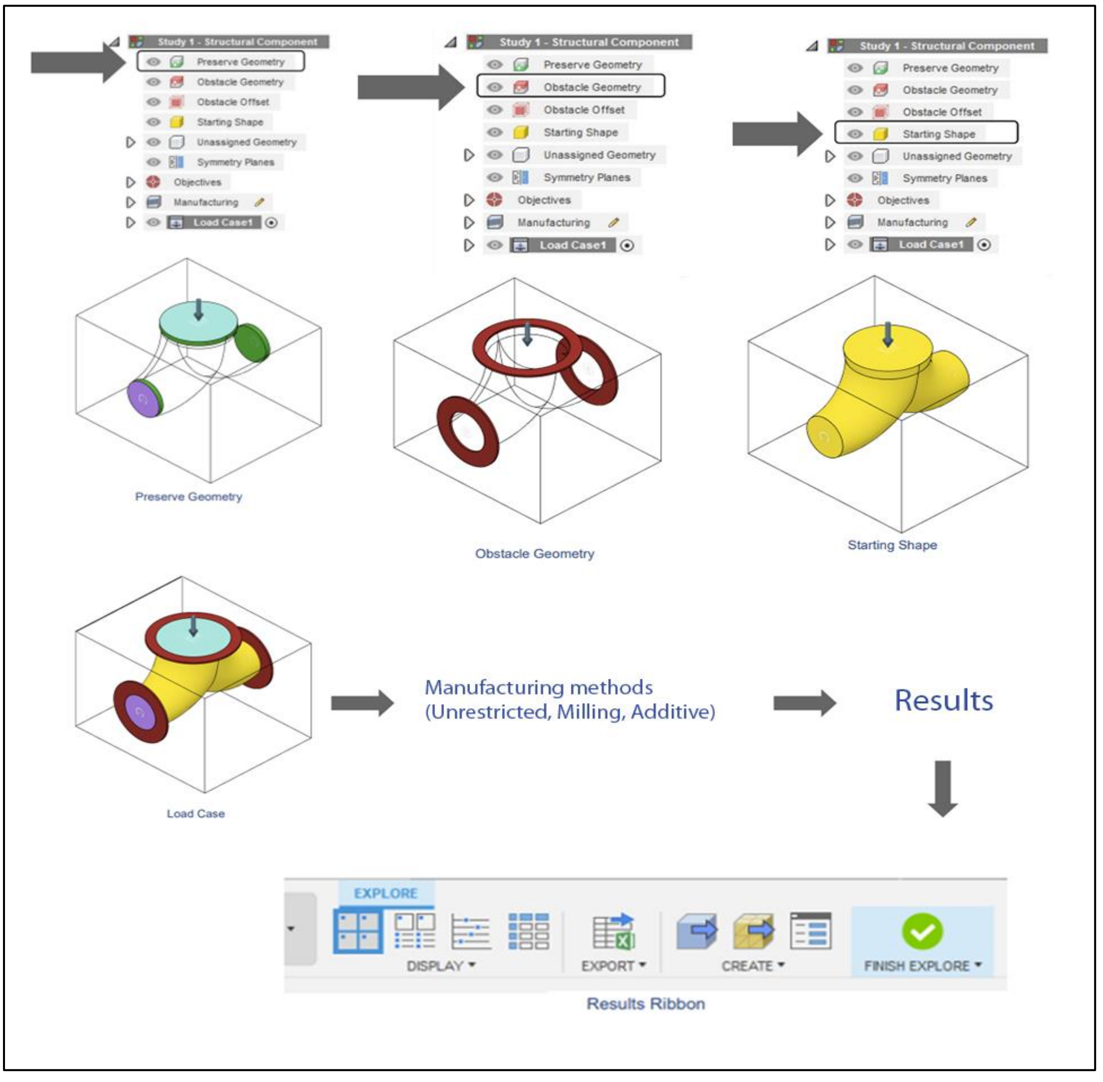
Flow Chart of Design Preparation (Savage, 2022)



In the Figures 3.5 and 3.6, represents generative design preparations process for two distinct parts. Before the generative design process begins, essential inputs must be entered. The obstacle geometry, shown in red, indicates the boundaries beyond which the design should not extend. The green areas denote the geometry that must be preserved, while the yellow areas represent the initial shape where the process will be applied. Generative design techniques were then used on these specified areas. In the fourth stage, the forces acting on the component are identified. Once these four stages are fully and accurately defined, the production methods are chosen and the optimization process begins.

Figure 3.6

Fusion 360 Generative Design Sample Preparation Steps (Savage, 2022)



In Figure 3.6, the stages that need to be completed while preparing the generative design mentioned in the section above are shown in more detail with cross-sections on Fusion 360. In Fusion 360 Generative Design, the design preparation stages initially require determining the design purpose. If the purpose of the part to be designed is not clearly defined, the model made will not be designed for its purpose. The potential volume to be designed should be determined. This area represents the area where generative design will be made. Then, the parts to be assembled, fixed areas such as screw holes are determined. Then, the areas where generative design is not desired (constraints) and the forces that will affect the part should be determined. The areas that must be there in terms of assembly or function (Preserve Geometry) should be determined. Finally, before the beginning of the solution and simulation process, the process is started by selecting the material and manufacturing method.

Research Design Scope

Robotic technologies are rapidly developing and robots exhibit significant performances in national and international competitions held every year. These competitions play a critical role in both testing existing technologies and introducing new technologies. The superior performance of robots in such environments is possible not only with existing engineering knowledge, but also with the application of innovative and original design techniques. In this context, studies on robot design and development require a multidisciplinary approach between engineering disciplines. Therefore, in this study, it is aimed to apply innovative design techniques together with contemporary engineering methods in order to increase the functionality and competitiveness of robot systems. In this way, it is aimed to present more efficient and effective robot prototypes that are optimized in terms of both aesthetics and functionality.

General Rules

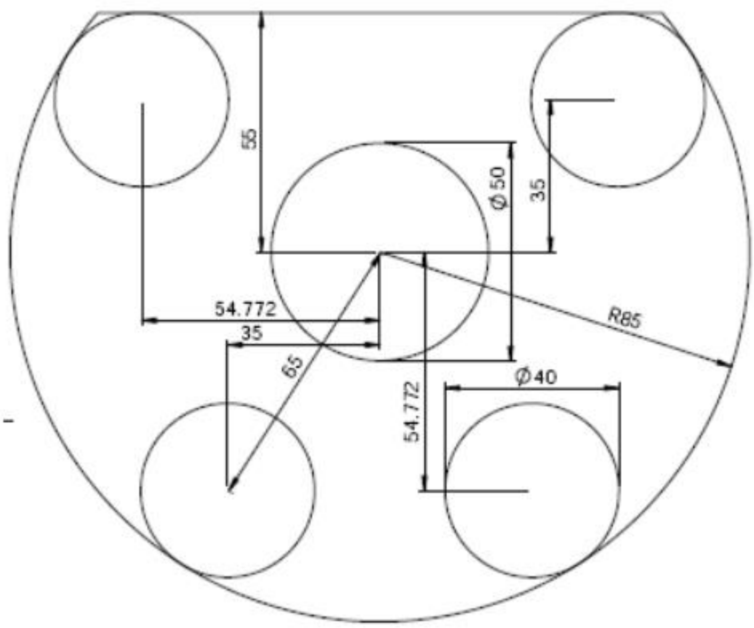
Vision Pattern All participating teams must adhere to the given operating requirements of the shared vision system. In particular, teams are required to use a certain set of standardized colors and patterns on top of their robots. To ensure compatibility with the standardized patterns for the shared vision system, all teams must ensure that all robots have a flat surface with sufficient space available on the top side. The color of the robot top must be black or dark grey and have a matte (non-shiny) finish to reduce glare. The standard vision pattern is guaranteed to fit within a circle with a radius of 0.085 meters that is linearly cut off on the front side of the robot to a distance of 0.055 meters from the center, as shown in Figure. Teams must ensure that their robot tops fully enclose this area.

Shape

A robot must fit inside a 0.18 meters wide and 0.15 meters high cylinder at any point in time. Additionally, the top of the robot must adhere to the standard pattern size and surface constraints.

Figure 3.7

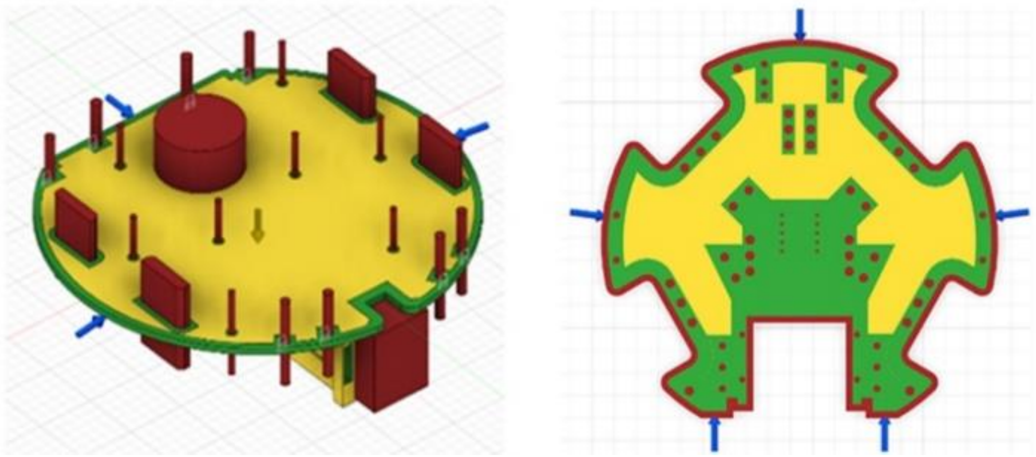
Robots Design Constraints (Vlah et al., 2020)



An example of the process preparation for new models that are desired to be created with the selected design inputs during generative design preparation is shown in Figure 3.7 on the EAM which is the body of the football robot and where the electronic components are assembled.

Figure 3.8

Sample Preparation of EAM.



In the generative design process, determining the design inputs correctly plays a critical role in terms of the algorithm producing functional, manufacturable and optimized solutions. In this context, parameters such as selected design targets, loading conditions, material options, manufacturing methods and geometric constraints must be introduced to the system as a whole. A practical example of this process is shown in Figure 3.8. In the related Figure, the generative design preparations performed on the main chassis that serves as the body of a football robot and the EAM component that also provides the assembly of various electronic components are given in detail. In this example, the design area was created by first defining the function of the EAM part. Accordingly, the assembly points and restrictions related to external force effects were defined. Then, the "obstacle geometry" was marked as the screwing, assembly and contact surfaces where the electronic components will be placed. Materials with a high strength/low weight ratio were preferred as materials for the Main chassis. For EAM, the most usable thermoplastics in additive manufacturing were selected in this study. 3-axis CNC machining and additive manufacturing were selected as production methods, and the low-weight with manufacturability conditions were compared.

Generative Design: Input Constraints and Parameters (Objectives)

- **Load Case:** 5, 15, 25 Newton (N) for EAM (Distributed Loads)
- **Factor of Safety:** 1.5
- **Minimizing mass:** The purpose of minimizing mass adjustment is to be resistant to applied loads and to achieve optimum weight reduction in the overall weight of the part to be designed.
- **Load Case:** 25 Newton (N) for Main Chassis (Distributed Loads)
- **Factor of Safety:** 2

Manufacturing Methods

- Additive Manufacturing for Electronic Assembly Member.
- Additive Manufacturing, 3 Axis CNC Machining, Restricted for Main Chassis.

Results and recommendations data calculated according to the objectives above.

Additive Manufacturing Input Parameters

In the 3D printing process, parameters such as printing speed, infill rate, layer height, nozzle diameter and infill type have a direct impact on the quality, strength and production time of the part produced. While printing speed determines production time, infill rate affects the internal structure and mechanical strength of the part. While layer height determines surface quality and detail precision, nozzle diameter controls the precision of the print and material flow. Infill type is selected to optimize the internal structural support of the part and the strength-performance balance. In this study, the prints were made according to the following values mentioned below and machine temperature settings illustrated in Table 3.4.

- **Print Speed**: 50 mm/s
- **Infill**: %100
- **Layer Height:** 0.3 mm
- **Nozzle Diameter:** 0.4 mm
- **Type of Infill:** Rectilinear
- **Type of Filament:** 1.75mm

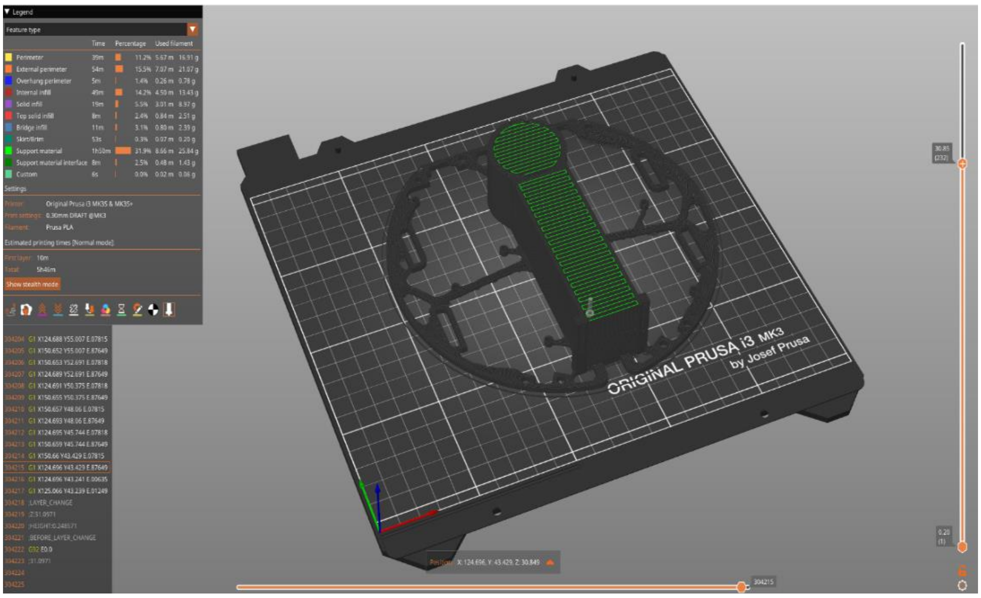
Table 3.4

Adjusting Extrusion and Table Temperatures Using Prusa Slicer

Material	**Nozzle Temp °c**	**Bed Temp °c**
PLA+	210	60
PETG	240	90
ABS	255	110
ASA	260	110

Figure 3.9

The Computer-Aided Manufacturing Preparation of The Design Output Model in The Prusa Slicer Program



Following the preparation of the generative design modelling, the optimum designs selected from the design results will be produced by the Fused Deposition Modelling (FDM) method, an additive manufacturing technology. Figure 3.9 above shows the computer-aided manufacturing preparation of the design output model in the Prusa Slicer program.

CHAPTER IV
Findings and Discussion

In this section, the generative design results of the Electronic Assembly Element and the main body chassis part are examined and detailed in figures and tables. After the electronic assembly element was simulated in the computer environment, its production and post-production processes were carried out. The design and comparison studies of the main chassis part were carried out in the computer environment and it was not put into production. As shown in Figures 11, 12 and 13, the outputs of four different materials and three different load conditions were compared, then the recommended design iterations were determined. The numbers 1, 2, 3, 4 in the figures represent ABS, PLA+, ASA, PETG materials, respectively. Generative design produces outputs using random values within the defined ranges for the specified variables, based on the constraints defined by the type of work. As a result, twelve different outputs were obtained.

Figure 4.1

Results Under 5N Load Condition Generative Design Results.

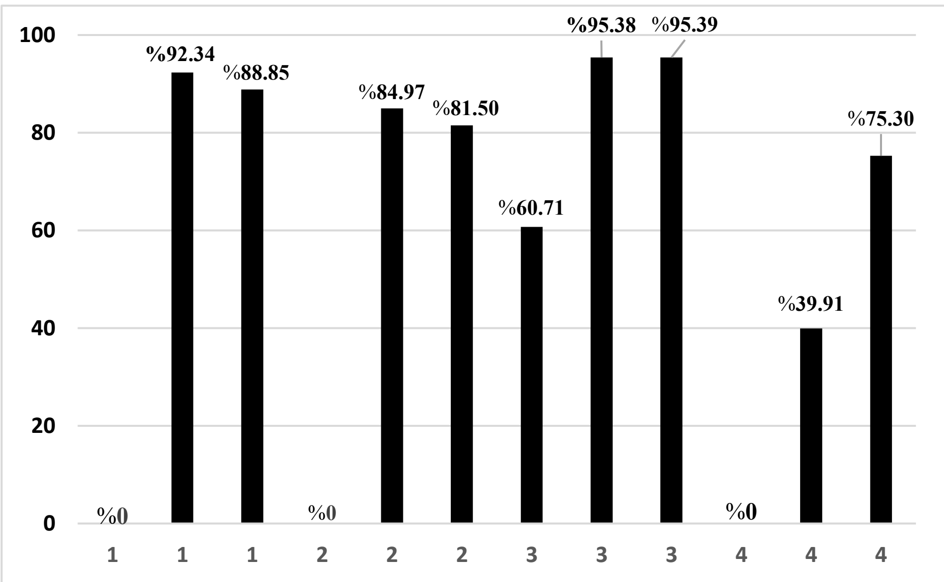


Figure 4.2

Results Under 15N Load Condition Generative Design Results.

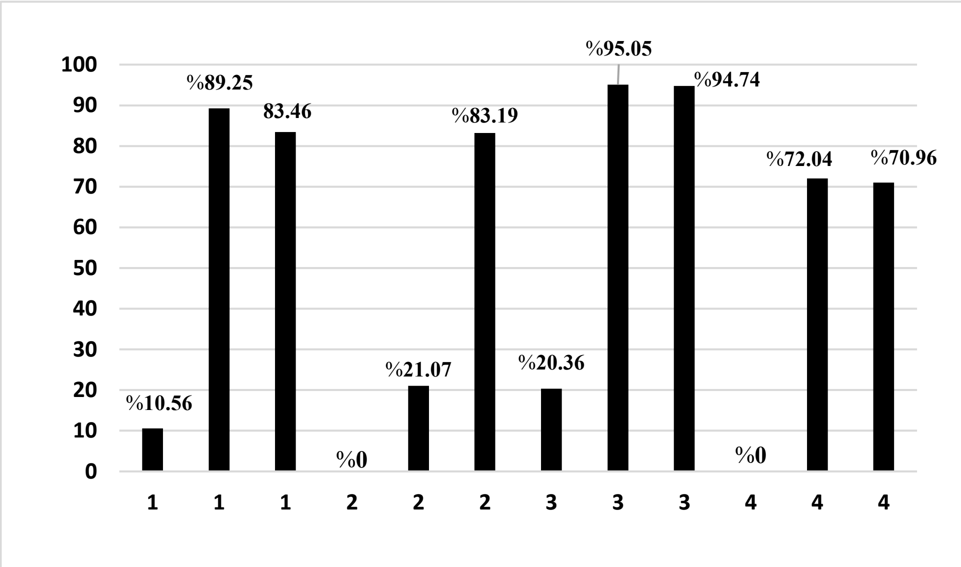
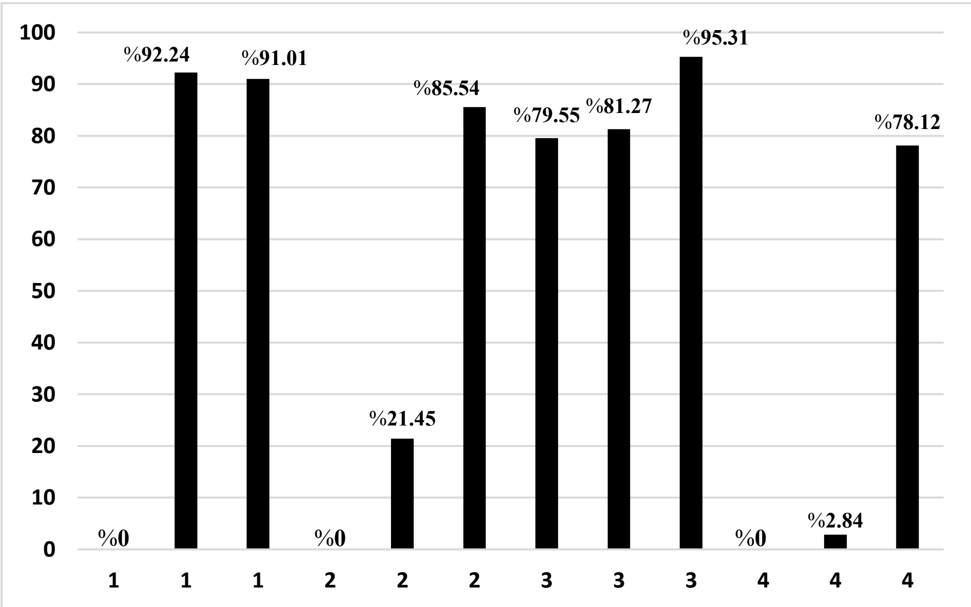


Figure 4.3

Results Under 25N Load Generative Design Results

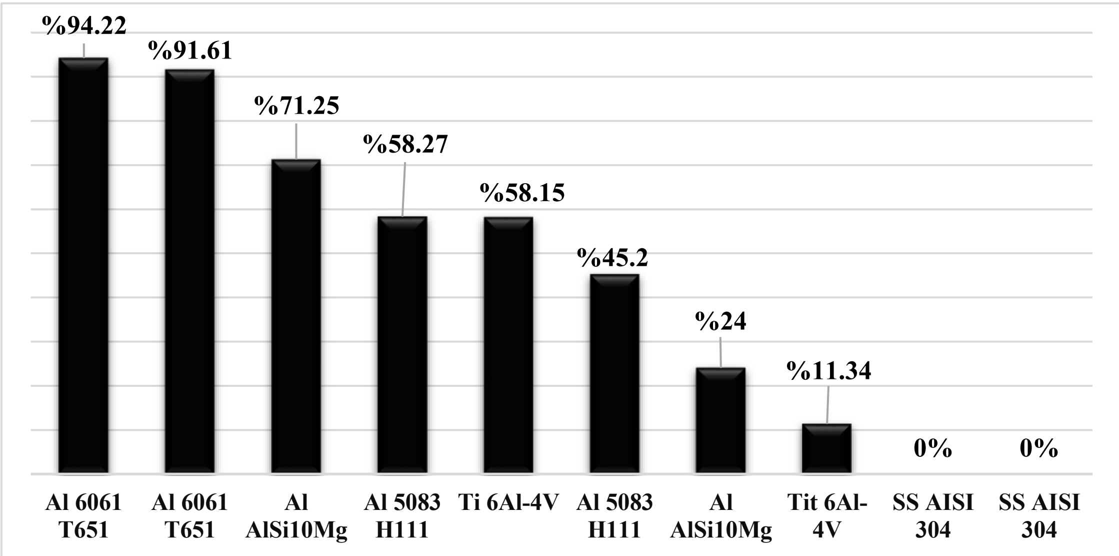


Five, Five-teen, and Twenty-five Newtons(N) were applied force for a fixed geometry and the recommended outcomes were max weight reduction settings in the test run. The GD outcomes for the analyzed primary chassis component of the robot are presented in Figure 4.4. Moreover, some abbreviations are listed. These are represented namely; Stainless Steel (SS), Titanium (TI), and Aluminium (Al). 25 Newtons force applied condition were analyzed for the main chassis.

As a result, the most suitable design was chosen after a thorough assessment of various iterations to ensure alignment with production and model requirements.

Figure 4.4

Generative Design Results Under 25N load of Main Chassis.

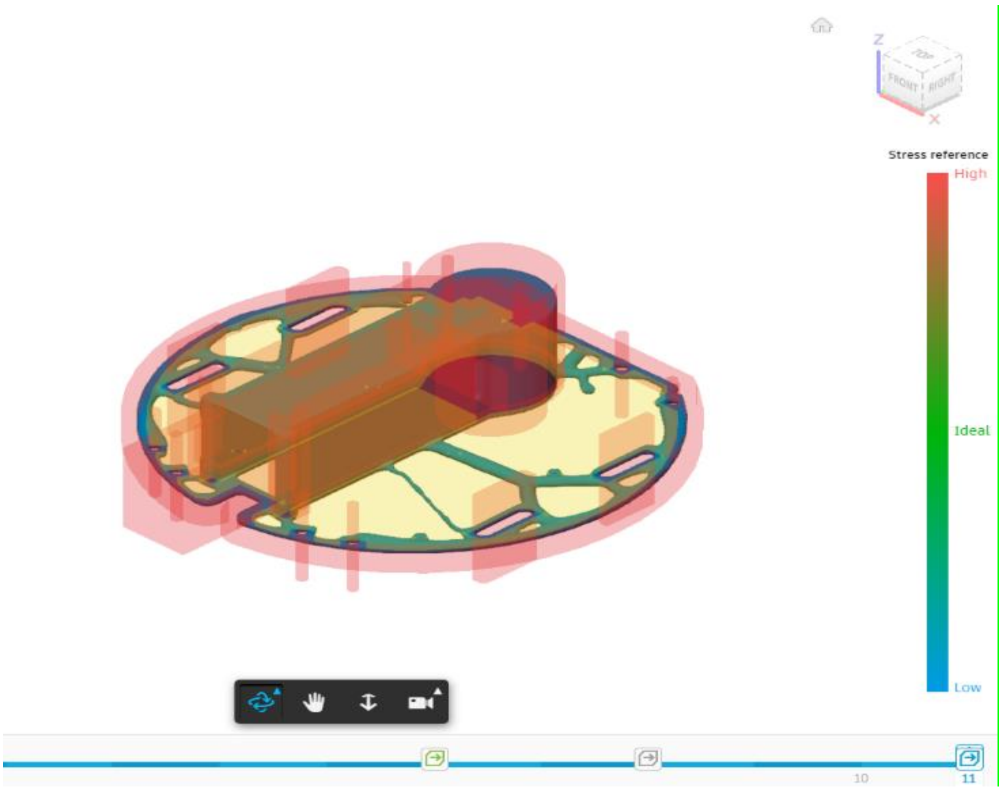


Generative Design Iterations

In this section, GD the iterations were calculated and finalized according to various mechanical factors such as load conditions, boundary conditions and material properties. The electronic assembly element was renewed and replaced. Then, the main chassis where the motor and kick mechanism systems that make up the chassis were mounted in the second GD example of the robot. Figure 4.5, shows the GD model output of the Fusion 360 program where these processes were performed and belong to the Electronic Assembly Member. Various studies in the literature demonstrate the potential of GD in engineering processes. For example, Çokatar et al. (2022) stated that the robot arm part was reduced in weight and increased in performance by using 20 times less material on the part with the GD method (Çokatar et al., 2022). Similarly, Zaimis et al. (2021) reported that the weight of the landing gear part of an unmanned aerial vehicle produced in a 3-axis CNC was reduced by up to 36% by optimizing complex geometries using GD in the aviation industry.

Figure 4.5

Generative Design Operation of Electronic Assembly Member

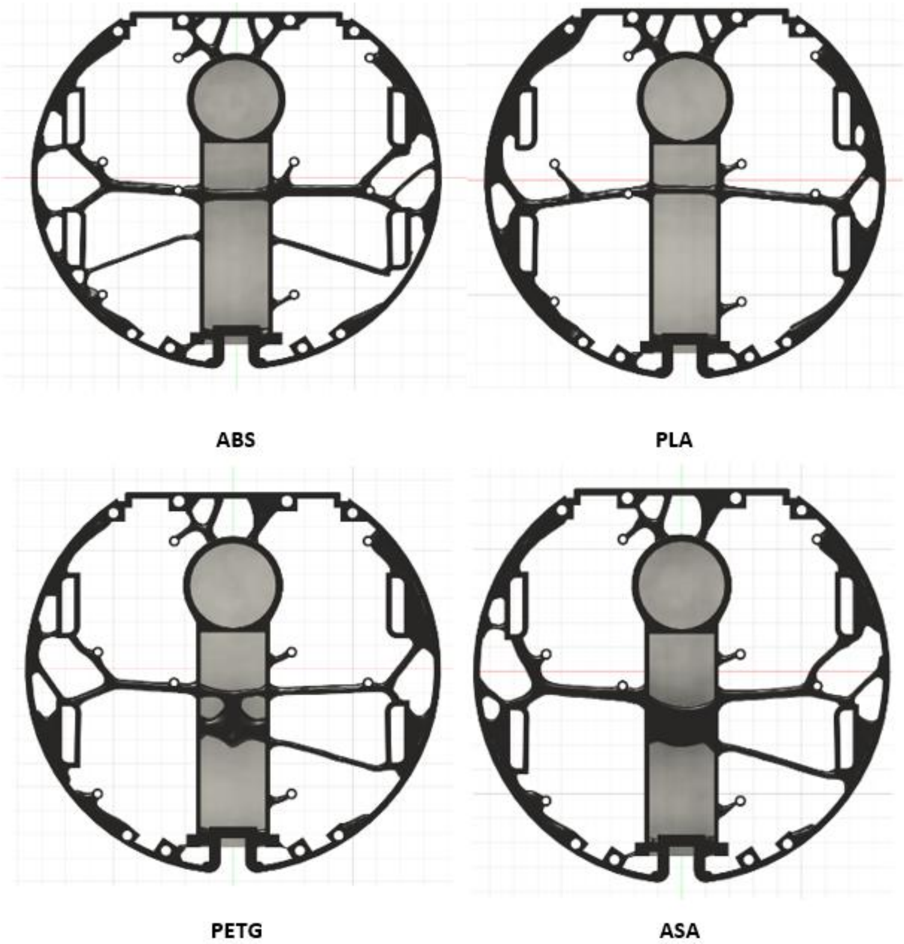


Optimum Design Selection

In this section, the GD outputs were examined and the most suitable model for the desired appearance and use of the robot was selected as a result of the comparisons made. All design outputs and the most suitable model is shown in Figure 4.6.

Figure 4.6

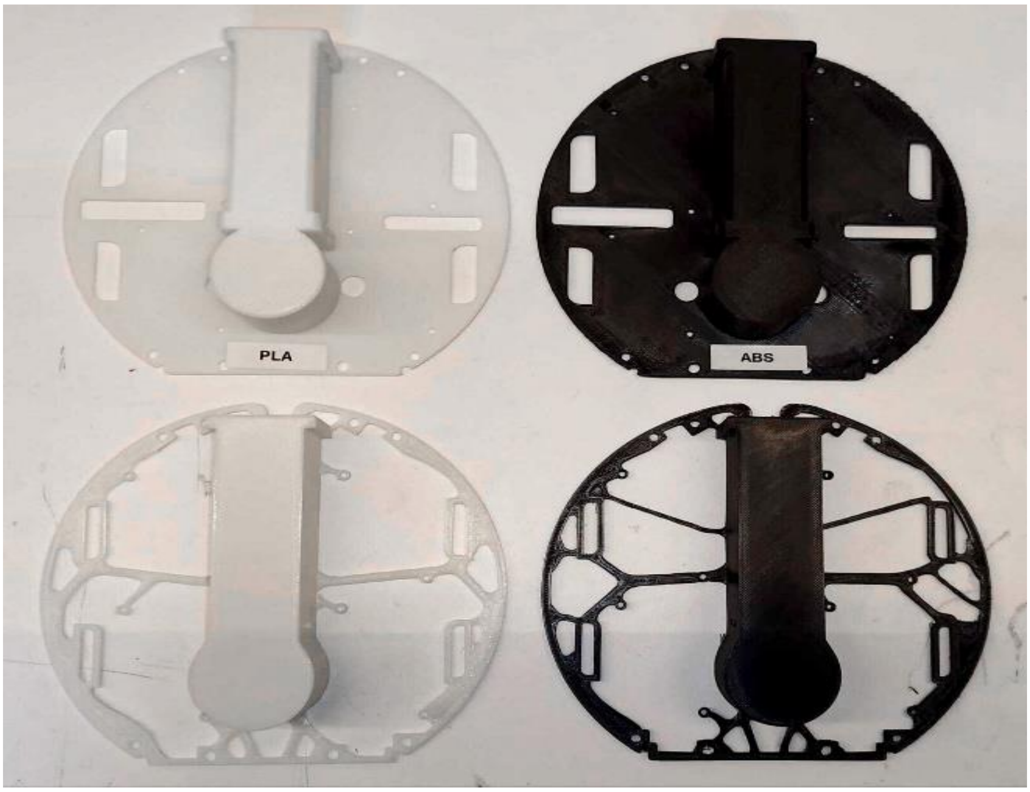
Generative Design Result Exploration



Four different materials were analyzed for the part in the middle layer of the robot. As a result of GD, the most suitable design for the robot was ASA with a %95 recommendation, as seen in Figure 4.6. A single prototype was fabricated utilizing ABS, ASA, and PLA+ materials, and its production was subjected to thorough examination. By examining the difference between ABS, PLA and ASA the production and analysis of the part was completed using the most suitable material with the Fused Deposition Modelling method (FDM). Figures 4.7 and 4.8, provide a visual comparison between the earlier version and the newly generated version of the part.

Figure 4.7

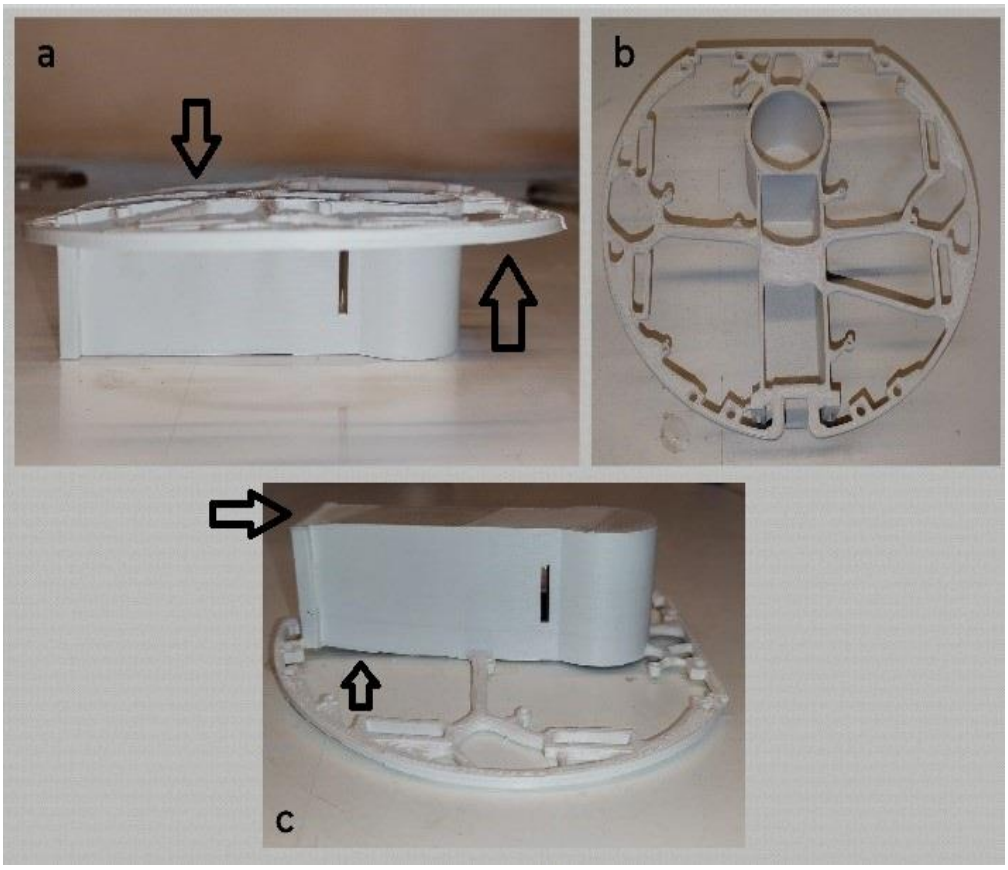
Optimum Designs of PLA and ABS.



As a result of GD, ASA with a %95 rate was obtained. Initially, ASA material was tested by applying optimum printing parameters and methods. In the initial trial, the chosen material was deemed optimal for GD. However, a production issue arose in the form of under-extrusion, resulting in inadequate material usage. Under-extrusion is a common challenge in 3D printing, characterized by insufficient filament extrusion, leading to compromised print quality and the presence of gaps between layers. The quality issue is clearly illustrated with the arrows in Figure 4.8.

Figure 4.8

Figure Investigation of 3D ASA Filament.



In the first printing attempts, a closed environment was created to maintain the stability of the environment. However, the resulting product was not completely satisfactory. The printing speed and temperature were adjusted according to the material properties and the default nozzle active cooling was on when using the 3D printing parameters. The first experiment exhibited problems such as poor surface quality, under extrusion and extruding enough plastic or insufficient material. In the desired model to be achieved, the nozzle active cooling was tried to be turned off and the printing orientation was changed. Hence, the printed test piece succeeded and the desired model was obtained. This was achieved by changing the printing direction as shown in Figure 4.9, and a final product was produced successfully.

Figure 4.9

Pre-Production Settings of ASA

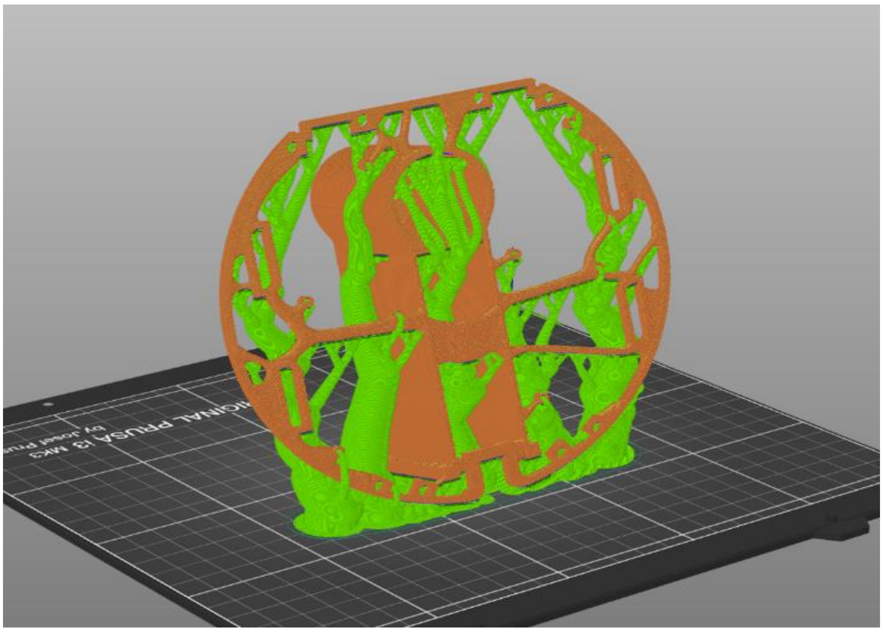
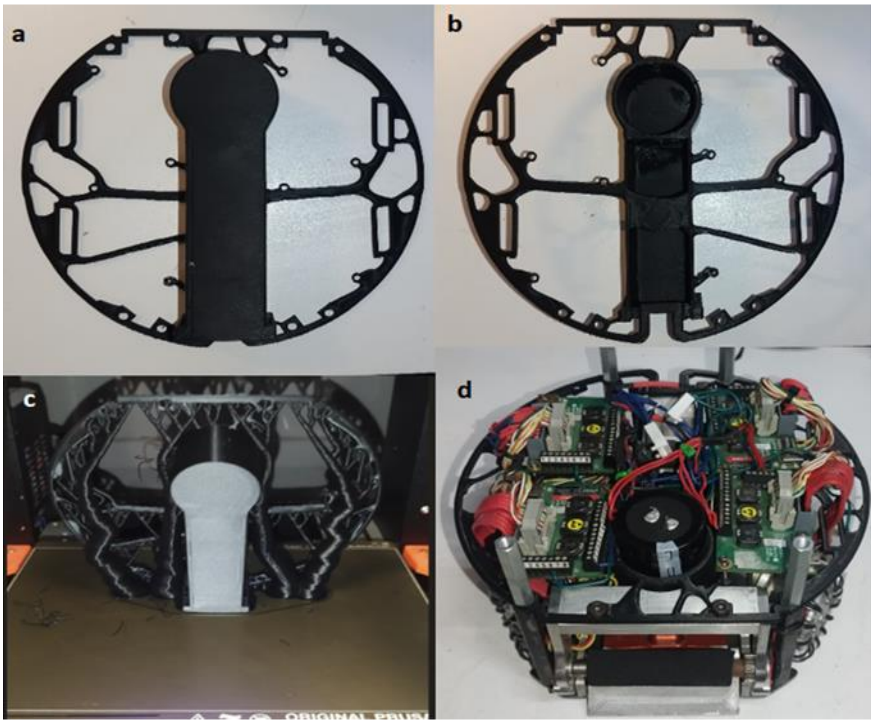


Figure 4.10

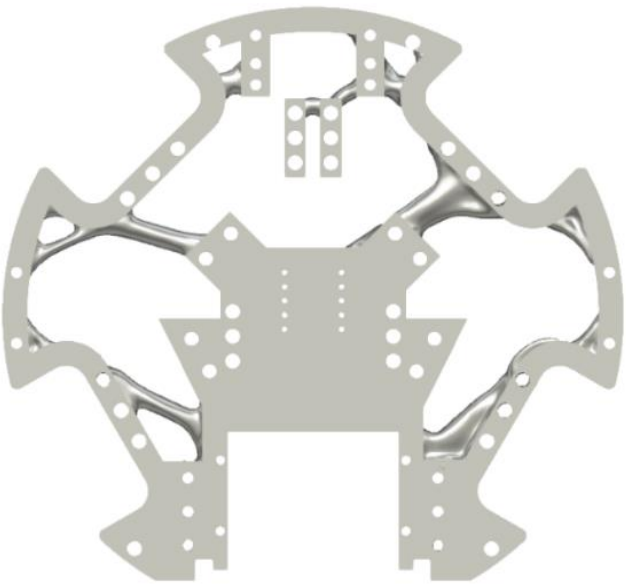
Final Production and Analysis of 3D Printed ASA Filament.



Figures 4.9 and 4.10, shows printing orientation of ASA filament and surface quality is better than the first orientation which was x direction. Achieved good surface quality with This orientation but the printing time increased to 8 and half an hour and used more material thorough to printing orientation and support settings. In addition, manufacturing cost increased by this setup.

Figure 4.11

Investigation of Main Chassis.



The metal part (as shown in Figure 4.11) was re-modified and designed with the GD module. Aluminium 6061 T651 alloy showed the highest performance with a recommendation percentage of 94.22% when manufactured using 3-axis milling and 91.62% under unrestricted manufacturing both with similar masses of around 0.092 kg. Aluminium AlSi10Mg alloy has a 71.26% recommendation in unrestricted manufacturing with a mass of 0.0909 kg, but its performance drops significantly to 24.03% when produced through additive manufacturing. Aluminium 5083 H111 has a 58.28% recommendation in unrestricted manufacturing with a mass of 0.09148 kg, and a slightly lower recommendation of 45.25% when using 3-axis milling. Titanium 6Al-4V alloy performed well under unrestricted manufacturing, with a 58.15% recommendation and a mass of 0.1534 kg, but its performance drops drastically to 11.34% in additive manufacturing, where its mass increased to 0.1579 kg. Stainless Steel AISI 304 performed the worst, with a 0% recommendation in both 3-axis milling and unrestricted manufacturing, accompanied by the highest mass of 0.27317 kg. This indicates that Aluminium 6061 T651 alloy was the best-performing material among various manufacturing methods, while Stainless Steel AISI 304 was not recommended for the processes studied.

Evaluation of Manufacturing and Post processes

In Table 4.1, manufacturing cost table of the parts according to the materials of the football robot produced using FDM printing technology are given calculations includes printing cost parameters such as labor time, material cost, electricity, etc. Also, ASA material was used to understanding calculation table.

Table 4.1

Cost Calculation of Design and Production Process (Kibtek. 2024)

Time (min)	**Material**	**Filament Weight(gr)**	**Cost €**
509	ASA	98.42	€10.39
	Electricity Price (1kW/h)		
Active	€0.21		
	Printer Consumption		
Prusa MK3S	0.12	kW	
	Filament		
Material	**Kilogram**	**Gram**	
ASA	€29.99	€0.04	
	Printer Depreciation		
Printer	Active Price	Depreciation	
Prusa MK3S	€999.00	25000	Hours
		€0.00	Dep/min
	Labor Cost		
Minimum Wage	€1,050.00	160	hrs/month
		€5.92	Hours

Table 4.2

Generative Design Outputs of Electronic Assembly Member

Material	Printing Time (min)	Filament Weight (g)	Final Cost (€)
ABS	329	69.9	€5.03
ASA	509	98.42	€9.89
PETG	319	85.25	€5.83
PLA+	346	93.6	€6.11

Table 4.2, include a comparison of the production and labor costs for four different materials used in the electronic assembly member part. It shows cost calculations for the GD outputs of the electronic assembly.

Table 4.3

Evaluation of EAM Outputs in Terms of Performance Criteria

Material	Printing Time (min)	Filament Weight (g)	Final Cost (€)
ABS	18% reduction (from 401 min to 329 min).	38% reduction (from 112.68 g to 69.9 g).	18.6% reduction (from €6.18 to €5.03).
ASA	27% increase (from 401 min to 509 min).	15% reduction (from 115.93 g to 98.42 g).	4.8% reduction (from €10.39 to €9.89).
PETG	24% reduction (from 420 min to 319 min).	38% reduction (from 137.6g to 85.25g).	21.9% reduction (from €7.46 to €5.83).
PLA+	13.7% reduction (from 401 min to 346 min).	30% reduction (from 134.35g to 93.6g).	17.3% reduction (from €7.39 to €6.11).

Analyzing the data for the filament types ABS, ASA, PETG, and PLA+ significant differences and trends emerge regarding printing time, printing quality, filament weight, and final price. Table 4.3, shows detailed comparative analysis of materials. The new version data set generally reflects faster printing times, particularly for ABS and PETG, while ASA's printing time increases significantly.

All filaments in Table 4.3, used less filament compared to Table 4.2. In Table 4.3, with ABS and PETG showing the largest reductions. The final costs were lower across the second data set, with reductions for all filaments. This could reflect improved material usage or cost efficiency.

The results obtained here have shown that this method is useful and that the product can be obtained very quickly, not only in terms of the weight of the product. But also, without the need for material waste, unnecessary costs, molding as in other methods. Moreover, these benefits and carbon environmental effects should not be ignored.

CHAPTER V
Discussion

The results of the experiments conducted on thermoplastic materials are stated in the Chapter 4 Results section, where ABS material shows the best performance especially in weight reduction and production cost. However, its printing is more difficult than PLA+ and PETG materials. Therefore, if the enclosure system and printing temperature change while printing, problems may occur in the prints. In this study, productions were made with 4 different materials. When factors such as ease of production, quality and printing adjustment are evaluated in the prints made, PLA+ emerges as the easiest material. In a similar study published in 2024, Souvanhnakhoomman and Chua A., (2024) designed a drone with a multi-rotor structure using the GD method and a unique octocopter configuration was obtained with the proposed method. During the design process, model outputs were analyzed with scoring and ranking techniques, and detailed evaluations for ABS and PLA materials revealed the critical role of material selection on design performance.

Aluminium 6061-T651 alloy is a prominent material in new generation production technologies thanks to its superior mechanical properties and machinability advantages. In this study, the analyses made in line with the physical properties and intended use of the part reveal that the most suitable solution is to optimize the 6061-T651 alloy with the GD approach and produce it with the 3-axis CNC machining method. This material has high tensile (310 MPa) and yield (276 MPa) strength (Aludepot, 2024). With the excellent corrosion resistance and good machinability properties, Al 6061-T651 alloy stands out as an ideal material in the production of complex geometries offered by GD with CNC machining. Also, in the literature, a study by McClelland, R. (2022) supports these findings and confirms that the 6061-T651 alloy provides an effective solution in the production of high-performance parts with the combination of GD and CNC machining. In conclusion, this study reveals that Al 6061-T651 Aluminium alloy is a strategic material choice in obtaining high-performance and highly manufacturable parts by integrating with GD and 3-axis CNC machining methods.

CHAPTER VI
Conclusion and Recommendations

Conclusion

This study clearly demonstrates the advantages offered by GD methods in the development of robotic systems. There are various studies in the literature that reveal the potential of GD in engineering processes. Some of these, Çokatar et al. (2022) stated that the robot arm part was reduced in weight and increased in performance by using 20 times less material on the part with the GD method. Similarly, Zaimis et al. (2021) reported that the weight of the landing gear part of an unmanned aerial vehicle produced in a 3-axis CNC was reduced by up to 36% by optimizing complex geometries using GD in the aviation industry. This study differs from other studies in that the current research goes beyond material optimization in robotic systems and addresses issues such as environmental sustainability and carbon footprint reduction. In the study, the first of the re-optimized parts, the electronic assembly element, was used to compare the cost, production and mechanical properties of 4 different polymer materials and optimize the designs. As a result of the optimizations, the highest savings rate in terms of both filament weight and production cost were achieved in ABS and PETG materials, with a decrease of 38% and an average of 20%, respectively. ASA material, although more recommended in terms of mechanical properties (95%), caused the production time to be extended due to the problems experienced in printing. However, despite this, although there is a decrease in material weight and cost compared to the first version, it is more expensive than other materials. PLA+ material generally provided a successful balance in filament saving and cost optimization. The results confirm the benefits of this method. In addition, this study is more comprehensive than other studies, and the possibility of producing both polymer materials and metal materials with traditional methods using a 3D printer. It was investigated and the design and production cost comparisons of the GD method were made. For these reasons, the importance of this study increases. In the study, the material savings ranging from 39.8 to 43% and the weight reduction of 45% obtained in the robotic body design, offers impressive results like similar studies in the literature. In particular, the superior performance of the Aluminum 6061 T651 alloy was highlighted in another influential study. Walia et al. (2021) compared Aluminum alloy, carbon fiber, and polymer PA 12 materials in the robotics industry, stating that optimizing it with GD achieved a weight reduction of between 85% and 90%. As a result, GD technology is a powerful tool in the development of robotic systems. Furthermore, this study highlights the importance of innovative methods in robotic design processes that are compatible with sustainability goals. In comparison to similar studies in the literature, this research highlights the diverse contributions of GD methods by considering not only technical outcomes but also environmental impacts. In this context, the study provides three main contributions to the literature in the field of robotic product design and development:

- **Performance and cost optimization:** The impact of the use of lightweight materials on the performance of the robots were quantitatively evaluated.

- **Material performance analysis:** Different material types and manufacturing methods are compared to create a comprehensive dataset to guide future designs.

- **Emphasis on sustainability:** The application of innovative approaches, material waste, and approaches aimed at reducing carbon footprint have encouraged the environmentally friendly design of robotic systems.

Recommendations

The findings and methods developed within the scope of this study can be used together with new approaches in the field of 3D production and design, and their impact on product development can be highlighted, and can form an important basis for making robotic systems more intelligent, agile and efficient in the future. In particular, the integration of contemporary engineering approaches used in the mechanical design of robots with artificial intelligence-supported decision-making systems and sensor technologies can further improve performance. In addition, the widespread use of sustainable materials and rapid prototyping techniques will increase cost efficiency in production processes and contribute to the reduction of environmental impacts. As a result of this study, suggestions regarding various areas of improvement and development that can be taken into consideration in future research in the light of the data obtained include the following;

- The effects of environmental variables on performance can be examined by testing robotic systems outside of the laboratory environment, under real tournament conditions.

- Iterative design processes can be modelled with feedback based on the field performance of developed prototypes.

- The performance and cost effects of metal printers, Selective Laser Melting (SLM) and electron beam melting (EBM) technologies on robotic components can be examined comparatively.

- Comparative analysis of designs created by artificial intelligence-supported GD software under different production constraints can be performed.

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Appendices

Appendix A

Experimental works and Manufacturing Process of Generative Design

Figure A1

Fusion 360 Generative Design module user interface.

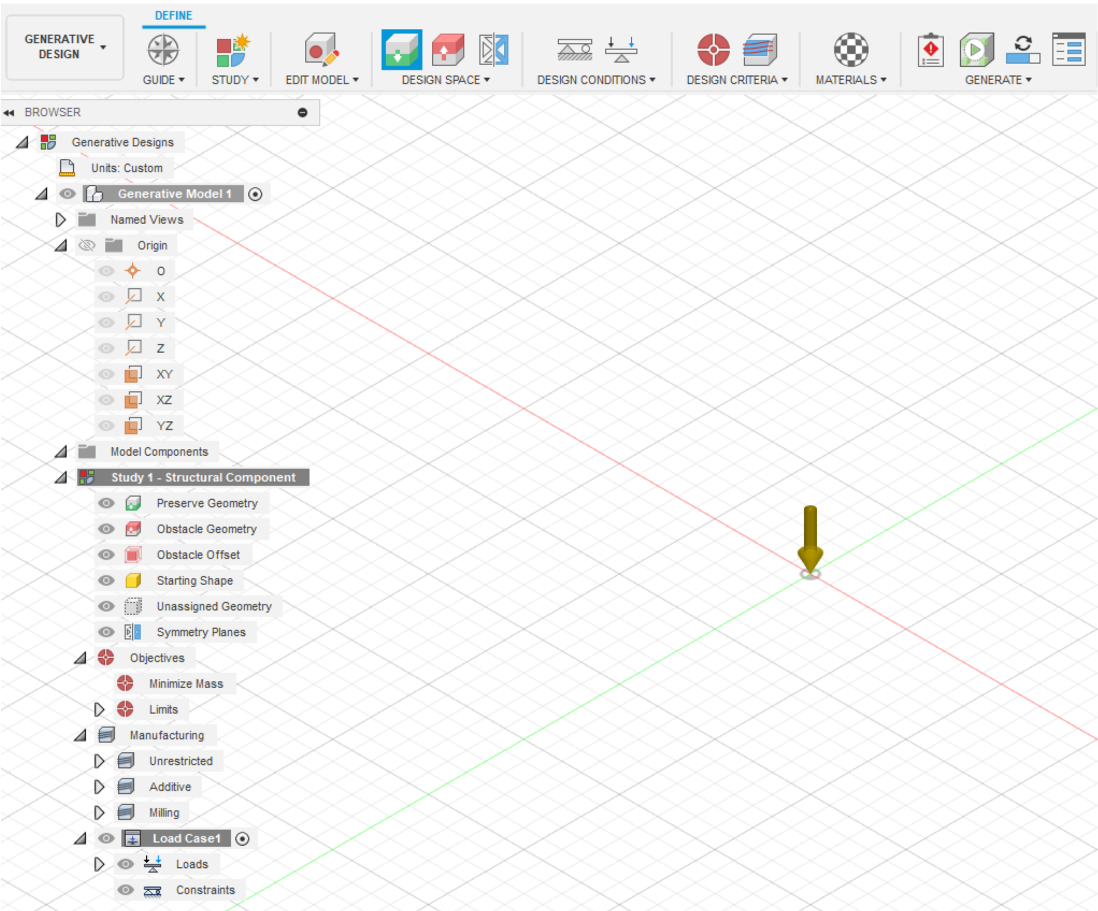


Figure A2

Preparation of Generative Design Process.

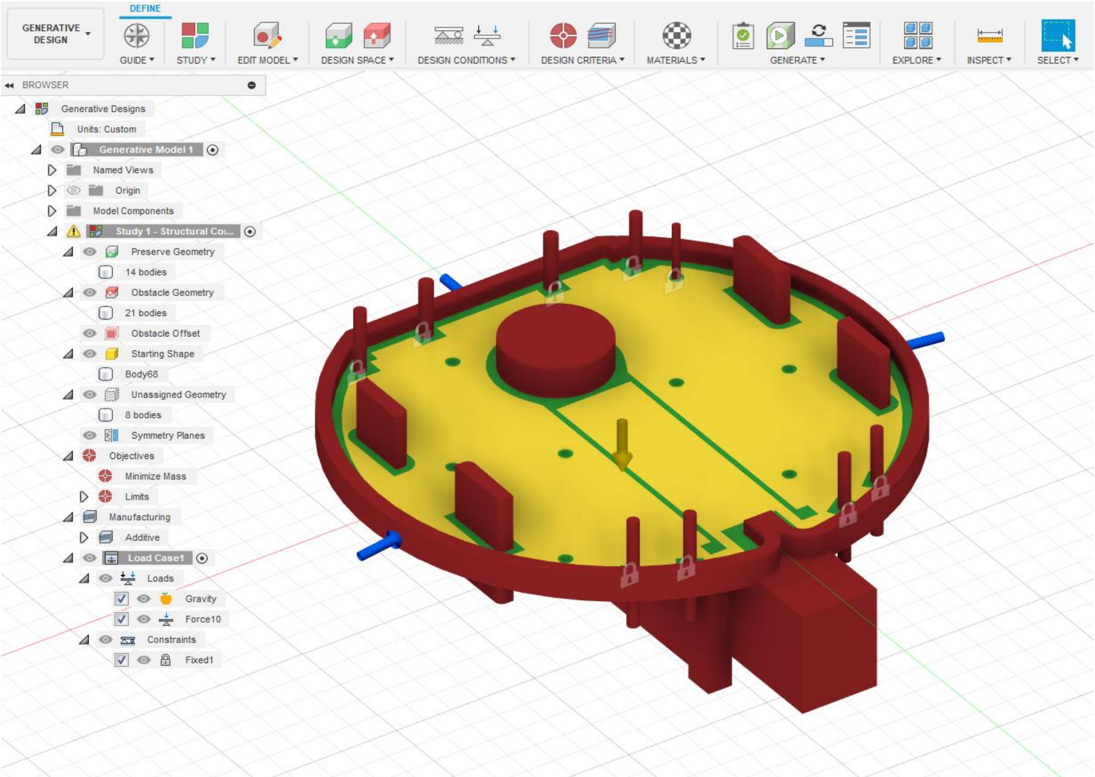


Figure A3

Settings up on slicer before printing the model.

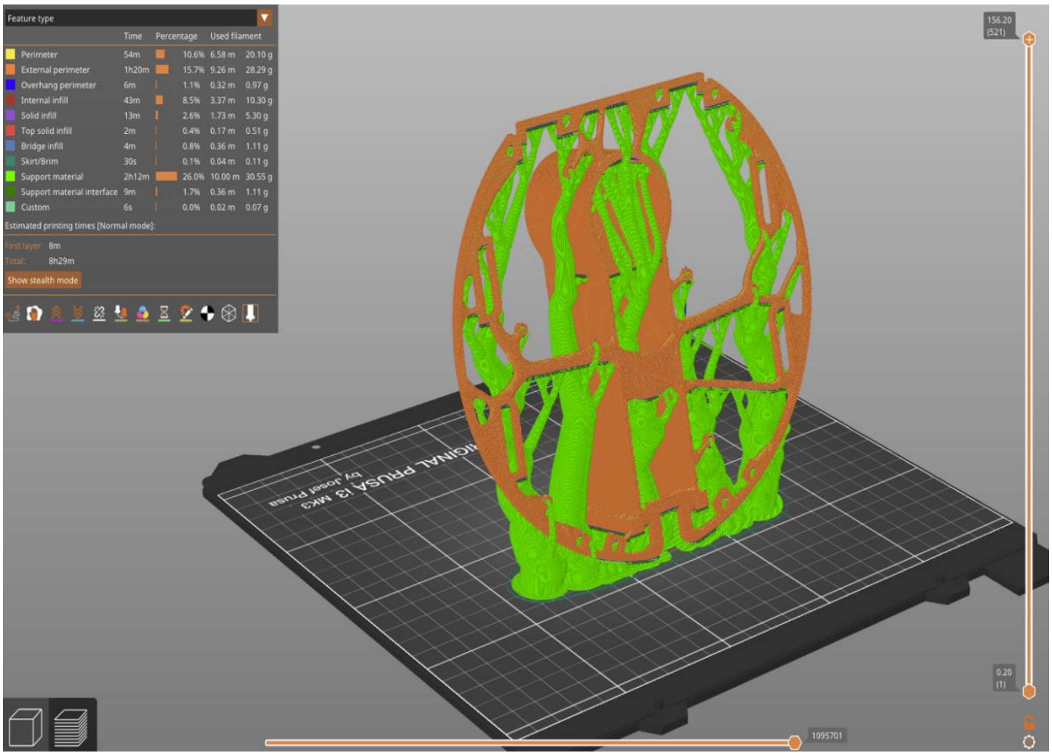


Figure A4

ASA Printing Fail while Printing.

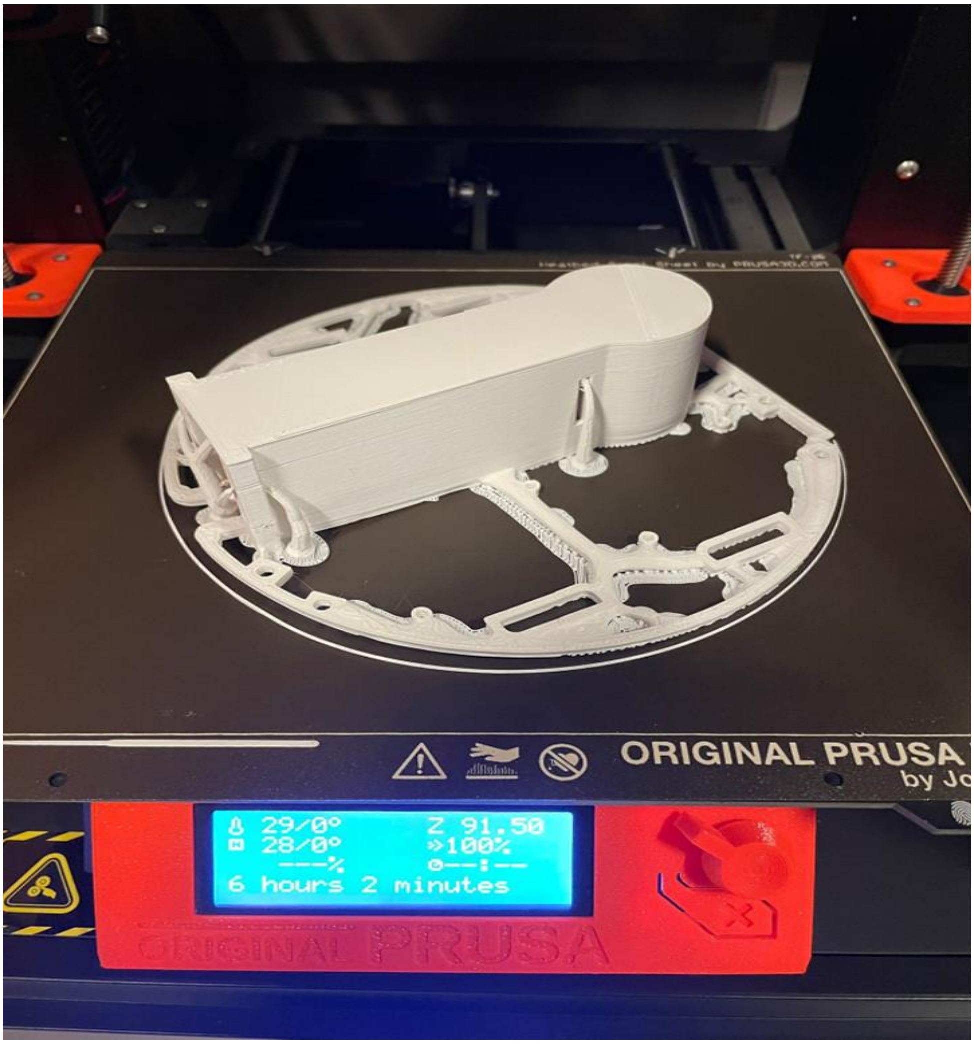


Figure A5

First Layer Calibrations of the Machine

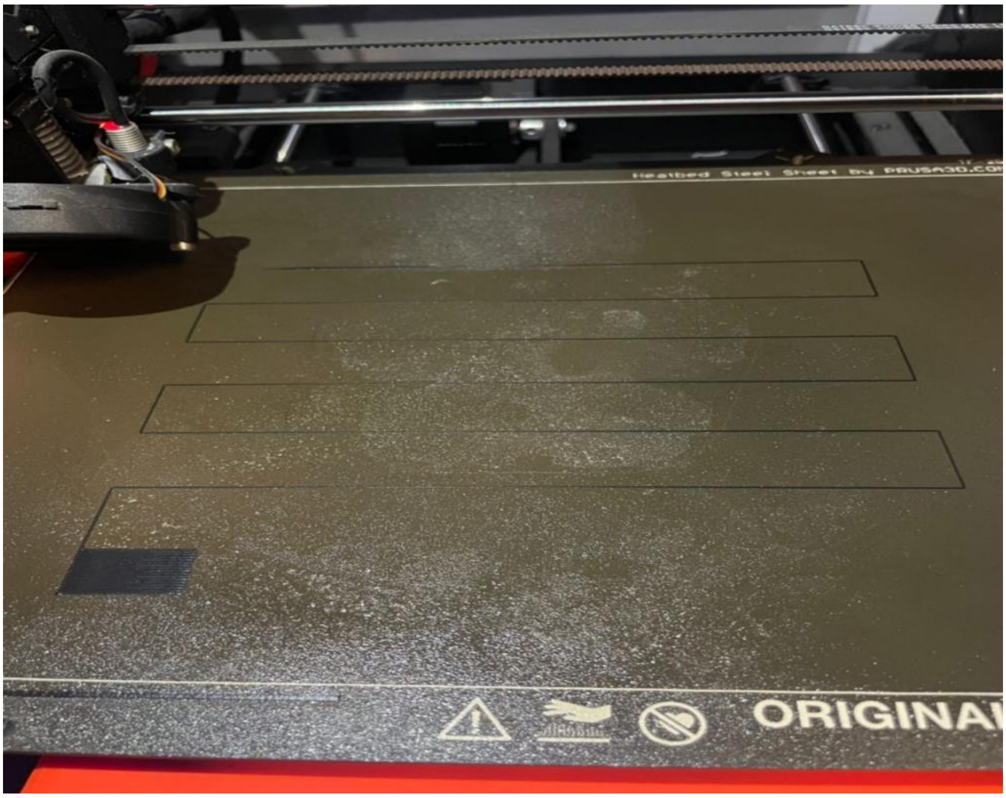


Figure A6

Generative Design iterations of EAM.

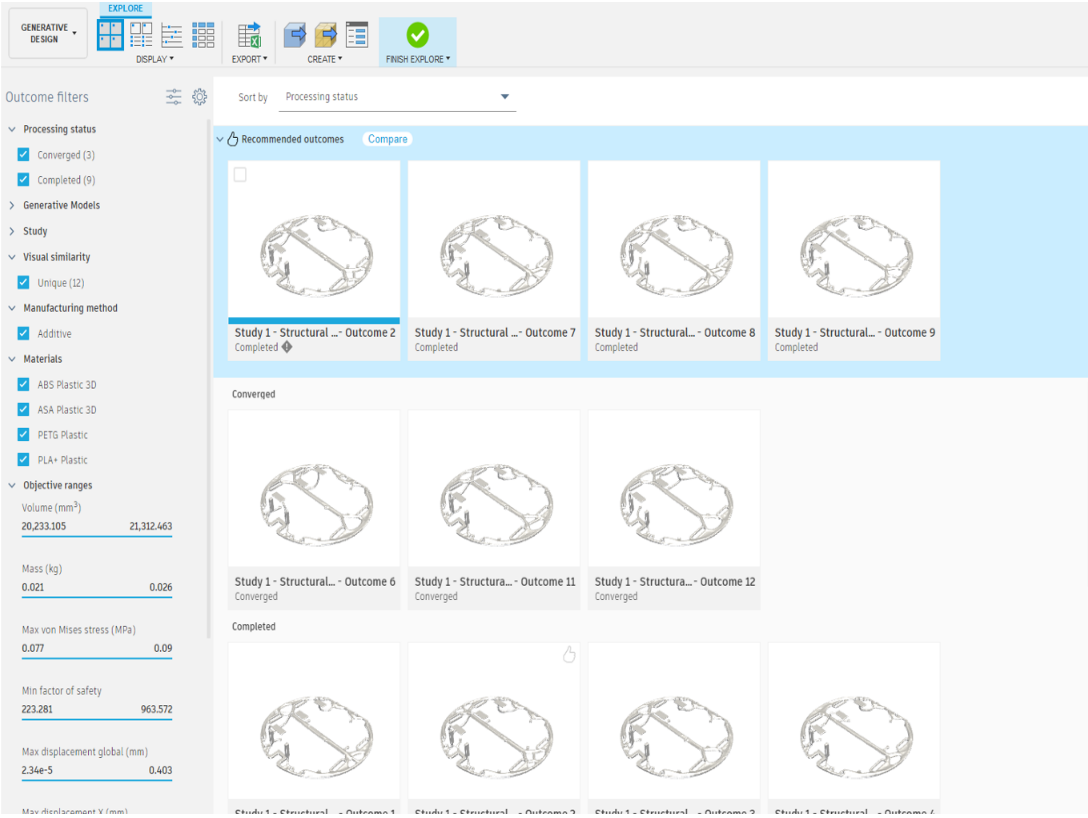


Figure A7

Generative Design iterations of main chassis.

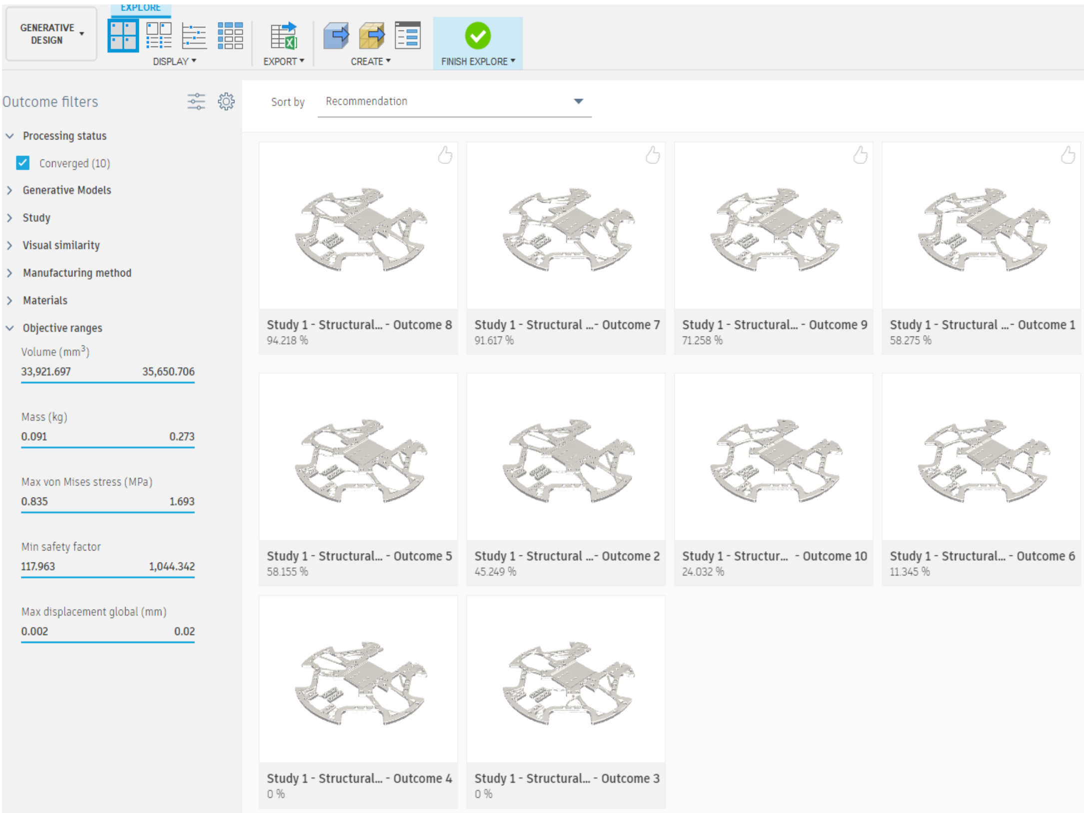


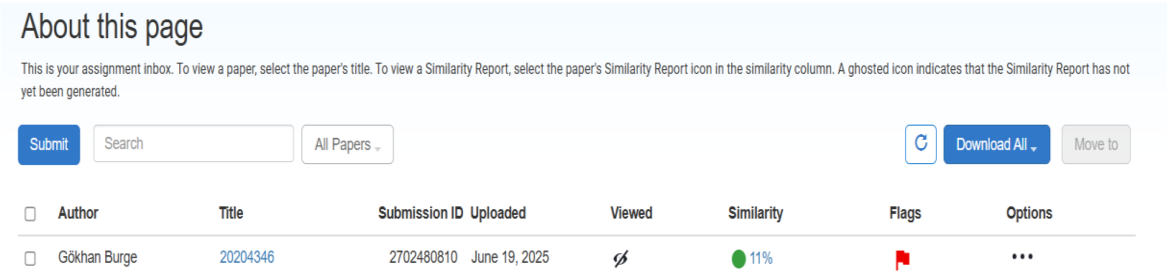
Figure A8

Near East University 3D Laboratory.

Appendices

Appendix B

Similarity Report



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....

Appendices

Appendix C

Curriculum Vitae

Personal Information

Name Surname: Gökhan Bürge

Date of Birth: 30-01-1993

Place of Birth: Nicosia, CYPRUS

Table B1

Education

Degree	Department/Program	University	Year of Graduation
B.Sc.	Automotive Engineering	Near East University	2017
M.Sc.	Mechanical Engineering	Near East University	2020
Ph.D.	Mechanical Engineering	Near East University	2025

Table B2

Work Experience

Title	Place	Year
Automotive Engineer	Günsel EV	2017-2018
Mechanical Research and Design Engineer	Innovation Center / NEU	2018-Present

Publications in International Journals

Abiyev, R. H., Gunsel, I., Akkaya, N., Aytac, E., Abizada, S., Say, G., ... & Makarov, P. (2020). Decision making and obstacle avoidance for soccer robots. *In 10th International Conference on Theory and Application of Soft Computing, Computing with Words and Perceptions-ICSCCW-2019* (pp. 455-462). Springer International Publishing. https://doi.org/10.1007/978-3-030-35249-3_58

Akkaya, N., Aytac, E., Say, G., Abizada, S., Yirtici, T., Burge, G., ... & Abiyev, R. H. (2021, August). Intelligent Fuzzy System for Stray Pet Care Appliances. *In International Conference on Intelligent and Fuzzy Systems* (pp. 849-856). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-85626-7_99

Bürge, G., Çamur, H., & Savas, A. M. (2025) Optimization of a Soccer Robot Components Using Engineering Generative Design Approach. *Tehnicki vjesnik/ Technical Gazette, 32*/4. Croatia. https://doi.org 10.17559/TV-20241016002064

Bürge, G., Aytaç, E., Evcil, A., & Savaş, M. A. (2020, October). An investigation on mechanical properties of PLA produced by 3D printing as an implant material. *In 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)* (pp. 1-6). IEEE. https://doi.org/10.1109/ISMSIT50672.2020.9254387

Kassem, Y., Çamur, H., Burge, G., Netshimbupfe, A. F., Sharfi, E. A., Demir, B., & Al-Ani, A. M. R. (2022). Using Machine Learning Techniques for Estimating the Electrical Power of a New-Style of Savonius Rotor: A Comparative Study. *In Intelligent Computing & Optimization: Proceedings of the 4th International Conference on Intelligent Computing and Optimization 2021 (ICO2021) 3* (pp. 167-174). Springer International Publishing. https://doi.org/10.1007/978-3-030-93247-3_17

Makarov, P. A., Yirtici, T., Akkaya, N., Aytac, E., Say, G., Burge, G., ... & Abiyev, R. H. (2019). A model-free algorithm of moving ball interception by holonomic robot using geometric approach. *In RoboCup 2019: Robot World Cup XXIII 23* (pp. 166-175). Springer International Publishing. https://doi.org/10.1007/978-3-030-35699-6_13

Mammadov, E., Aytaç, E., Türk, A., Akkaya, N., Say, G., Yılmaz, B., ... & Kırgül, E. (2020). *Üç boyutlu biyo-üretim: İlk izlenimlerimiz ve Çocuk Cerrahisindeki potansiyeli. Çocuk Cerrahisi Dergisi, 34*(3), 79-84. https://doi.org/10.5222/JTAPS.2020.78095