Material Selection in Additive Manufacturing for Aerospace Applications using Multi-Criteria Decision Making

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DEDICATION

This thesis is dedicated to my dear parents, who have been a constant source of support and encouragement during the challenges of my post graduate studies and life and whose good examples have taught me to work hard for the things that I aspire to achieve.

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ABSTRACT

A decision-making methodology for the material selection is presented in this paper. A multi-criteria decision-making (MCDM) based hybrid approach, AHP-TOPSIS, was used to choose the appropriate additive manufacturing (AM) material for aerospace applications. This study evaluated nine polymer-based AM materials for an aerospace application. Experts from both industry and academia carefully finalized the selection criteria by using Delphi technique. Selected criteria are divided into three main categories: performance, economic and environmental. Firstly, the AHP approach was used to get the weights of criteria chosen via pairwise comparisons. Second, a decision matrix containing the properties of materials was created. The TOPSIS method was then applied using the AHP criteria weights and decision matrix, resulting in the final ranking of materials. ULTEM material ranked number 1 and was selected as the appropriate material for an aerospace application. Additionally, sensitivity analysis was also carried out to check the proposed method's reliability and robustness.

Keywords: Additive manufacturing, MCDM, decision making, materials selection, AHP, TOPSIS, aerospace

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LIST OF ABBREVIATIONS

AM	Additive Manufacturing
AHP	Analytic Hierarchy Process
MCDM	Multi-Criteria Decision Making
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UAV	Unmanned Aerial Vehicle
ABS	Acrylonitrile Butadiene Styrene
PPSU	Polyphenylsulfone
PEEK	Polyether Ether Ketone
PEKK	Polyether Ketone Ketone
ULTEM	Polyetherimide
PSU	Polysulfone
PC	Polycarbonate
PVDF	Polyvinylidene Fluoride
Nylon 12 CF	Nylon Carbon Fiber

CHAPTER 1: INTRODUCTION

1.1 Background

During the last ten years, additive manufacturing (AM), also commonly referred to as three-dimensional (3D) printing, has emerged as a new technology that is continuously growing at a fast pace (Venturi & Taylor, 2023). Various industries, from aerospace to healthcare around the globe, are transforming the way of manufacturing and adopting additive manufacturing methods for prototyping and end-user products (Fidan et al., 2023). A recently published document by the International Organization for Standardization (ISO) defines the AM as the "process of joining materials to make parts from 3D model data, usually layer upon layer" (ASTM & ISO, 2021), which is opposite to the subtractive or traditional methods of manufacturing.

The ISO/ASTM standard mentioned above also classifies AM processes into seven categories that are Material extrusion (MEX), Material jetting (MJ), Directed energy deposition (DED), Powder bed fusion (PBF), Binder jetting (BJ), Sheet lamination (SL), and Vat photopolymerization (VPP) (ASTM & ISO, 2021). A few main steps involve creating a part by additive manufacturing, which starts with creating a 3D model through CAD software (e.g., SolidWorks, etc.). After digitally modelling the part shape, the designer must convert the required 3D model into Standard Tessellation Language/Stereolithography (STL) file format. This file is then transferred into the AM machine, which reads the file. Before the setup of an AM machine for manufacturing a product/part, it is necessary to involve the stakeholders and their requirements (constraints, parameters, etc.) (Palanisamy et al., 2020). During the build stage, the AM machine uses the loaded raw material in an automated process and prints the object according to the specifications of the CAD model. 3D Printed parts may need post-processing to improve the surface quality or increase strength by applying some treatment methods. The final stage part is ready for application or may need to be assembled to make a particular product (Gibson et al., 2021).

When deciding which AM process to use for building an object, material selection is crucial in the decision-making process. Selecting the appropriate material depends on its availability and its properties. The availability of AM materials and their development are highly dependent on the market demand and the economic factors that are determined by the application value (D. Patel & Chen, 2022).

Various AM materials are utilized to manufacture products layer-by-layer, and these materials are the main requirement of additive manufacturing technology. Many industries around the globe, including aerospace, automotive, healthcare, and consumer products, are taking advantage of AM. A broad range of materials is available, and manufacturers are producing more and more new materials daily per increasing demand(Alami et al., 2023). These materials include thermoplastics, metals, biocompatible resins, and advanced composites. Manufacturing sustainable products requires identifying AM materials that are suitable for the manufacturing process. The material selection procedure is considered complex because of the various processing parameters and criteria (e.g., performance-related or cost, etc.) involved (Malaga et al., 2022).

The choice of materials is of utmost importance in the design process of structural components. It becomes crucial for designers or decision-makers to select the appropriate material from various options due to the rapid progress of technology (YADAV et al., 2019) The selection of the best materials helps increase quality and extend the product life cycle, whereas inadequate selection might result in sudden failure. The selection process typically considers several significant criteria, such as physical properties (density, etc.), mechanical features, wear and durability, material cost, environmental concerns associated with materials, aesthetics, and recyclability (P. Chatterjee et al., 2018). When choosing suitable material for developing or designing a new product from a large option or set of materials, designers face challenges because of the conflicting criteria. This finally creates a strong relation between the decision of materials selection and multi-criteria decision-making (MCDM) methods (Siva Bhaskar & Khan, 2022).

MCDM methods are a set of mathematical techniques applied to address complicated MCDM problems. These problems frequently occur in practical scenarios when decision-makers must choose from a wide range of options with multiple criteria or dimensions. A few main MCDM methods were highly cited between the years 2021 and 2022, such as Elimination and Choice Expressing Reality (ELECTRE), graph theory, Analytic Hierarchy Process (AHP) which is also used in AM by various researchers (Abas et al., 2023; Alghamdy et al., 2019; Armillotta, 2008; Kadkhoda-Ahmadi et al., 2019; L. Kumar & P. K., 2010; Liu et al., 2020; Mançanares et al., 2015; Zaman et al., 2018), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytic Network Process (ANP) which is also used in fibre based composite materials selection (Mastura et al., 2022), VIKOR, Decision Making Trial and Evaluation Laboratory (DEMATEL), Fuzzy Analytic Hierarchy Process (FUZZY AHP), Simple Additive Weighting (SAW), and Best Worst Method (Taherdoost & Madanchian, 2023c).

The objective of MCDM is to determine the right choice of alternatives by considering the weights and priorities given by subject matter experts or decision-makers. MCDM problems are frequently shown using a matrix format. The matrix values or elements show the properties of an alternative according to the related criterion. The experts are thereafter required to assign priorities or weights to criteria by pairwise comparisons or the comparative weight given to each criterion in the decision-making procedure. A participant involved in judgment needs to ensure that the significance of each criterion has been well assessed and the alternatives are well chosen. Deciding on material selection requires the consideration of various criteria, including performance, durability, physical and technical characteristics, price of material, and environmental considerations. Because of the involvement of multiple values and properties for these criteria brings difficulty in comparing and assessing alternatives using just one parameter or a single value (Zakeri et al., 2023).

1.2 AM Material Selection in Aerospace Industry

The right materials selection is crucial to producing high-quality, stronger, lightweight, and high-fatigue strength parts in aerospace applications (Omidvarkarjan et al., 2023). The aerospace sector was one of the early adopters of AM when 3D Systems, a world-leading AM company, made a 3D printer in the 1980s. Many companies in Europe and the USA, such as Pratt & Whitney, started their manufacturing of aerospace components using AM (Gibson et al., 2021). In the 1990s, polymer materials were initially used by Boeing to produce non-structural uses, but since then, the company has been using both metals and plastic materials in their production of end-user parts. To date, more than 50,000 aerospace parts manufactured by Boeing have been incorporated into military and commercial aircraft (Wohlers Associates, 2020). Space companies such as ESA, SpaceX and NASA also use parts manufactured by AM in their space vehicles and rockets (Sacco & Moon, 2019).

Several factors are involved while choosing AM materials, such as functional and structural needs, environmental considerations, and lowering maintenance and manufacturing costs (Zaharia et al., 2023). To minimize the environmental concerns (such as carbon emissions), saving fuel cost and meeting the safety regulations, materials must possess the combination of lightweight and high strength properties (Cruz & Borille, 2017). As the aerospace industry grows rapidly, the environmental problems have also increased. To overcome this issue, aerospace manufacturers are prioritizing alternate lightweight materials to minimize the environmental impact. Various AM materials can be used in AM technology according to their compatibility. Metallic (such as titanium, steel, aluminum, and nickel-based alloys) and non-metallic (such as thermoplastics) materials in AM techniques are used for aerospace applications. Metallic materials are best known for their high strength and are an excellent choice when high-temperature resistance and thermal conductivity are required. The issues with metallic materials are heavy weight, low corrosion resistance, high costs, low availability and limited AM processes. The aerospace industry uses metal alloys to produce jet engine parts, airframes, propulsion systems, rocket parts and other structural components. The AM of non-metallic parts mainly includes the production using polymer materials such as Acrylonitrile butadiene-styrene (ABS), most commonly used, Polycarbonate (PC), an engineering grade industrial material, Polyether ether ketone (PEEK), an ultra-performance material, Polyethylene terephthalate glycol (PETG), etc. These polymer materials are utilized in various applications, from prototyping to end-use parts such as cabin & interior parts, unmanned aerial vehicles (UAV) or drone parts (Cruz & Borille, 2017). FDM technology is well known for processing polymer materials through the MEX process. This technology is fast and provides low-cost manufacturing of complex parts of UAVs(Klippstein et al., 2018). In a recent development, Aurora Flight Sciences, a US-based UAV manufacturer, built an aircraft using 80% of its parts manufactured by AM using FDM technology. Lightweight thermoplastic materials were also used to achieve speed and reduce the overall weight to just 14 kg(Aaron Pearson, 2020).

1.3 Research Gap

Based on the limitations of studies in literature review, the research gap was drawn

- Selecting suitable materials for the aerospace industry is complex due to the diverse range of available materials.
- MCDM techniques have shown potential in material selection. However, the combined application of AHP-TOPSIS (MCDM) specifically for aerospace functional parts using AM remains unexplored.
- Various studies are available pertaining to the selection of AM processes neglecting materials' selection.
- AM material selection considering environmental criteria are rare.
- A comprehensive material selection strategy employing MCDM methods is needed.

1.4 Problem Statement

Additive manufacturing has emerged as a transformative technology and providing significant benefits to the industry in terms of design flexibility, weight reduction, and cost savings in aerospace industry. Full potential of AM is not being obtained due to improper selection of materials. The wide range of material options is available in AM which necessitates a systematic approach that may account multiple criteria such as mechanical properties, cost, weight, durability, recyclability and environmental factors. Failure to consider these factors comprehensively may result in suboptimal material choices and less environment-friendly materials.

1.5 Research Questions

The primary aim of this research is to select the appropriate AM materials for aerospace applications. The following research questions have been developed to achieve the goal:

Question 1: What are the critical criteria for selecting materials in additive manufacturing for aerospace applications?

Question 2: What are the suitable materials in AM available for aerospace?

Question 3: How can the weightage of finalized criteria be determined and rank the materials with MCDM methods?

Question 4: How can the materials' ranking order change by changing criteria importance?

1.6 Research Objectives

The research objectives of study are:

i. To identify and establish the criteria including environment conscious criteria for the selection of materials in AM for aerospace
ii. To identify suitable materials available in AM
iii. To determine the weightage of the finalized criteria and rank the materials using MCDM methods
iv. To analyze the rank changing by varying the criteria weights

1.7 Thesis Structure

This thesis is structured into six chapters as follows:

1.7.1 Chapter 1: Introduction

This chapter provides an overview of the study, presenting the background, problem statement, research objectives, and research questions. It sets the context for the research by highlighting the importance of material selection in additive manufacturing for aerospace applications and the need for a comprehensive evaluation framework.

1.7.2 Chapter 2: Literature Review

An extensive review of the existing literature related to material selection, additive manufacturing, and multi-criteria decision-making (MCDM) methods was done. This chapter examines previous studies on AM processes, material selection and MCDM approaches to identify gaps in the literature and provides a theoretical foundation for the research.

1.7.3 Chapter 3: Research Methodology

This chapter covers the research methodology employed in the study. It describes the research design, the selection, and characteristics of research participants, and the MCDM techniques used, specifically focusing on the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

1.7.4 Chapter 4: Application

This chapter presents an industrial case study in the aerospace sector. It outlines the criteria relevant to aerospace applications and describes the procedure for selecting these criteria. The chapter also details how these criteria are applied to the case study, demonstrating the practical implementation of the research framework.

1.7.5 Chapter 5: Results and Analysis

This chapter explains the findings of the study and discusses their implications. The results of the material selection process using the combined AHP-TOPSIS approach are presented, and their significance is analyzed in the context of aerospace applications.

1.7.6 Chapter 6: Conclusion and Recommendations

This chapter summarizes the key findings of the study and offers recommendations based on the results. It reflects on the research objectives and questions, discusses the contributions of the study to the field of additive manufacturing, and suggests directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Additive Manufacturing Process

Although there are many different types of additive manufacturing (AM) processes discussed in the literature and will be addressed later on, but all AM processes follow the same workflow from the design phase to build phase. An eight-step method for additive manufacturing is depicted by Gibson et al. (2021), as seen in the Figure 1.

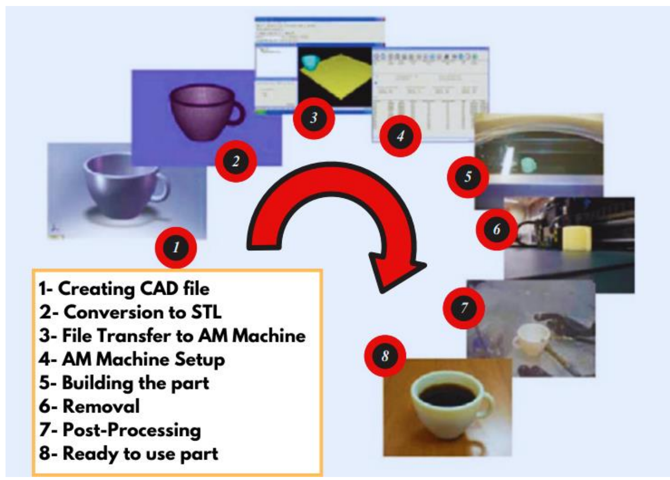

Figure 1: Workflow of an AM process from CAD to final part for use (Gibson et al., 2021)

2.1.1 CAD Model

Computer-Aided Design (CAD) model is the first step for an any AM process which plays a crucial role in AM. It is utilized for creating and evaluating 3D models suitable for practical applications. This 3D model helps to define the part's surface boundaries, external & internal geometry, and tolerances. AutoCAD, SolidWorks and Creo are the main CAD software products for professional use and commonly used across industries.

2.1.2 STL File Creation

After creating the CAD file of the part, the next step is conversion of this file to STL (Standard Tessellation Language / Stereolithography) which is a triangulated representation of the 3D model. STL file describes the surface geometry of the part or object using a series of interconnected triangles. It also represents outer closed surfaces of the originally created 3D model and serves as the foundation for calculating the individual slices. Converting to STL is a crucial step to verify that all surfaces are completely specified and enclosed.

2.1.3 Slicing and Transferring of File

By using slicing software, an STL file is transformed into several thin layers and produces a set of code-driven instructions for the AM machine. Slicing software comprises front-end and back-end components. The front-end facilitates user interaction and visualization of the CAD model and G-code, while the back end manages the logic and processing of data flow in AM. The sliced file is divided into layers and contains information pertaining to the material to be utilized in the layer-by-layer deposition process, layer height, AM machine's nozzle settings and machine configurations. Software also facilitates the use of support structures for objects, infill patterns, adjustments of density, and other configurations which affect the print quality and structural integrity (Fabheads).

2.1.4 AM Machine Setup

Before starting the AM process, it is necessary to properly configure the machine. These configurations or settings would apply to manufacturing parameters such as power source, material feedstock, calibration, speed or feed rate of machine, slice height, safety checkups, environmental controls to avoid humidity and warping issues.

2.1.5 Building the part

Once the AM machine is set at desired parameters, part will be built in an automatic process with minimal supervision. At this point, a basic level of monitoring is enough to prevent any problems like power disruption, software malfunctions or shortage of material.

2.1.6 Removal

This step includes the removal of objects from machine after completion of build process. During this stage, it may be required to work on AM machine, which may have safety interlocks installed. These interlocks are used to check that specific requirements are fulfilled prior to the removal procedure, such as ensuring that the temperature has decreased or that there are no active machine parts that may pose a danger. Implementing these safety procedures is essential for the safety of both the operator and the installed system.

2.1.7 Post-Processing

After the AM process, the newly manufactured object may need some extra work or treatment to meet the quality standards and design specifications. This includes heat treatment to enhance the mechanical properties, surface finish to improve surface quality and aesthetics, UV curing and supports removal. After this step the part becomes ready for use.

2.2 Materials in AM Processes

2.2.1 Material Extrusion (MeX)

Material Extrusion (MeX) process commonly uses polymer materials such as thermoplastics in its feedstock to build a 3D object. This process involves pushing a material continuously through a tiny orifice or heated nozzle and material in feedstock deposits layer by layer to create parts of a 3D model. Commercially this process is also known as Fused Deposition Modelling (FDM) which is the most famous technology of AM. In 1990, an American based AM company Stratasys, Ltd. commercialized the FDM technology, originally developed by S. Scott Crump through an US patent (Scott Crump, 1992). This is now second most used technology in AM (Choong, 2022). When using FDM technology, it is important to consider that the presence of air gaps in layers, filament material orientation, breadth and layer height are the main factors which can affect mechanical properties of the part. Platform in the material extrusion must be heated properly and fillets should be incorporated in sharp corners to mitigate the risk of warpage

(Mohamed et al., 2015). A wide range of polymeric materials for different applications are used in MeX such as PP (Polypropylene) a flexible material, Polycarbonate (PC) having high tensile strength, ABS (acrylonitrile butadiene styrene) used for general purpose applications, Polyethylene terephthalate glycol (PETG) usually used in bottle manufacturing, (PA / Nylon) Polyamide a tough material, and PPSF (Polyphenylsulfone) etc. are among common materials used in this process. (Choong, 2022; Haghighi, 2023; Saleh Alghamdi et al., 2021). The FDM technology has been extensively embraced by various sectors such as hobbyists, academics, manufacturing industries, and consumers for fabricating prototypes, scale models, end-user products and working components using general and high-performance thermoplastics. This is because it is reliable, inexpensive, and simple (Daminabo et al., 2020; Penumakala et al., 2020). For some applications, MeX might be a more cost-effective option than traditional processes such as injection molding, especially in low-volume scenarios (Chua & Leong, 2016)

2.2.2 Vat Photopolymerization (VPP)

In this AM technology, polymerization of liquid photopolymers takes place in a vat through UV laser beam or light source to form objects. VPP technology is categorized into two categories which are "top-down" and "bottom-up" configuration. The latter configuration uses curable resin from the base of the vat and then cures the resin layer-by-layer by raising the build platform. In former configuration light or laser source placed above and cures each layer by descending the build platform. Recent study indicates that for some parts geometries being fabricated such as the ratio of ${}^{length}/_{width} > 2$, the "bottom-up" and "top-down" configurations could bring different results. The parts fabricated using "bottom-up" method may have more failures Click or tap here to enter text.(Santoliquido et al., 2019). The main technologies in VPP are DLP (Digital light processing) which cures the area using light-emitting diodes (LEDs) or lamp as the UV source and SLA (Stereolithography) which is an old technology and broadly used in AM invented by Charles W. Hull and patented in 1986 (W. Hull, 1986). Polymer based UV resin used in VPP process and divided into six categories that are standard resins, structural (Grey pro), elastic & flexible (Elastomeric polyurethane & flexible polyurethane), tough & durable (polypropylene & ABS-like), ceramic and castable Wax (filled with silica &

20% wax), bioinks (hydrogel) and biocompatible (dental resins) (Pagac et al., 2021). VisiJet FTX Silver, VisiJet SL Clear, VisiJet SL Tough, VisiJet FTX Cast, E-Dent 100, E-Guard and Accura 60 are the most common and well-known commercially available materials in SLA & DLP and manufactured by 3D Systems and EnvisionTEC (Choong, 2022). VPP could be seen in water resources, robotics, tissue engineering, dental, automobile and aerospace applications (Pagac et al., 2021).

2.2.3 Material Jetting (MJ)

MJ is defined as *"An additive manufacturing process in which droplets of build material are selectively deposited"* (ASTM & ISO, 2021) MJ build objects through a process that closely resembles to 2D inkjet printer. The working principal of MJ is that the build material is filled into a container to heat the loaded material and convert it to the liquid form. The stream or droplets of liquefied build material is produced and emitted through a nozzle for the deposition at the exact location on a platform to create layers. The material spreads and undergoes through a process of curing or solidification when it lands on or next to the previously created layer. This process continues until the desired 3D shape or part is manufactured. MJ techniques combine the operation of melting and jetting simultaneously to avoid the overtime and extra costs associated with pre-processing (e.g. powder preparation in powder-based AM processes).

Therefore, MJ technologies saves cost and give higher speed in comparison with other AM processes Click or tap here to enter text.(Gilani et al., 2023). Waxes and polymers (e.g., ABS-like, PP, MED610 & rubber-like) are suitable materials for this process because of the transformation of these materials into liquid form. But overall, the number of materials is limited to use in MJ. The main strength of this process is that it can print multiple materials at the same time and makes it perfect for prototypes that need to be practical with smooth surface finish and similar in the properties (thermal & mechanical) of part created with injection molding (Saleh Alghamdi et al., 2021). This strength of MJ also provides major possibilities for the development of novel materials for the broad range of AM applications and fabrication of microstructures (Ren et al., 2022). For instance, in a study researchers designed and manufactured microfluidic circuits using the MJ process and materials (Sochol et al., 2016).

2.2.4 Sheet Lamination (SL)

SL is defined as *"an AM process in which sheets of material are bonded to form an object"* (ASTM & ISO, 2021) In SL both metal (Aluminum, titanium, copper etc.) and polymer materials as well as paper are used to create objects. There are few technologies that are subset of SL process including UAM (ultrasonic additive manufacturing) technology which processes metal sheets and bound together through ultrasonic welding, LOM (laminated object manufacturing) creates object using layer-by-layer approach, but the material used to manufacture is paper and instead of welding which bounds the material in UAM, paper bounds together using adhesive. In UAM post-processing is required to remove the extra material or unbounded material, mostly CNC machines used for post-processing operations. Parts that are created by LOM technology are not a good choice for functional components, but parts or products can be used for visual and aesthetics models. The most common applications of LOM and UAM are full color architectural models/topography visualization and hybrid manufacturing respectively Click or tap here to enter text.(Dassault Systèmes). PSL (plastic sheet lamination) is another technology used in SL and processes polymers or plastic sheets such as PVC sheets which melt together by heat and pressure and do not require adhesive. Layer thickness of material influences the quality of manufactured parts in SL (Saleh Alghamdi et al., 2021).

2.2.5 Powder Bed Fusion (PBF)

It is defined as *"An additive manufacturing process in which thermal energy selectively fuses regions of a powder bed"* (ASTM & ISO, 2021). In the last few years, PBF process has grown and become an advanced technology in AM. The reason behind that it can manufacture highly valuable and complex parts at low cost that are not feasible to manufacture using traditional manufacturing methods. Aerospace and medical industry are the two top users of PBF to produce highly complex geometries at low production scale. PBF is also the most popular area of interest among researchers. In this process powder-based materials are used to produce objects with no or minimal support structure. It enables the selection of different materials including polymers, glass, metals, and their alloys in powder form. Recycling of material is also possible and one of its best qualities as the powder can be recycled (Leary, 2020; R. Singh et al., 2019). In PBF process, laser or electron beam works as a heat source to melt or fuse powder material and consolidates fine powder layer-by-layer to form 3D object. During the process, depending on the build material, manufacturing system operates at room temperature under Nitrogen or Argon environment. PBF process is further divided into different technologies based on heat source and material class used in each such as SLM (Selective Laser Melting) for metals, SLS (Selective Laser Sintering) for thermoplastics, EBM (Electron Beam Melting) both for metals and thermoplastics and MJF (MultiJet Fusion) for rigid and flexible thermoplastics and use infrared energy source. In metals nickel-based alloys (Inconel 625 and Inconel 618), copper and bronze alloys, and Aluminum (AlSi10Mg) are most common in aerospace and biomedical. In polymers nylon with glass filled, polyamide, polyurethane powders are widely used to form parts. (Choong, 2022).

2.2.6 Binder Jetting (BJ)

"An additive manufacturing process in which a liquid bonding agent is selectively deposited to join powder materials" (ASTM & ISO, 2021) In this process powder material is used which is placed on the powder bed and through moving inkjet nozzles, drops of adhesive material (usually glue) fall to bind the build material powder on platform. BJ is mostly used for metal materials but other materials such as ceramics and polymers can be used for fabricating 3D objects. In BJ process no support structures are required which saves the material and it has ability to create complex geometries at higher printing speed with high surface finish. Most common materials in BJ are stainless steel, glass, zircon, plaster-like and silica. Recent research showed that the molds printed using silica sand as printing material in BJ provides better properties, accuracy, and less harmful chemicals than the traditional method of making sand molds Click or tap here to enter text.(Hasbrouck et al., 2020).

2.2.7 Directed Energy Deposition (DED)

This process is defined as *"An additive manufacturing process in which focused thermal energy is used to fuse materials by melting as they are being deposited"* (ASTM & ISO, 2021). DED process is similar to PBF, but it is most complex process and commonly used for the repairing or adding material into existing parts. In this process, build material melted using high energy sources such as electron beam or laser before the deposition through nozzle layer-by-layer. DED can process multiple materials at same time and most of the material class that is used in this process are metals such as cobalt chrome, nickel, zirconium, and titanium. The other commercially available technologies of DED are EBAM/BEAM (Electron beam additive manufacturing), (LENS) laser engineered net shaping and (DMD) direct metal deposition. Industries are adopting DED with hybrid manufacturing options. In a recent development US Airforce took repair services of an US based AM company Optomec for repair of titanium-based engine components of F22 Raptor and F35 Lightning II using DED process which resulted in estimated more than 80% costs saving (Watson, 2022).

2.3 Classification of AM Materials

In AM processes a diverse range of materials available and generally categorized into polymers, ceramics, and metals according to their bonding, structure, and strength. These classes of materials are further mixed with other materials to form the composites to get the desired properties and features through reinforcement. Initially in AM only waxes, polymers and paper laminates were used, but with the passage of time more developments were seen and now composites, ceramics, biomaterials, and metals are also being used for the manufacturing of functional parts(Srivastava et al., 2022) . Hence the AM fabricated parts are now having better accuracy, strength, and reliability. In AM, high quality materials usage that meet the stringent criteria requirements in process is important to fabricate accurate and reliable products. Various industries and researchers are seeking to expand the variety of AM materials for developing different products through AM (Kanishka & Acherjee, 2023).

2.3.1 Polymers

Polymer materials could produce parts with complex geometries at the higher level of customization and flexibility, because of this reason polymers obtained a lot of attention in AM Click or tap here to enter text.(Park et al., 2022). High grade polymers mostly have good strength, resistance to corrosion, ease of processing, minimum thermal and electrical conductivity, wide range of colors, lightweight, toughness and affordability (Brinson & Brinson, 2015). As a result, polymer class is extensively used in AM, making them one of the most utilized materials classes. Polymers are further divided into three categories that are thermoplastics, elastomers, and thermosets. These materials can be processed in any physical form including liquid, solid, powder, sheets, or wire. Thermoplastics can be used for manufacturing when heated above their melting point and then phase change occurs from solid to liquid form. The cooling process retains the state of thermoplastics, and they are also conducive for recycling. Thermoplastics are mainly used for the materials extrusion technologies such as FDM while thermosets are used in liquid form for MJ technologies and regular UV-curable thermosets are used in VPP processes such as acrylics and epoxies. The chances of degradation with the passage of time are high for the parts printed from UV-curable thermosets and in that way, parts also become weak in mechanical characteristics (Bourell et al., 2017).

The filaments of PLA (Polylactic acid) and ABS (Acrylonitrile butadiene styrene), PA (Nylon) and Polyethylene terephthalate glycol (PETG) are the most common thermoplastic materials use in MeX technologies due to their low melting points and acceptable mechanical properties. These popular AM materials are not suitable to be used for applications where higher levels of strength, thermal characteristics and durability are required. To overcome these issues in selection of thermoplastics for engineering or functional applications (e.g., aerospace, or automotive), researchers and AM companies have developed machines to process the engineering-grade and high-end materials such as PEEK (Polyether ether ketone) and polyamide (PEI) which process at higher temperatures and exhibits the excellent properties (thermal, mechanical & physical). These special materials also have good chemical resistance and not easily degrade (Peng et al., 2020).

2.3.2 Metals

Contrary to polymer, metallic materials have less range and materials are limited in metal AM. Mostly metal materials are processed in traditional manufacturing methods to make parts. AM has lot of benefits if metal materials are used in compatible AM technologies which have abilities to form complex geometries, save costs and time. Industries such as biomedical, electrical, automotive, defense and aerospace can take advantage of the metal AM for producing functional parts that require high performance or working in extreme temperatures. The key advantages offered by metal AM includes better part quality with compared to parts manufactured by casting or forging and ability to print highly complex 3D shapes such as lattice or structures that are not easily manufactured by conventional methods. The manufacturing time is also reduced, extra costs is minimized because of the subtraction of traditional manufacturing steps such as assembly, cutting, and materials wastage (Gorsse et al., 2017).

Literature has found in metal AM materials that are used for different applications for example titanium alloys have been used for the fabrication of implants and prostheses (Amaya-Rivas et al., 2024). In another study titanium-based alloy (Ti Al) is reported to produce more than 300 parts of GE9X engine which is most powerful jet engine, these additively manufactured parts installed in different sections of engine for Boeing 777X which resulted overall 10% of fuel saving, 25% cost cutting and 40% lightweight for each component (Armstrong et al., 2022; Blakey-Milner et al., 2021). The National Aeronautics and Space Administration (NASA) used Fe-Ni superalloy to develop their own AM material NASA HR-1for rocket engine. NASA HR-1 is excellent in fatigue strength, resistance to corrosion, elongation, resistance to hydrogen and thermal properties (Gradl et al., 2021). SpaceX has adopted AM technology and produced engine chambers of its Super Darco rockets using Inconel material, a metal superalloy that is used for high stress applications. After multiple tests of this additively manufactured component, SpaceX approved the rocket’s engine for human flight (Sher, 2019). The construction industry is also benefited by AM, a Dutch company MX3D constructed 3D printed world’s first footbridge which has 10.5 meters span. Stainless steel AM material (308 LSi) was used in metal AM process and resulted in saving time and cost (Gardner et al., 2020).

2.3.3 Ceramics

The AM of ceramic materials with compared to polymer and metal materials is in early stages, but it has attained significant attention of researchers in this area (Cramer et al., 2022; Wu et al., 2023). The addition of ceramics in AM has increased the prospects for the practical applications and gave the hope to industries or manufacturers to print the complex parts that are not possible through traditional methods such as tape casting, ceramic injection molding and slip casting. Manufacturing through these traditional techniques involves consuming lot of time in process and costs. The post processing methods drilling and milling are also required which affects the properties of ceramic-built part because of its brittle nature and lead to significant costs. Parts with interconnected channels and high complexity are unfeasible to manufacture through molding methods. By considering all these concerns researchers and scientists or AM materials manufacturers has introduced ceramic materials to provide characteristics such as high strength properties, hardness, heat and chemical resistance, insulation, and compatibility with living tissues for uses in aerospace, automobile, defense, and power sectors (Bai et al., 2023). Ceramics materials have been extensively used in the production of electronics equipment due to its higher insulation characteristics. The chances of expansion in ceramics are also very low and maintains the shape even in changing temperatures because they have low thermal expansion coefficients. They are also resistant to wear, friction, and corrosion with offering excellent mechanical properties which attract the industries especially aerospace, nuclear power sector and automotive (Saha & Mallik, 2021).

There are two main methods to process ceramic materials, one is single step or direct and the second method is multi-step and indirect process. In multi-step method, the final part needs post-processing steps that are de-binding and sintering of formed green body, while single step method sinters the ceramic material directly to create a final part. (Lakhdar et al., 2021). Mainly two AM processes Powder based fusion (PBF) and Binder jetting (BJ) are used in ceramics AM. Common materials are zirconia, silicon carbide, alumina, boron carbide, hydroxyapatite, porcelain, and nitride aluminum. Zirconia ceramics materials are used for dental applications and processed in AM technologies such as SLA, inkjet and BJT. A new AM process “IntrinSIC” has been developed by Schunk

Group for printing complex parts with maximizing the part quality (Wätjen et al., 2014). Alumina has been widely used for structural applications because of its excellent hardness, thermal properties and affordable. Silicon nitride and silicon carbide materials have attained considerable attention as very strong materials, especially in aerospace, because denser parts with excellent mechanical properties are required. Hydroxyapatite and bio-glasses are biocompatible materials used to produce implants and synthetic bone grafts (Dadkhah et al., 2023).

2.4 Materials Selection

There are various materials as mentioned previously in the materials section that have been developed for additive manufacturing and commercially available for usage in multiple industries according to their need. The appropriate selection of material becomes difficult for the manufacturer or designer from the large pool of materials available in market. The right materials selection has great importance in the new product development and manufacturing environment. This task is time-consuming and careful considerations are required, because there are complex relationships between various conflicting criteria for choosing the best alternative. Appropriate selection also has an impact on manufacturing costs which govern the competitive position of the industries. The kind of material used in a manufacturing process to create a product determines its performance, quality, weight, reliability, and robustness. For example, weight is the most important factor in the aerospace industry and selection of materials must have the criteria to reduce the weight of a component or product (Emovon & Oghenenyerovwho, 2020). The main aspects that need to be considered during the material selection process are the mechanical, physical, environmental, durability, cost, and the manufacturing capabilities. The selection criteria and their significance vary depending on the sector in which the material is used. Research and development are increasing at rapid pace and in a result number of alternatives (materials) with different characteristics is also increased (Ajith et al., 2022). High production costs are incurred due to the inappropriate choice of materials. Many resources are allocated by industries towards lowering costs initiatives such as process innovations to stay in competition, the presence of higher production costs clearly hinders these attempts. Furthermore, poor material selection might result in decreased productivity, unfavorable design, dissatisfied customers, operational breakdowns, and unsatisfactory performance (S. Chatterjee & Chakraborty, 2021) In this scenario, a multicriteria analysis is crucial for the selection of materials. Materials could not be selected as individual without the consideration of other factors such as related process for material shaping, assembly, associated costs and environmental impact of production and application both Click or tap here to enter text.(Zheng et al., 2023b). The individuals that are involved in the decision-making process must possess a deep knowledge of the functional requirements of each component and a strong understanding of the criteria associated with a particular application to choose the most suitable material from a wide range of alternatives, each with unique properties, uses, strengths, and limitations.

An online database of AM materials Senvol has reported a total of 4186 AM materials by various manufacturers in their records till date and this wide range of materials are available to engineers and designers. The continuous emergence of novel materials with unique properties has extended the range of alternatives and posed a challenge for designers to decide the best material for their purpose and meet their needs (Senvol, 2024; Zheng et al., 2023a). In some designs, selected criteria are required to minimize or maximize by decision makers for example while designing a part the criteria of its durability should be maximized, costs and environmental impact should be minimized. Additionally, the materials also have different properties which makes the selection process more complicated. This process complexity is also because of the two reasons as highlighted in some studies. First, thorough comprehension is required regarding the uses, performance, strengths and shortcomings of various materials and their impact on the quality and characteristics of manufactured part, which is challenging task. Second, several materials within the same material class might exhibit significant overlapping similarities in terms of properties, limitations, performance, and suitability, which further makes the materials selection process difficult (Rodrigues, Bairrão, et al., 2022; Rodrigues, Cipriano Farias, et al., 2022). In that context, a decision methodology is required for this tedious material choosing task (Şahin, 2023). In various studies researchers used and developed different tools for the materials selection and presented this as a multi-criteria decision making (MCDM) problem.

2.5 MCDM Methods for Selection and Ranking

MCDM is a subfield within the domain of operations research focuses on the comprehensive assessment of various conflicting criteria during the decision-making process (A. Kumar et al., 2017). First developed in the 1970s and until now more than 60 methods have been established (Więckowski et al., 2023). MCDM methods have gained significant attention from researchers and can be further divided mainly into two categories that are multi-objective decision making (MODM) and second is multi-attribute decision making (MADM). In MODM, multiple objectives are optimized simultaneously by considering the preferences and constraints from the decision maker (A. Singh & Kumar Malik, 2014). It is particularly useful in situations where there are a large or infinite number of alternatives and multiple, often conflicting, objectives that need to be balanced, such as in resource allocation, project selection, or environmental management. On the other hand, in MADM, the appropriate alternative is selected from a predetermined set of alternatives depending on their properties with the single goal of choosing the best option. Limited number of alternatives are typically used for problems in MADM methods and are known for their ability to provide a ranking of alternatives based on their overall performance (Rao, 2007). Within the field of MCDM, various strategies have been devised, each with its own analytical models or frameworks, information criteria, underlying suppositions, and decisions (Aruldoss et al., 2013). The selection of the most suitable methodologies is of paramount importance to figure out the problem under investigation. Otherwise, opting for an unsuitable methodology may lead to improper selections. As a result, financial losses could occur due to poor decisions. Hence, the selection of the most suitable method to tackle the problem is of utmost importance and requires careful consideration to choose from the extensive range of MCDM approaches available. The MCDM approaches are used in literature for industry problems such as AM process selection (Mançanares et al., 2015), supplier selection (Ashish Vishnu et al., 2018), material selection (Babu et al., 2017), and facility location selection (Liang & Wang, 1991), capacity allocation (Kang, 2011). Still, MCDM approaches have advantages and disadvantages. All the alternatives (materials) that are being considered are evaluated in terms of their strengths and weaknesses by comparing them with each other and then ranked according to the technical, environmental, and economic criteria. This evaluation is carried out with the help of

MCDM methods (Kappenthuler & Seeger, 2020) In addition to the properties of materials, MCDM approaches can also be applied for the evaluation of appropriate solution for the manufacturing processes and ranking the solutions according to how well they perform in terms of required attributes Click or tap here to enter text.(Ghaleb et al., 2020). There are MCDM methods that are designed to assist decision makers to solve complex AM materials selection problems. These approaches are employed to offer the best solution to the modern decision-making problems that include multiple criteria and alternatives (Ceballos et al., 2016). Various researchers and studies discussed the MCDM approaches with their use for different kinds of applications. For instance, the tools of MCDM used for decision making processes are AHP (analytic hierarchy process), FAHP (fuzzy analytic hierarchy process), TOPSIS (technique for order performance by similarity to ideal solution) and COPRAS (complex proportional assessment), DEMATEL (decision making trial and evaluation laboratory) etc., (A. Kumar et al., 2017). DEMATEL, TOPSIS and FAHP methods are found in literature used for AM applications (Durão et al., 2018; Z. J. Wang, 2018). Apart from that, MCDM methodologies are also used in various sectors and captured a lot of attention within the domains of strategic management (Mardani et al., 2015; Radmehr et al., 2022), sustainable supplier selection (Amindoust et al., 2012; Karakoç et al., 2024), inventory management (de Assis et al., 2019), green supply chain management (Banasik et al., 2018; Paul et al., 2021), product planning and development (W.-C. Chen et al., 2022). The Fuzzy TOPSIS method is also employed for facility layout planning and design and failure modes and effects analysis (FMEA) risk evaluation (Nenzhelele et al., 2023; P. Sharma & Singhal, 2017; Vahdani et al., 2015).

MCDM methods are widely used by authors in various research studies and literature for several applications including AM. These methods are used to help decision makers consider all criteria or objectives simultaneously to rank or select the best alternative. Below is a brief overview of different MCDM approaches frequently used in literature including in material selection and additive manufacturing applications. These methods were also compared with each other to create a proposed MCDM framework that can be used for decision-makers to choose the best alternative efficiently from the available large pool of options. This section also presents the hybrid MCDM methods as studied in the literature reviewed.

2.5.1 AHP:

For solving the material selection problems AHP method has been widely used and found beneficial by researchers (Huang et al., 2011; Jahan et al., 2011; Roth et al., 1994). This method was developed by Thomas Saaty and starts by the decomposition of decisions into hierarchical framework which consist of goal on top level and then criteria and alternatives (T. Saaty, 2001; T. L. Saaty, 1990. When compared to other MCDM methods the advantages of AHP method are ease of use, flexibility, ability to convert verbal judgments into quantifiable format, assurance of consistency and ability to provide efficient solutions to a real world complex hierarchical problem (Hambali et al., 2010; Ishizaka & Labib, 2011. Because AHP method is dependent on the decision maker's criteria judgments, understanding, intellect, intentions, it lies in the category of subjective weighting approaches which uses experts' level of knowledge and expertise. These methods are frequently employed when insufficient data is available and challenging to quantify (Zakeri et al., 2023.

The pairwise comparisons in AHP method are used to simplify the process and conceptual complexity is reduced. These pairwise comparisons are performed between the identified criteria to create an evaluation framework for assigning weights to criteria and develop a hierarchy. Afterwards, the alternatives are prioritized according to their relative significance, with the most important one being listed first and the least important one being placed last (Uğur & Baykan, 2017. During the sensitivity analysis of AHP method for the selection of material in research, it showed that the material ranked by AHP is matched in 6 different sensitivity analysis approaches (Hambali et al., 2010. This method also gives a coherent hierarchal ranking of alternatives according to the importance given to the criteria (Zhao & Cheng, 2013). The process of establishing criteria weights to address interdependencies within a system enables quick revision of assigning weights to check the consistency in the judgments by decision maker. This also allows to involve group of decision makers for group judgements when natural consensus cannot be reached, making AHP a valuable contribution in the domain of MCDM. Since the AHP approach is developed, it is used in numerous fields because this method has a strong mathematical algorithm and process of collecting data through pairwise comparisons. The areas include management, engineering, economics, and sciences (Vaidya & Kumar, 2006). There is a diverse range of research studies seen in literature during past years. In a study, researchers replaced the conventional materials with the natural fiber materials to reduce the environmental impact. The AHP method was used for assigning weights to criteria and sub-criteria then a software tool "Expert Choice" was used to compute the results. The fiber based composite material hemp-polypropylene (hemp + pp) was ranked first aligned with the industrial specifications and recommended to parts manufacturers in the automotive sector (Ali et al., 2015). In the context of additive manufacturing AHP is used for solving multiple problems and provided the optimal decisions. For example, AHP approach was used for the selection of AM process by (Bikas et al., 2021; Liu et al., 2020), AM machine selection (Raja et al., 2022), evaluation and selection of alternative mechanical system (Psarommatis & Vosniakos, 2022), selection of adhesives for the bonding of AM built parts (Arenas et al., 2012), selection of parts suitable for AM (Foshammer et al., 2022; Muvunzi et al., 2021), selection of material-design-process (Hodonou et al., 2019), assessment of AM social impacts (Bappy et al., 2022), ranking of AM implementation factors (Sonar et al., 2021), production scheduling in AM (Ransikarbum et al., 2020), 3D printed COVID-19 mask design selection by (Rochman et al., 2021).

2.5.2 ANP

Analytic network process (ANP) is an expanded version of AHP that allows the exchange of information and interaction within and between clusters, resulting in an all-encompassing tool for the decision-making process (Taherdoost & Madanchian, 2023b). Although AHP method is used in many scenarios to solve the complex problems, but the elements or criteria in this method are considered independently without consideration of possible interdependencies or interrelationships among them (Thomas & Sodenkamp, 2010). Consequently, a new generalized approach was presented by (T. L. Saaty, 2006) to solve this problem. ANP consists of a generic form of decision model which uses network interactions between the criteria and alternatives which leads to better modeling of the complexity using networks (T. Saaty & Kułakowski, 2016). Since these interrelationships can be seen between any of the ANP decision model elements, this model will not remain a hierarchy as in AHP, clusters substitute the levels of hierarchy and each cluster contains elements and form a network in ANP (Gonzalez-Urango et al., 2024).

Material selection problems could be solved through the ANP approach. There is evidence in literature that some researchers used this method for material selection. For instance, it was discussed that how the material selection process for non-metallic gear is a network problem and criteria and alternatives have interdependencies as opposed to the classic AHP (Milani et al., 2013). The ANP method was applied to help designer in choosing the sustainable materials to minimize environmental impact (Mahmoudkelaye et al., 2018). Some other researchers used the ANP approach with other MCDM techniques. In the field of additive manufacturing, selection of natural fibers was carried out using the integration of AHP and ANP methods for the AM technology FDM (Mastura et al., 2022).

2.5.3 TOPSIS

TOPSIS is a well-known and widely used MADM method for solving the decision-making problems and it was developed by (Hwang & Yoon, 1981). This method is categorized in the distance based MCDM methods. The rationale underlying the TOPSIS method is very logical and easily comprehensible, so the mathematical calculations in this method are more precise and straightforward. There are numerous research papers available in literature in which researchers used a single TOPSIS approach or integrated with any other MCDM method. Basically, the logic behind this method is that the ranked alternative should have least distance from the ideal solution and greatest distance from the negative or worst ideal solution (Swain, 2014). For the material selection problems, TOPSIS is an excellent choice because it allows many alternatives (materials) and the criteria. Therefore, TOPSIS can effectively provide realistic modelling approach and an optimal decision to a decision maker through measurement of distance (Rahim et al., 2020).

In a study, researchers used TOPSIS method to rank the biodegradable composite materials (Jha et al., 2018). A methodological tool was developed by (Shanian & Savadogo, 2006c) to assist the designer in the selection of appropriate material based on required criteria for metallic bipolar plates for PEFC. In another study material selection methodology was proposed for the paper making industry using TOPSIS (Anupam et al., 2014). In the field of additive manufacturing, TOPSIS studies in literature were also found such as AM process and technology selection by (Iç, 2012; Saxena et al., 2021; Yildiz & Uğur, 2018), AM machine selection (Raja & Rajan, 2022), part orientation (Yu et al., 2019), prioritization of sustainable AM challenges (Alsaadi, 2021), AM process parameter optimization by (Kamaal et al., 2021; M. et al., 2021).

2.5.4 BWM

The best worst method (BWM) is a latest, but a popular and advanced MCDM approach (Kheybari & Ishizaka, 2022). The method was developed by (Rezaei, 2015) to address some limitation of the AHP method, which used to solve the decision-making problem using the large number of pair-wise comparisons. The BWM method is used to solve the complex problems which helps decision makers in better comprehension of problem (van de Kaa et al., 2020). The number of comparisons in BWM are reduced to 2n-3, which enhances its usability. By using the small numbers of comparisons, the user chooses the best and worst criteria, afterwards by pairwise comparisons user compares the best criterion with each individual criterion, as well as comparing each criterion with the worst. (Rezaei, 2015). By eliminating the redundant comparisons during the decision-making process enhances the consistency of the results (Pamučar et al., 2020).

The BWM method is utilized for different areas such as in supply chain management by (Badri et al., 2017), evaluating the firm's performance (Salimi & Rezaei, 2018), segmentation of suppliers (Rezaei et al., 2015), facility location selection (Kheybari et al., 2019), sustainability assessment in an aircraft company (Raj & Srivastava, 2018) and evaluation of key success factors in remotely-piloted helicopters (RPH) industry (Ghaffari et al., 2017). In AM context only one study found in literature that used BWM method for the selection of suitable AM machine (Palanisamy et al., 2020).

2.5.5 PROMETHEE

The PROMETHEE (preference ranking organization method for enrichment evaluation) approach was first proposed by (Brans et al., 1986), and this method belongs to the category of outranking MCDM methods. In this class of methods, the decision maker compares the alternatives pairwise and assigns a level of preference based on the criteria. The PROMETHEE method provides a practical procedure to solve complex MCDM problems through partial and comprehensive ranking. The method is very useful in complex decision-making environments especially when the criteria are difficult to quantify, and decision makers need to compare alternatives based on various criteria (Taherdoost & Madanchian, 2023d). Multiple variants of PROMETHEE have been developed, each possess its own strengths, properties, and requirements. PROMETHEE I and II variants are the most used methods in literature, latter used for the partial ranking based on one criterion while the former used for full alternative ranking problems based on multiple criteria. PROMETHEE III is designed for ranking based on intervals, whereas IV is intended for continuous situations. PROMETHEE V is specifically designed to handle problems related to segmentation constraints, while VI focuses on the depiction of human brain (Glavinovic & Vukic, 2023). In the material selection problems, PROMETHEE I, II and PROMETHEE-GAIA (Brans et al., 2005; Maity & Chakraborty, 2013; Zindani & Kumar, 2018) variant have been seen in literature, while the other versions are not reported in material selection field. PROMETHEE does not provide specific instructions for determining the weight of factors and instead depends on the decision makers to use acceptable aggregation criteria. However, incorporating the recommended material from PROMETHEE would theoretically enhance the performance and efficiency of the application (Rahim et al., 2020). In literature there was no study found using single PROMETHEE approach for AM applications.

2.5.6 ELECTRE

Like PROMETHEE method, ELECTRE an acronym of ÉLimination Et Choix Traduisant la REalité (Elimination and Choice Translating Reality) is also an outranking method and belongs to MCDM family. ELECTRE was developed by Benayoun, Roy and Sussman in 1960s at a European consultancy company SEMA to solve a real-world complex problem (Govindan & Jepsen, 2016). The ELECTRE method is employed to eliminate alternatives that do not satisfy the criteria and then the right alternatives are generated (Siregar et al., 2021). Further variants of ELECTRE are developed and used by researchers in literature such as ELECTRE I, II, III, IV, IS, TRI, TRI-B, and TRI-nC methods. Each method is used for different kinds of decision problems, but the concepts behind all methods are the same. Research showed that ELECTRE I appear to be well-suited for assignment kind of problems and other for the ranking problems especially ELECTRE III, a most suitable and used method for different applications (Mary et al., 2016).

In the field of materials selection, ELECTRE method was used to select the best material for thermal loaded conductor and results showed a good agreement between the past research and used methods (Shanian & Savadogo, 2006a). The ELECTRE IV method was used to pick the optimal material for the bipolar plate of a polymer electrolyte fuel cell by. This solution made it possible to eliminate the problem of optimizing the criteria one by one. The effect of changes was examined in the performance indices on the ranks of ranking of materials. The results were consistent with previous studies (Shanian & Savadogo, 2006b). ELECTRE III technique was applied to solve the problem of selecting the best material for a spur gear. The material's performance indices and specific characteristics were evaluated. This method gave different solutions in each case. Results differed in terms of ranking when low, mid, and high limits were applied for the criteria. The ELECTRE III method considered the uncertainty and incompleteness of the available material data. It was determined that the decision maker's uncertainty in deciding the weights may be eliminated by considering the iterative process of dilation and focus (Milani & Shanian, 2006).

However, ELECTRE methods have a significant drawback which is that when the alternatives are increased, the complexity of calculations rises. Additionally, it does not provide a uniform measure of performance for each alternative; instead, it merely provides a ranked shortlist. In the context of AM, a study used ELECTRE method for the selection of plastic filament for a 3D printer and results showed virgin high-density polyethylene material as the best material among other alternatives (materials) (Exconde et al., 2019a). In another recent study employed the ELECTRE method for the selection of appropriate recycled material for 3D printing from waste plastic stream that consist of combination of polymers. Polyethylene terephthalate (PET) material was ranked as best material and surpassed all other plastic material in selection process (D. Zhou, 2022).

2.5.7 VIKOR

VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) is a well-known MCDM approach to rank alternatives and identify the compromise solution that is most near to the "ideal" (Gul et al., 2016). VIKOR method is developed by Serafim Opricovic in 1990s to solve decision-making problems and achieve a multi-criteria enhancement of complex systems with criteria that cannot be compared or are incompatible. It is used to rank and choose the best alternatives in the presence of contradictory criteria. Alternatives can be ranked with various criteria weights and allow decision maker to evaluate how these weights influence the compromise solution. Decision-makers, in such a way, could minimize the trade-off on achieving the best alternative (Opricovic & Tzeng, 2004). VIKOR method can be recommended as the most suitable approach for the selection and ranking for the large-scale decision-making environments (Ahmed & Majid, 2019).

The VIKOR method is similar with some concepts of TOPSIS, but there are some differences between two methods. TOSPIS uses vector normalization while VIKOR uses linear normalization (Taherdoost & Madanchian, 2023a). The appropriate alternative is selected and ranked by only considering the closeness to ideal solution. Whereas TOPSIS uses both the ideal and non-ideal solutions. When the objective is to achieve a value that is as close to the ideal value then the usage of VIKOR method would be an efficient strategy (P. Chatterjee et al., 2009). In material selection problems VIKOR is a valuable tool and it assist designers when they are unable to articulate their preferences at the beginning of the product design phase (Zindani et al., 2020). In the field of AM, fuzzy VIKOR method was used to choose the AM technology in an agile environment and results showed that FDM technology as the best solution which was then accepted by decision-makers (Vinodh et al., 2014). The VIKOR method is also used for the optimization of process parameters for the FDM technology by using the ABS material and ranking the set of parameters (Raykar & D'Addona, 2020).

2.5.8 Hybrid Decision Methods for AM Problems

Various researchers in literature also integrated two or more MCDM approaches simultaneously to solve the complex problem. Several publications have reported on the utilization of hybrid method in the field of AM and appeared as a notable development. Two or more methods are combined to increase their strength and minimize the limitations. Combined approaches also provide increased decision support, accuracy, robustness and enables more extensive decision analysis (Sahoo & Goswami, 2023). In AM, six MCDM methods were applied to select the appropriate AM process and then compared with each other. Research result showed that not all six approaches generated the same process rankings (Borille et al., 2010).

A generic methodology was proposed by (Venkata Rao & Patel, 2010), two MCDM approaches AHP and PROMETHEE were used to choose the rapid prototyping system among six alternatives. Hybrid MCDM methodology was developed to select the AM process from four alternatives (FDM, LOM, SLA & SLS) by considering the sustainability concepts. Researcher found that FDM is best process, and combining SWARA and COPRAS decision methods helps decision makers and managers for easy implementation for manufacturing as well as reducing carbon dioxide emissions (Chandra et al., 2022). By considering the design for additive manufacturing (DfAM) guidelines, researchers developed a decision methodology combining AHP, DEMATEL and TOPSIS approaches for the selection of AM process and machines (Algunaid & Liu, 2022). AM process parameters were selected by using VIKOR-AHP method for FDM (Patil et al., 2022). Table 1 is provided to present the MCDM approaches used for solving AM problems.

Table 1: MCDM methods in AM

Publication	MCDM approach	Application/Case study for selection	No. of criteria	No. of Alternatives
(L. Kumar & P. K., 2010)	AHP	Generic (Rapid prototyping technology)	17	6
(Armillotta, 2008)	AHP	Techniques for prototypes manufacturing	11	16

(Kadkhoda-Ahmadi et al., 2019)	AHP	AM machine for car light bezel	3	6
(Khaleeq uz Zaman et al., 2017)	AHP	Materials & Machine selection (Drilling grid case study)	7 (machines) 6 (materials)	5 (machines) 32 (materials)
(Malaga et al., 2022)	IEM-CODAS	Materials for metal AM	9	8
(Mançanares et al., 2015)	AHP	AM Machine (3 case studies)	6	45
(Liu et al., 2020)	AHP	AM Process Selection (Exhaust gas duct)	5	12
(Kek et al., 2016)	ANP-TOPSIS	Rapid prototyping process selection	25	4
(Byun & Lee, 2005)	Modified TOPSIS	Process Selection	6	6
Liao et al. (2014)	DEMATEL-VIKOR	Service Providers Selection	12	6
(Vahdani et al., 2011)	Fuzzy modified TOPSIS	Process selection	4	6
(Vinodh et al., 2014)	Fuzzy VIKOR	AM technology selection (Pump impeller)	5	3
(Y. Wang et al., 2018)	Modified TOPSIS	Process Selection	4	10
(Alghamdy et al., 2019)	AHP	Materials Selection (Car door Hinge)	3	3
(Abas et al., 2023)	AHP-MARCOS	Materials Selection (Ankle foot orthoses)	11	7
(Palanisamy et al., 2020)	BWM	Materials (Industrial Gasket)	8	7

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents a brief overview of the methodology used to evaluate material selection problem in additive manufacturing. Research methodology plays an essential role as an integral part in the process of conducting research. This section provides how this study has been conducted, sources of data, and type of data collection procedure. The methodology adopted, in this study, for appropriate material selection has two parts. In first part, relevant criteria that used to evaluate material selection problem were identified using literature review and expert interviews. Second part was to develop a framework for material selection using MCDM. Material selection consists of two MCDM approaches for the evaluation of criteria, assigning weights, selection and ranking of appropriate material. Developed framework has further divided into two stages, in first stage selected experts assigned weights to the criteria and in second stage the alternatives were ranked.

3.2 Research Design

The research design delineates the method by which various study components are integrated coherently and logically, assuring a comprehensive and successful approach to addressing the research problem. It serves as the blueprint for data collection, measurement, and data analysis (Saliya, 2022). “Research design is a set of methods and procedure using different variables by the researcher to handle the research problem efficiently”. The framework for a study is distinguished by various components and strategies. The research design process encompasses numerous interconnected decisions and gathering the relevant information for a research study (Sileyew, 2019). The type of research design can be varied. It could be either exploratory, explanatory, correlational or descriptive.

The proposed research used descriptive research and focused on both the qualitative and quantitative types of data. The descriptive research design type analyzes the situation as it exists in its current state and identifies the attributes of a particular phenomenon through observations. However, this type works independently without considering relationships between variables (Williams, 2011).

3.3 Research Type

The research can be categorized into two main types that are fundamental or basic and applied research. Fundamental research aims to broaden the current body of knowledge in a certain field and has a wide scope. It does not address the creation of a novel product, process improvement or solving a present problem. Whereas applied nature of research helps in identifying the practical solutions to specific problems by using accepted and well-known theories or principles (Stewart, 2023). Therefore, this proposed research is applied research as the proposed framework is developed by integrating two well-known MCDM techniques and then applied on a real-world industrial application.

3.4 Data Collection

In research data collection refers to the systematic gathering information or data from various sources in order to address research problems, answering research questions, assessing outcomes, and predicting trends and probability. It is a crucial stage in all kinds of research, decision making and analysis. Mainly, the data collection methods are categorized into two classes which are primary data collection and secondary data collection. The data collected from the original source and firsthand information that is not published anywhere or altered by anyone called primary data while the data collected from already published resources or the data collected by any other and used for any purpose. Primary data could be obtained by questionnaires, interviews, or observations etc., whereas secondary data could be obtained through different techniques including online databases, academic journals, publicly available data etc. Figure shows the techniques used for the collection of data for research. This research is conducted using both primary and secondary data types. For the primary data collection questionnaire and interviews. For the secondary data collection different published studies and material properties databases used (Taherdoost, 2021). Figure 2 presents the methods of data collection.

3.4.1 Questionnaire

In this study a digital questionnaire with an AHP judgment form was designed and disseminate through Google forms to collect the data from experts in the field of aerospace and additive manufacturing.

The questionnaire was structured in the following manner:

i. Aim of research
ii. Explanation of Criteria & Sub-Criteria
iii. Instructions to fill the questionnaire with examples
iv. Criteria & Sub-Criteria pairwise comparisons

Figure 2: Data collection techniques [Adopted from (Taherdoost, 2021)]

3.5 Research Participants

In this study, a group of 6 experts participated in research. These experts were selected using the 12-point system that various researchers used to qualify the respondents as experts. This scale evaluates and chooses the participants based on their qualifications, working experience, expertise & knowledge, and research studies related to the field (Hallowell & Gambatese, 2010). Careful selection of experts ensures the results and decision-making process are more reliable and robust. All selected experts had more than five years of experience. Two senior-level experts were from the aerospace industry, having expertise in AM and aerospace, and four experts were from the academic setting, having a Doctor of Philosophy (PhD) along with industrial knowledge and expertise in the aerospace sector. Selected participants finalized relevant criteria and sub criteria then performed pairwise comparisons in AHP for assigning weights to the criteria.

3.6 Research Philosophy

Research philosophy involves the nature, source, and evolution of knowledge. It is belief regarding the ways or procedures for collecting, analyzing, and using data (Bajpai, 2018). Research philosophy provides guidance on the appropriate approach to conducting research and considers an individual's beliefs about the nature of reality and the acquisition of knowledge (Collis & Hussey, 2014). The four main research philosophies are pragmatism, realism, positivism and interpretivism. Positivism involves tangible and quantifiable and uses objective nature of measurement to derive the scientific knowledge and conclusions. Positivists believe that solutions can be obtained by carefully measuring and analyzing numerical data. Realism assumes the presence of an independent reality that is distinct from human perception and can be understood through empirical observations and data analysis. The concept of realism is commonly associated with qualitative research methods. In contrast to positivism, interpretivism assumes that reality is subjective in nature and socially developed. This reality could be understood only by human experiences and interpreted by individuals. Interpretivism emphasizes the use of qualitative research methods such as interviews, observations, and textual analysis to obtain the meanings and experiences of research participants. In pragmatism, concepts of both positivism and interpretivism could be combined and qualitative and quantitative both methods can play a part depending on the context and research questions of the study. This research paradigm is flexible and adaptable and deals with real world problem solving by practical applications of knowledge (Rashid, 2023; Tashakkori & Teddlie, 2010). For this research study, pragmatism research philosophy has been used as study uses the mixed data types considering real industrial material selection problem solution.

3.7 Data Analysis

As previously mentioned, data was collected from experts through online forms. The type of data was mixed that are qualitative and quantitative data. Identification of criteria was based on qualitative data whereas the data used for the AHP judgments was quantified by comparing the criteria pairwise using numeric values scale by (T. L. Saaty, 2008). The values or properties of alternative under their relevant criteria was in the form of quantitative data and taken through the secondary data collection methods. In this way, to answer the research questions both primary and secondary data were combined which resulted in practical, effective, credible, and reliable insights.

3.8 Participant Confidentiality

In the conduction of this research all the participants of the research interviewed by the researcher are treated with respect. It was ensured in this study that none of the participants' names and organization are disclosed. The data was taken from all the participants with their consent.

3.9 Techniques Used

Various MCDM techniques are used for problem solving or decision-making processes where multiple criteria are involved. Some techniques were discussed in the literature review section which were used for the material selection problem by various researchers. Two MCDM techniques are selected in this study for the material selection in additive manufacturing problem that are AHP and TOPSIS method. Both techniques are combined and called hybrid AHP-TOPSIS in this research. The reason of choosing AHP over other MCDM techniques is that it compares the criteria pairwise and then the output of comparison extracted in the form of numbers and values that could be measured (Hyun et al., 2008). Several researchers have employed the AHP method for assigning weightages to criteria and prioritization in different areas as mentioned in previous chapter 2. The significance of the factors involved in the process is evaluated based on the weights assigned to the criteria. Various techniques have been developed for the weights assigning to the criteria such as objective, subjective and hybrid methods. In subjective weighting methods, the criteria weights are determined based on the preferences of the user. However, this approach is insufficient when the number of criteria increased in a decision-making process. Whereas object type of methods considers the computational procedures which generate criteria weights by a decision matrix without considering user or decision makers' judgments. The combination of objective and subjective methods is more desirable to get the characteristics and qualities of these techniques (Keshavarz-Ghorabaee et al., 2021). Combined or integrated MCDM techniques provide more accurate weights by including both the judgments by users and data from decision matrix (C.-H. Chen, 2020; Du & Gao, 2020; Kılıç Delice & Can, 2020). Hybrid AHP-TOPSIS enhances the decision-making process by refining the subjective judgment of decision makers (V. Kumar et al., 2021). This approach also gives more reliable and error-free outcomes (Mathew et al., 2020). In this study, these methodologies are utilized together because AHP effectively assigns weights to criteria using a panel of selected experts, and TOPSIS aids in identifying the optimal alternative (material) through the materials properties available in databases or directly available on manufacturer's websites like Stratasys or 3D Systems. As discussed earlier in chapter 2, ANP technique is also similar to AHP, but it considers dependence between criteria. In this study AHP is chosen due to the independence of the alternatives under consideration. The significant benefit of TOPSIS is its ability to rapidly pinpoint the best alternative with less subjective involvement from decision-makers (Dağdeviren et al., 2009). Figure 3 shows the research methodology flow chart.

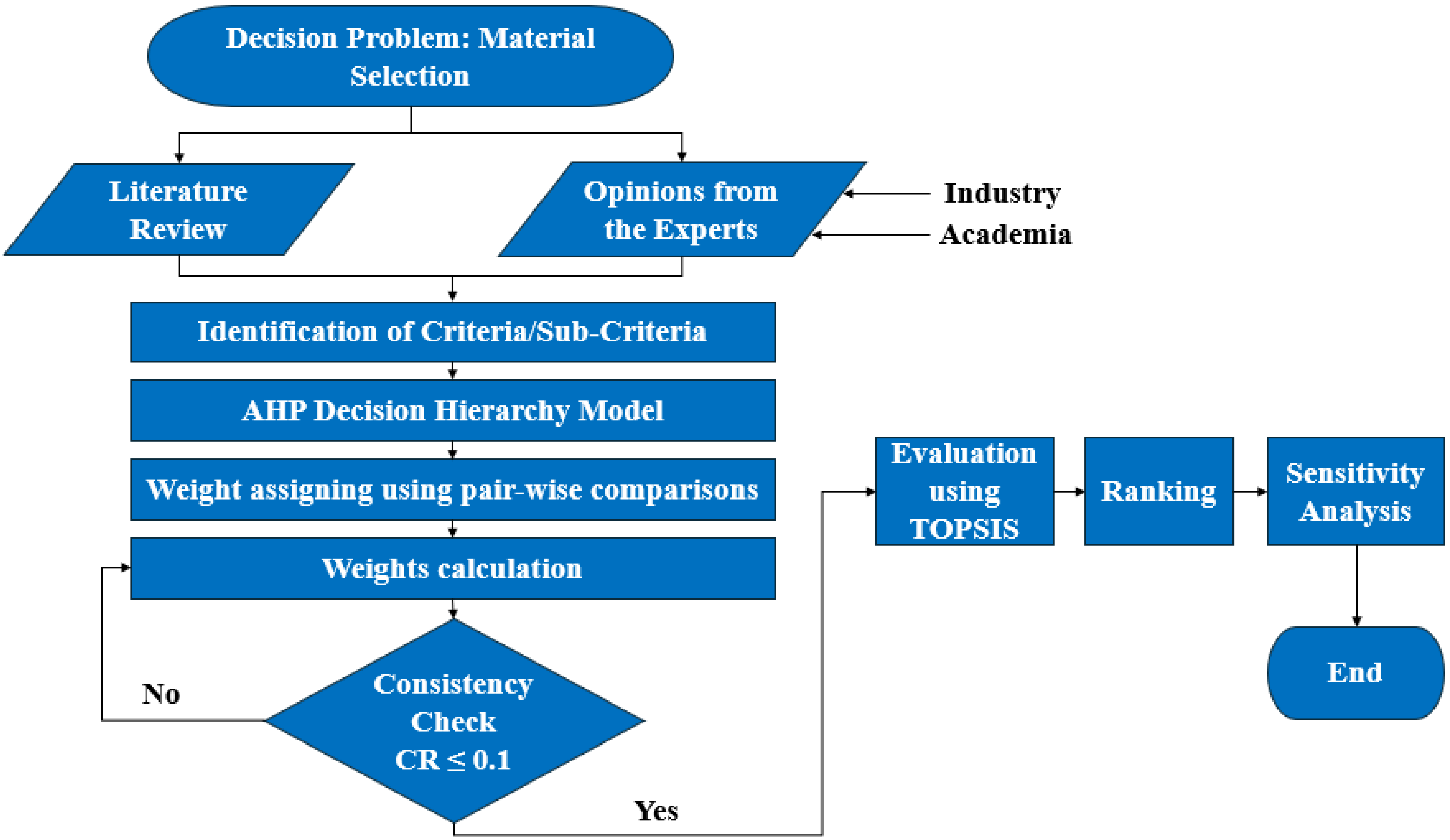

Figure 3: Flowchart of methodology

CHAPTER 4: APPLICATION

A case study was conducted based on the proposed methodology, and an aircraft part, "Inlet duct", was selected. The aerospace industry is required to manufacture a strong inlet duct for an engine-based UAV by AM and requires polymers as the building material. Nine materials were extracted as polymer materials from the literature review and based on the availability in the market. The aerospace industry also required that the material should give a good balance between performance and cost. Fatigue strength was important to maximize to withstand cyclic loading and ensure long-term durability. The goal was to select the best material from the set of materials using the given criteria. The materials and criteria identified by literature, materials availability in the market and experts are given in Table 3. Materials with their properties are given in Table 4.

4.1 Criteria Identification

This section contains the criteria and sub-criteria used to select materials, these relevant criteria, and sub-criteria specific to the materials in additive manufacturing were extracted from the literature. These criteria were discussed with aerospace experts in industrial setting and academia, incorporating insights from both industrial and academic perspectives. In this research, the criteria and sub-criteria were chosen based on their applicability to the aerospace industry. The 3 criteria and their related 32 sub-criteria with reference studies are mentioned in the following table and further narrowed down by experts.

Table 2: Identified sub-criteria of performance, economic and environment

Sr. No	**Criteria Cluster**	**Sub-criteria**	**Source**
1.	Performance	Density	(Malaga et al., 2022; Mousavi-Nasab & Sotoudeh-Anvari, 2018), (Karande et al.,

			2013), (Mastura et al., 2022), (Qin et al., 2023)
2.		Melting Point	(Ren et al., 2022), (Malaga et al., 2022), (Exconde et al., 2019a)
3.		Specific heat	(Malaga et al., 2022)
4.		Operating Temperature	Recommended by experts
5.		Tensile strength	(Khorshidi & Hassani, 2013; Mastura et al., 2022), (Qin et al., 2023), (Palanisamy et al., 2020)
6.		Flexural Strength	(Agrawal, 2021), (Siva Bhaskar & Khan, 2022), (Abas et al., 2023)
7.		Thermal Conductivity	(Mastura et al., 2022), (Alper Sofuoğlu, 2019)
8.		Hardness	(Qin et al., 2023), (Palanisamy et al., 2020), (Siva Bhaskar & Khan, 2022)
9.		Electrical resistivity	(Qin et al., 2023)
10.		Youngs modulus	(Agrawal, 2021), (Fayazbakhsh et al., 2009), (Mastura et al., 2022), (V. Sharma et al., 2022)
11.		Elongation	(Khorshidi & Hassani, 2013), (Mastura et al., 2022), (Palanisamy et al., 2020), (Zhang et al., 2020)

12.		Layer adhesion	(Agrawal, 2021)
13.		Visual quality	(Agrawal, 2021)
14.		Coefficient of thermal expansion	(Alper Sofuoğlu, 2019), (Exconde et al., 2019b)
15.		Glass transition temperature	(Mastura et al., 2022), (Exconde et al., 2019b)
16.		Specific gravity	(Agrawal, 2021)
17.		Compressive strength	(Ul Haq et al., 2023)
18.		Fractural strength	(Agrawal, 2021)
19.		Heat deflection temperature	(Algunaid & Liu, 2022)
20.		Durability	(Mesa et al., 2020), (Abas et al., 2023)
21.		Wear Resistance	(Karande et al., 2013),
22.		Fire Resistance	(Fayazbakhsh et al., 2009)
23.		Fatigue Strength	(Mesa et al., 2020; Mousavi-Nasab & Sotoudeh-Anvari, 2018)
24.		Specific Toughness	(Alper Sofuoğlu, 2019)
25.	Economic	Cost of material per Kg	(Mousavi-Nasab & Sotoudeh-Anvari, 2018),(Khorshidi & Hassani, 2013), (Qin et

			al., 2023), (Palanisamy et al., 2020) , (Karande et al., 2013)
26.		Cost of Disposal	(Kazemi et al., 2015)
27.		Recyclability	(ANSYS Inc., n.d.), (Zhang et al., 2020), (Ul Haq et al., 2023)
28.	Environment	Energy consumption	(Mesa et al., 2020), (Zhang et al., 2020), (Chandra et al., 2022)
29.		Carbon Footprint	(Mesa et al., 2020), (Zhang et al., 2017), (Ul Haq et al., 2023)
30.		Processing CO_2	(Mesa et al., 2020), (Zhang et al., 2017)
31.		Water Usage	(ANSYS Inc., n.d.), (Zhang et al., 2017)
32.		Toxic Level	(Ahmed Ali et al., 2015)

4.2 Experts Selection

As discussed earlier in Chapter 3, the experts were selected using the 12-points scale proposed by Hallowell & Gambatese (2010). According to this method, experts in panel must attain a minimum level of qualification by scoring points in different categories, as mentioned in Table. It is recommended that each expert earns at least one point in four different achievement or experience categories, with a cumulative minimum of 11 points to be eligible for participation. Following table 3 contains the point against each category and then checked the boxes for each expert, in the end total score has been calculated.

Table 3: Experts' selection points table

	Points	EXP 1	EXP 2	EXP 3	EXP 4	EXP 5	EXP 6
Professional Registration	3	Y	Y	Y	Y		
Year of Experience	1	Y	Y	Y	Y	Y	Y
Conference Presentation	0.5				Y	Y	
Member of a committee	1						
Chairperson of committee	3						
Peer-Reviewed Journal article	2	Y	Y	Y	Y	Y	
A faculty member at university	3		Y	Y		Y	Y
Author of the book	4						
Author of a book chapter	2					Y	
Advanced degrees							
BS	4	Y	Y	Y	Y	Y	Y
MS	2	Y	Y	Y	Y	Y	Y
Ph.D	4		Y	Y	Y	Y	Y
Total Points		12	19	19	19.5	18.5	14

4.3 Delphi Study

The Delphi method was applied to finalize the criteria, Delphi method is group decision making analytical technique commonly used in qualitative research. This method was first originated from the defence industry and based on the experts' judgments (Loo, 2002). This approach involves assembling a panel of experts who individually complete a survey or questionnaire. Their responses are then anonymized and shared with the panel to facilitate feedback and discussion. The experts are subsequently given the same questions again, and the process is repeated. This iterative process is designed to help the panel reach a consensus over time (Linstone & Turoff, 1975).

The number of experts recommendation is not clear in literature and there is a little consensus regarding the exact size of an expert panel (Keeney et al., 2001). The experts' size of Delphi panels in different research studies has varied from as few as three to as many as 80 members (Rowe & Wright, 1999).

The round in Delphi study varies and it is conducted in multiple rounds, and there are two main objectives first is to minimize variance and second is to improve the precision (Hallowell & Gambatese, 2010). According to different studies the number of rounds in Delphi study ranged from 2 to 6 (Linstone & Turoff, 1975; Naseem & Ahmad, 2020; Pill, 1971).

This study used 2 rounds of Delphi, in first round an open-ended questionnaire was disseminated between the experts and asked to verify the criteria extracted from the literature review and add any other related criteria based on the experts' experience. In second round, experts were again asked to give importance to the criteria on a 1-5 Likert Scale.

4.3.1 First Round:

In these round experts verified the criteria which were extracted from literature review relating to Performance, Economic and Environment. Some criteria that was not much important, having same meanings or redundant was removed. An updated list was prepared and sent to experts for the second round. Table 4 represents the list of sub-criteria through first round.

Table 4: List of criteria identified through first round of Delphi

Sr. No	Criteria Cluster	Sub-criteria	Frequency	Percentage
1.	Performance	Density	6	100%
2.		Melting Point	4	67%
3.		Specific heat	2	33%
4.		Operating Temperature	6	100%
5.		Tensile strength	6	100%
6.		Flexural Strength	5	83%
7.		Thermal Conductivity	2	33%
8.		Hardness	4	67%
9.		Electrical resistivity	2	33%
10.		Youngs modulus	6	100%
11.		Elongation	6	100%
12.		Layer adhesion	2	33%
13.		Visual quality	3	50%
14.		Coefficient of thermal expansion	4	67%

15.		Glass transition temperature	6	100%
16.		Specific gravity	2	33%
17.		Compressive strength	2	33%
18.		Fractural strength	4	67%
19.		Heat deflection temperature	4	67%
20.		Durability	6	100%
21.		Wear Resistance	6	100%
22.		Fire Resistance	4	67%
23.		Fatigue Strength	6	100%
24.		Specific Toughness	1	17%
25.	Economic	Cost of material per Kg	6	100%
26.		Cost of Disposal	3	50%
27.		Recyclability	6	100%
28.	Environment	Energy consumption	6	100%
29.		Carbon Footprint	6	100%
30.		Processing CO_2	6	100%
31.		Water Usage	5	83%
32.		Toxic Level	3	50%

4.3.2 Second Round

In the second round of the Delphi study, experts rated the importance of factors using a 5-point Likert scale, where 1 indicated "not at all important" and 5 indicated "very important." This rating was applied to the updated list of sub-criteria related to the three main criteria cluster derived from the first round. There is no universally agreed-upon cut-off point for consensus in Delphi studies; however, using the mean score as a threshold is a common practice (Choi & Sirakaya, 2006). For this study, an average score of 3.5 was set as the cut-off point (Naseem & Ahmad, 2020). Following this second round, 14 sub-criteria with mean scores of 3.5 or higher were selected for the further evaluation through AHP and TOPSIS approach and given in table 5.

Table 5: List of criteria identified through second round of Delphi

Criteria Cluster	Sub-Criteria	Mean
Performance	Density	3.83
	Operating Temperature	4.17
	Tensile strength	5.00
	Flexural Strength	3.50
	Youngs modulus	3.67
	Elongation at break	3.67
	Durability	4.33
	Fatigue Strength	4.83
Economic	Cost of material per Kg	3.83
	Recyclability	3.67

Environment	Energy consumption	3.50
	Carbon Footprint	4.83
	Processing CO2	4.67
	Water Usage	3.67

4.4 Criteria Weightage using the AHP Approach

The decision hierarchy is formed using the finalized criteria and sub-criteria, and then weights are computed using the AHP. The process includes the following steps:

Step i) The MCDM problem was decomposed into a 4-level decision hierarchy. The first level shows the overall goal of a problem; at the second level, three main criteria are kept, while the third and fourth levels consist of sub-criteria and alternatives (materials). In this study, experts identified three main criteria and associated 14 sub-criteria for an aerospace application.

Step ii) After the decision hierarchy was constructed, pairwise comparisons were made using Saaty scale rating value from 1 to 9 (Table 6) for each criterion about the goal and for each sub-criterion about the major criteria, using the (mxn) decision matrix.

Step iii) After developing the pairwise decision matrix, the sum of each column in the matrix was determined. The matrix was then normalized by dividing each element by the total sum of its respective column.

Step iv) To check the reliability and consistency of judgements, it is important to calculate the overall consistency ratio (CR). The CR value must be less than 0.10; if it is greater than 0.10, then the pairwise comparisons should be made again.

Table 6: 9-point scale for pairwise comparisons of criteria (Saaty, 2008)

Value	Description	Value Reciprocal
9	Extreme Importance	1/9
8	Very, very strong importance	1/8
7	Very strong importance	1/7
6	Strong plus	1/6
5	Strong importance	1/5
4	Moderate plus	1/4
3	Moderate importance	1/3
2	Weak or Slight Importance	1/2
1	Equal importance	-

4.5 Ranking using TOPSIS

Step 1: Through AHP criteria pairwise comparisons from experts, weights of all the 14 criteria are determined. A normalized matrix will be formed, which will be calculated further using the TOPSIS method. Therefore, each criterion will be standardized to the same unit scale by this normalization process. Below is equation (1) used to normalize the decision matrix containing the criteria values for each alternative (material) i, and each criterion j. In equation (1), the normalized value is shown by s_{ij}, g_{ij} is the original value of alternative i on criterion j, and p is the no. of alternatives (materials).

$$s_{ij} = \frac{g_i}{\sqrt{\sum_{j=1}^{p} (g_{ij})^2}} \quad j = 1,2,3,4 \dots, n \; ; \; i = 1,2,3,4, \dots, p \qquad (1)$$

Using equation (1), a normalized decision matrix (N) will be formed.

Step 2: Equation (2) will be used to calculate the weighted normalized decision matrix (WN), the criteria weights (w_j) obtained by AHP were multiplied the normalized decision matrix (N).

$$v_{ij} = s_{ij} \times w_j, \; j = 1, \dots, p, \; i = 1, \dots, m \tag{2}$$

Step 3: In this step the positive ideal solution (IS^{++}) and negative solution (IS^{--}) will be determined by using this equation:

Equation for positive ideal solution (IS^{++}) is:

$$\begin{aligned} IS^{++} &= \{v_1^+, v_2^+, v_3^+, \dots \dots \dots, v_n^+\} \\ &= \left\{\left(\max_i v_{ij}, j \in K\right)\left(\min_i v_{ij}, j \in K'\right)\right\} i = 1,2, \dots, m \end{aligned} \tag{3}$$

Where K is representing positive or benefit criteria while $K'$is non-beneficial or negative criteria.

Equation for positive ideal solution (IS^{--}) is:

$$IS^{--} = \{v_1^-, v_2^-, v_3^-, \dots \dots \dots, v_n^-\}$$

$$= \left\{\left(\min_i v_{ij}, j \in K\right)\left(\max_i v_{ij}, j \in K'\right)\right\} \; i = 1,2, \dots, m \tag{4}$$

Where K is representing positive or benefit criteria while $K'$is non-beneficial or negative criteria.

Step 4: In this step Euclidean distance of each alternative (material) from the positive ideal solution (D^{++}) and negative ideal solution (D^{--}) is computed using the formulas:

$$D_i^{++} = \sqrt[2]{\sum_{j=1}^{p}(v_{ij} - v_j^+)^2} \quad , i = 1, \dots, m \tag{5}$$

$$D_i^{--} = \sqrt[2]{\sum_{j=1}^{p}(v_{ij} - v_j^-)^2} \quad , i = 1, \dots, m \tag{6}$$

Step 5: The closeness from the ideal solution will be calculated using this equation:

$$Cl_i = \frac{D_i^{--}}{D_i^{++} + D_i^{--}}, i = 1, \dots, m \tag{7}$$

$$\text{If } Cl_i = 1 \rightarrow IS_i = \text{IS}^{++}$$
$$\text{If } Cl_i = 0 \rightarrow IS_i = \text{IS}^{--}$$

Here the Cl_i value varies between 0 and 1. If the Cl_i value is near or close to 1, alternative priority will be higher.

Step 6: In this step all alternatives will be ranked.

CHAPTER 5: RESULTS AND ANALYSIS

A case study was conducted based on the proposed methodology, and an aircraft part, "Inlet duct", was selected. The aerospace industry is required to manufacture a strong inlet duct for an engine-based UAV by AM and requires polymers as the building material. Nine materials were extracted as polymer materials from the literature review and based on the availability in the market. The aerospace industry also required that the material should give a good balance between performance and cost. Fatigue strength was important to maximize to withstand cyclic loading and ensure long-term durability. The goal was to select the best material from the set of materials using the given criteria. The materials and

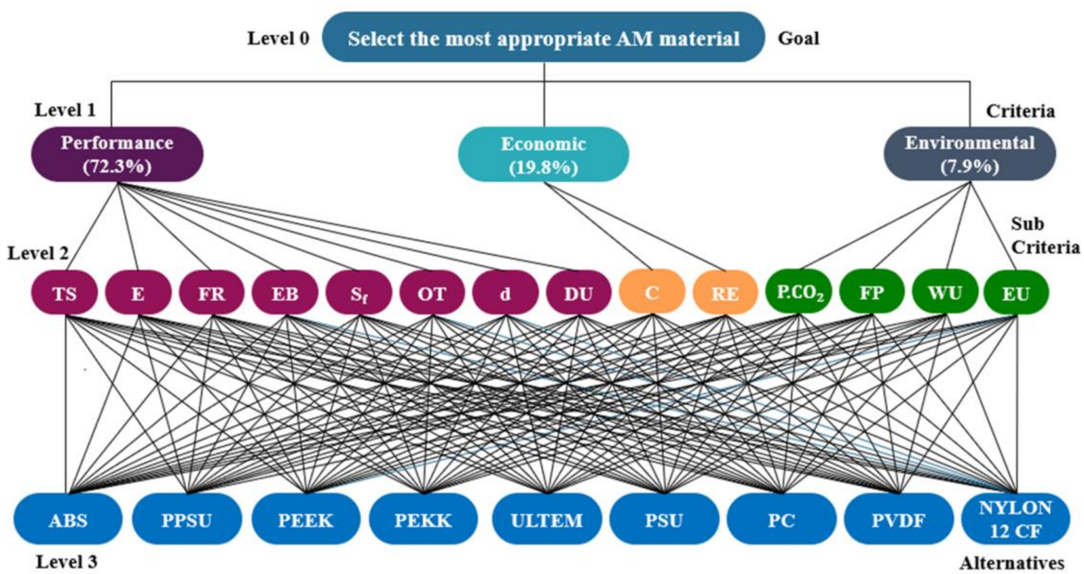

Figure 4: AHP Decision Hierarchy

criteria identified by literature, materials availability in the market and experts are given in Table 7. Materials with their properties are given in Table 8.

5.1 Results obtained by AHP

The AHP approach was used to obtain the expert criteria weights as mentioned above in chapter 3. AHP method was performed, and results were generated by using an AHP Online System (AHP-OS) software tool (Goepel, 2018). Final weights by pairwise comparisons are given in Table 4. It can be observed that experts assigned the highest priority to performance criteria and its sub-criteria. The overall weight of performance is 72.3%, the economy 19.8%, and the environment has less priority, which is 7.9%. Among sub-criteria, tensile strength (TS) has the highest weight, 18.3%; cost (C) criteria have the second highest weight, 16.8%; Young's modulus and fatigue strength have 13.9 % and 13.7% weights, respectively. Environment-related criteria have low weights than other sub-criteria. The CR value is 0.03, less than 0.1, so it is acceptable for this process. AHP decision hierarchy is given in Figure 4. Table 9 shows the weights given by experts.

Table 7: Selected criteria and alternatives

Selected AM Materials	ABS, PPSU, PEEK, PEKK, ULTEM, PSU, PC, PVDF, Nylon 12 CF	
	Need to Maximize (beneficial) 8	Need to Minimize (non-beneficial) 6
Criteria		
Performance (PE)	Tensile Strength (TS) Flexural Strength (FR) Elongation at Break (E@B) Young's Modulus (E) Fatigue Strength (Sf) Operating Temperature (OT) Durability (DU)	Density (d)
Economic (EC)	Recyclability (RE)	Cost (C)
Environmental (EV)	-	Processing CO2 (P. CO2) Carbon Footprint (FP) Water Use (WU) Energy Use (EU)

5.2 Results obtained by TOPSIS

Using equation (1), the decision matrix in Table 4 will be normalized according to step 1 of TOPSIS. In that way, a normalized matrix has been generated, as shown in Table 6. AHP criteria weights from Table 5 were used to multiply with the normalized matrix to form a weighted normalized matrix using equation (2), as shown in Table 9. Using the method previously described in TOPSIS, the positive and negative ideal solutions were separated using equations (3) and (4). based on the aim to maximize or minimize (Table

8). Euclidean distance using equation (5) and equation (6) of each material from the positive ideal solution (D^{++}) and negative ideal solution (D^{--}) was measured, and then the closeness (Cl_i) from the ideal solution was found using equation (7) that is equal to 1. The *Cl* value given in Table 9 will be close to 1 and will be ranked as the best alternative. Results show that the value of ULTEM materials is close to 1, and the second close value is 0.638, which is PEKK material. The order of ranking is ULTEM > PEKK > NYLON 12CF > PSU > PC > ABS > PVDF > PPSU >PEEK. Figure 3 illustrates the ranking of materials

Table 8: Decision Matrix (Properties of materials) (3DX, 2024; 3dxtech, 2024; ANSYS Inc., n.d.; Bourell et al., 2017; Jafferson & Chatterjee, 2021; Schiller, 2015; Tan et al., 2020)

Material (Alternatives)	TS (Mpa)	E (Mpa)	FR (Mpa)	EB (%)	Sf (Mpa) 10^7 Cycles	OT (°C)	d (g/cm3)	DU	C ($/kg)	RE	P. CO_2 (kg/kg)	FP (kg/kg)	WU (l/kg)	EU (Mj/kg)
ABS	40	2451	60	10	16	104	1.0	1	36	1	0.43	4	6.0	0.12
PPSU	70	2344	91	3	28	220	2.6	3	250	1	0.48	13	6.2	0.13
PEEK	107	3854	110	28	43	150	1.3	4	595	1	0.48	17	6.2	0.13
PEKK	98	4406	193	5	39	161	1.3	4	195	0	0.79	18	7.9	0.20
ULTEM	97	5929	152	3	39	216	1.3	4	220	1	0.48	11	6.2	0.13
PSU	99	2689	121	8	40	189	1.2	2	200	1	0.48	10	6.1	0.13
PC	63	2306	90	75	25	183	1.2	2	168	1	0.47	5	6.1	0.12
PVDF	51	2450	80	25	14	160	1.7	4	190	1	0.46	16	6.0	0.12
Nylon 12 CF	63	3800	90	2.1	59	158	1.2	2	174	0	0.47	27	6.0	0.12

Rating Scale for DU: Poor = 1, Fair = 2, Good = 3, Excellent = 4 (ANSYS Inc., n.d.)

Rating Scale for RE: Recyclable = 1, Not Recyclable = 0

Table 9: Criteria weights obtained by AHP

Criteria	TS	E	FR	EB	Sf	OT	d	DU	C	RE	P.CO2	FP	WU	EU
Weights	0.18	0.14	0.08	0.05	0.14	0.04	0.05	0.05	0.17	0.03	0.02	0.02	0.02	0.02

Table 10: Normalized Matrix in TOPSIS

	TS	E	FR	EB	S_f	OT	d	DU	C	RE	P. CO_2	FP	WU	EU
ABS	0.167	0.230	0.172	0.117	0.147	0.199	0.233	0.108	0.045	0.378	0.282	0.083	0.317	0.300
PPSU	0.291	0.220	0.262	0.035	0.258	0.420	0.577	0.323	0.313	0.378	0.311	0.286	0.325	0.315
PEEK	0.448	0.361	0.316	0.329	0.395	0.287	0.292	0.431	0.744	0.378	0.311	0.376	0.325	0.315
PEKK	0.408	0.413	0.554	0.059	0.358	0.308	0.294	0.431	0.244	0.000	0.513	0.399	0.417	0.487
ULTEM	0.404	0.556	0.435	0.035	0.358	0.413	0.285	0.431	0.275	0.378	0.314	0.251	0.326	0.318
PSU	0.415	0.252	0.347	0.094	0.368	0.361	0.278	0.216	0.250	0.378	0.309	0.229	0.324	0.313
PC	0.264	0.216	0.257	0.881	0.234	0.349	0.258	0.216	0.210	0.378	0.302	0.107	0.321	0.305
PVDF	0.213	0.230	0.229	0.294	0.129	0.306	0.384	0.431	0.238	0.378	0.296	0.360	0.317	0.298
Nylon 12 CF	0.263	0.356	0.258	0.025	0.540	0.302	0.263	0.216	0.218	0.000	0.303	0.596	0.317	0.305

Table 11: Weighted normalized matrix

	TS	E	FR	EB	S_f	OT	d	DU	C	RE	P. CO_2	FP	WU	EU
ABS	0.0305	0.0318	0.0145	0.0054	0.0201	0.0073	0.0108	0.0056	0.0075	0.0124	0.0060	0.0021	0.0049	0.0052
PPSU	0.0532	0.0305	0.0221	0.0016	0.0353	0.0154	0.0268	0.0167	0.0518	0.0124	0.0066	0.0071	0.0050	0.0054
PEEK	0.0819	0.0501	0.0267	0.0152	0.0540	0.0105	0.0135	0.0222	0.1232	0.0124	0.0066	0.0093	0.0050	0.0054
PEKK	0.0745	0.0572	0.0467	0.0027	0.0490	0.0113	0.0136	0.0222	0.0404	0.0000	0.0109	0.0099	0.0064	0.0084
ULTEM	0.0737	0.0770	0.0367	0.0016	0.0490	0.0151	0.0132	0.0222	0.0455	0.0124	0.0067	0.0062	0.0050	0.0055
PSU	0.0758	0.0349	0.0293	0.0043	0.0503	0.0133	0.0129	0.0111	0.0414	0.0124	0.0066	0.0057	0.0050	0.0054
PC	0.0482	0.0300	0.0217	0.0407	0.0319	0.0128	0.0120	0.0111	0.0348	0.0124	0.0064	0.0027	0.0049	0.0053
PVDF	0.0389	0.0318	0.0194	0.0136	0.0176	0.0112	0.0178	0.0222	0.0393	0.0124	0.0063	0.0089	0.0049	0.0051
Nylon 12 CF	0.0481	0.0494	0.0218	0.0011	0.0738	0.0111	0.0122	0.0111	0.0360	0.0000	0.0064	0.0148	0.0049	0.0053

Table 12: Positive ideal solution and negative ideal solution

	TS	E	FR	EB	S_f	OT	d	DU	C	RE	P. CO_2	FP	WU	EU
$(\boldsymbol{IS}^{++})$	0.0819	0.0770	0.0467	0.0407	0.0738	0.0154	0.0108	0.0222	0.0075	0.0124	0.0060	0.0021	0.0049	0.0051
$(\boldsymbol{IS}^{--})$	0.0305	0.0300	0.0145	0.0011	0.0176	0.0073	0.0268	0.0056	0.1232	0.0000	0.0109	0.0148	0.0064	0.0084

Table 13: Euclidean distance of each alternative (material) from the positive ideal solution ($\boldsymbol{D}^{++}$) and negative ideal solution ($\boldsymbol{D}^{--}$) and closeness ($\boldsymbol{Cl_i}$) from ideal solution

Materials	$\boldsymbol{D}^{++}$	$\boldsymbol{D}^{--}$	$\boldsymbol{Cl}$
ABS	0.101	0.118	0.540
PPSU	0.094	0.080	0.460
PEEK	0.125	0.073	0.370
PEKK	0.062	0.110	0.638
ULTEM	0.062	0.111	0.644
PSU	0.073	0.103	0.586
PC	0.081	0.103	0.558
PVDF	0.098	0.089	0.474
Nylon 12 CF	0.073	0.109	0.597

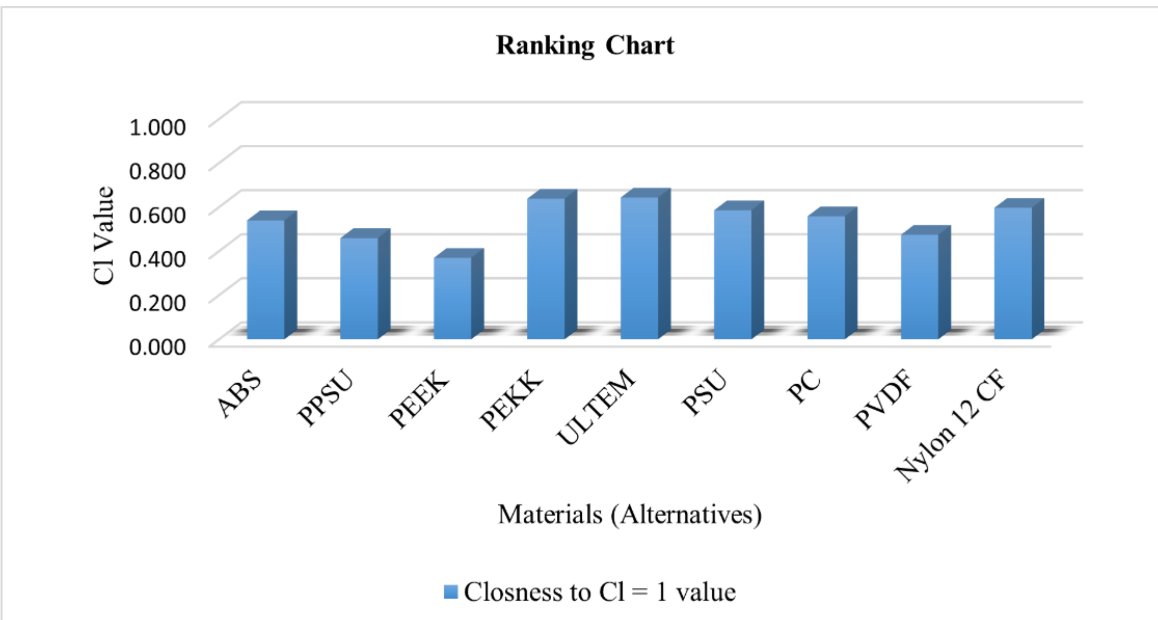

Figure 5: Materials ranking obtained from AHP-TOPSIS approach

5.3 Sensitivity Analysis

To check the robustness of the methodology, sensitivity analysis was performed to check how much the proposed model is sensitive to any weight change in selected criteria. When solving problems using the MCDM methods, sensitivity analysis is important to understand the impact of varying weights on the final ranking of alternatives. In MCDM cases, input data may be incorrect, or erroneous judgments may be made during the decision; in that case, the people responsible for decision-making are keen to know how the outputs will change by altering the input data. So, in this case, sensitivity analysis becomes an effective method to check the stability of the results (Li et al., 2013). In this study, a similar method was used, as proposed by (Li et al., 2013).

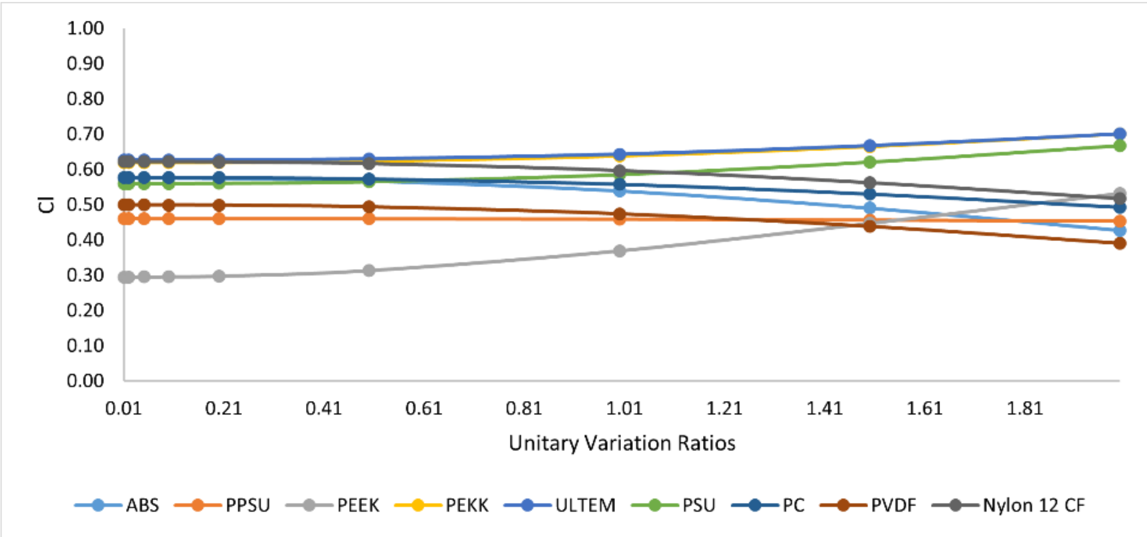

Figure 6: Sensitivity Analysis for AM materials [Closeness (Cl) values by applying nine unitary variation ratio]

Nine designed unitary variation ratios (Table 14) were applied to criteria weights, and all 14 weights for nine selected alternatives were recalculated. A total of nine sensitivity tests were performed. The results show that there was no significant ranking change observed in alternatives, but the PEEK material was sensitive to the imposed recalculated weight at the value of 1.5. ULTEM material, originally ranked one from all other materials, remained unchanged, but at the test value of 2.00, its rank changed from first to second. In most tests, alternative rankings were the same and unchanged. Figure 6 and 7 shows the results of sensitivity analysis on nine materials.

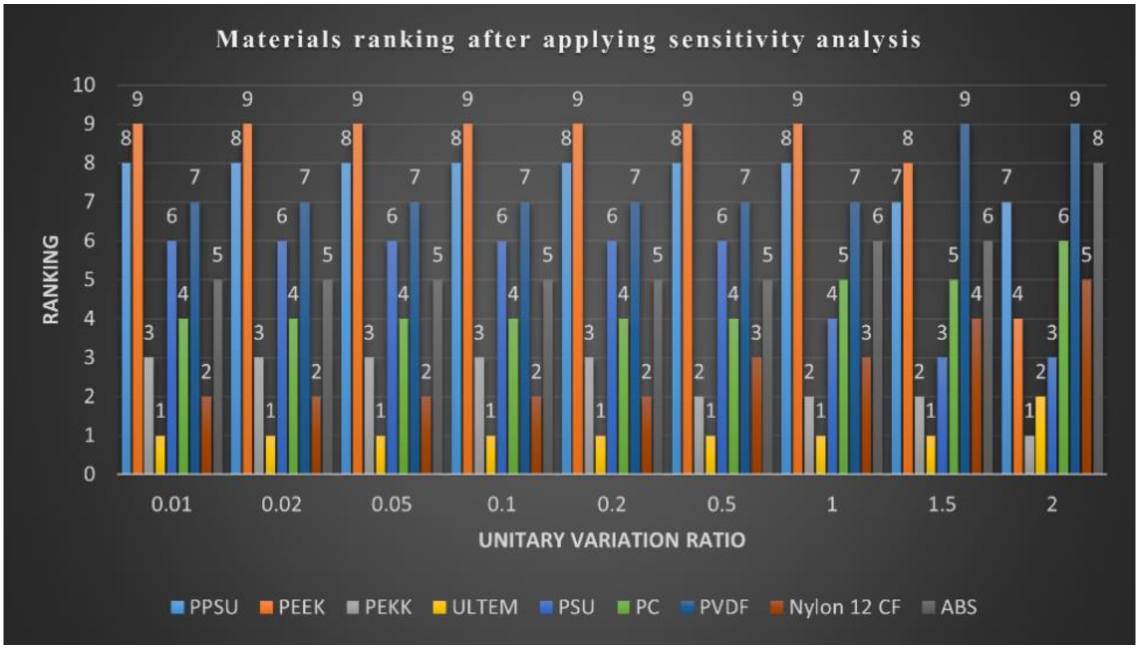

Figure 7: Rankings after applying sensitivity analysis

Table 14: Criteria weights after changing at different unitary values

Unitary ratios	TS	E	FR	EB	S_f	OT	d	DU	C	RE	P. CO_2	FP	WU	EU
0.01	0.002	0.169	0.103	0.056	0.167	0.045	0.057	0.063	0.202	0.040	0.026	0.030	0.019	0.021
0.02	0.004	0.169	0.103	0.056	0.167	0.045	0.057	0.063	0.202	0.040	0.026	0.030	0.019	0.021
0.05	0.009	0.168	0.102	0.056	0.166	0.044	0.056	0.062	0.201	0.040	0.026	0.030	0.019	0.021
0.1	0.018	0.167	0.101	0.056	0.164	0.044	0.056	0.062	0.199	0.039	0.026	0.030	0.018	0.021
0.2	0.037	0.163	0.099	0.054	0.161	0.043	0.055	0.061	0.195	0.039	0.025	0.029	0.018	0.020
0.5	0.091	0.154	0.094	0.051	0.152	0.041	0.052	0.057	0.184	0.036	0.024	0.028	0.017	0.019
1	0.183	0.139	0.084	0.046	0.137	0.037	0.046	0.051	0.165	0.033	0.021	0.025	0.015	0.017
1.5	0.274	0.123	0.075	0.041	0.121	0.033	0.041	0.046	0.147	0.029	0.019	0.022	0.014	0.015
2	0.365	0.108	0.066	0.036	0.106	0.028	0.036	0.040	0.128	0.025	0.017	0.019	0.012	0.013

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

A robust decision methodology was proposed in this research for the appropriate materials selection in additive manufacturing for the aerospace industry. This research employed multi-criteria decision-making (MCDM) approaches, combining Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for effective criteria weighting through subject matter experts (SMEs) and then ranking of materials by using the realistic data (material properties, cost, etc.).

An aerospace industrial case study was analyzed in this research by using the proposed methodology. Materials selection for UAV inlet duct using additive manufacturing technology fused deposition modelling (FDM) using nine polymer materials was carried out. Critical criteria for the application were identified and relative importance was given to each criterion by pairwise comparisons in AHP carried out by SMEs. The AHP results indicates that tensile strength with 18.3% weightage is most critical criterion for selected UAV part. This was followed by cost at 16.5%, young's modulus at 13.9% and fatigue strength at 13.7%. These criteria weights were then used in TOPSIS method with the real time data of materials to rank the materials. TOPSIS results shows that the appropriate material for the part is ULTEM from the list of nine alternatives.

At the end to check the robustness of method, sensitivity analysis was performed, and 9 variation ratios were applied to original weights, ratios modified the original weights and produced new weights which were then applied to check the new ranking of materials. The ULTEM ranking remained stable up to variation ratio 2 then this material changed its ranked from 1 to 2.

The findings of this study offer significant contributions to both academia and industry. In academia setting it opens new avenues for the research in the field of additive manufacturing by employing the MCDM approaches to enhance the potential of AM. In industry setting, this methodology provides a reliable and systematic approach for materials selection to decision makers and professionals in aerospace sector. High-performance aerospace parts by considering all critical criteria including environmental factors can be produced by using this method.

Other MCDM methods could be explored in future research work for the further improvement of this methodology. In this study materials selection was carried out for FDM process and future research may extend this study by employing other AM technology to obtain the more detailed insights of the material selection problem. There are 9 polymer materials which were taken as alternative for UAV duct, future studies can also take broader range of materials and evaluate them.

Furthermore, additional sustainability criteria (social, environment and economic) could also integrate in this methodology for the holistic assessment of materials selection problem, this would also help to align with rising emphasis on eco-friendly manufacturing practices.

Development of an automated database containing all aerospace materials compatible with AM is recommended in future work. This database would help decision makers or designers to pick right materials from easily accessible repository according to their requirements. This type of tool would also increase efficiency and accuracy when combined with MCDM methods.

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APPENDIXES

Appendix “A”

AHP Judgement Form:

Evaluation of Criteria for Choose Appropriate Material

Pairwise Comparison Performance

28 pairwise comparison(s). Please do the pairwise comparison of all criteria. When completed, click *Check Consistency* to get the priorities.

AHP Scale: 1- Equal Importance, 3- Moderate importance, 5- Strong importance, 7- Very strong importance, 9- Extreme importance (2,4,6,8 values in-between).

With respect to *Performance*, which criterion is more important, and how much more on a scale 1 to 9?

	A - wrt Performance - or B?		Equal	How much more?
1	◉ Tensile Strength	○ Youngs Modulus	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
2	◉ Tensile Strength	○ Flexural Strength	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
3	◉ Tensile Strength	○ Elongation @Break	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
4	◉ Tensile Strength	○ Fatigue Strength	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
5	◉ Tensile Strength	○ Operating Temperature	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
6	◉ Tensile Strength	○ Density	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
7	◉ Tensile Strength	○ Durability	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
8	◉ Youngs Modulus	○ Flexural Strength	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9
9	◉ Youngs Modulus	○ Elongation @Break	◉ 1	○2 ○3 ○4 ○5 ○6 ○7 ○8 ○9