

Research Article

Multi Objective Evolutionary Optimization of Additive Manufacturing Process Parameters for Enhanced Mechanical Performance and Surface Integrity

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Abstract: Introduction: Additive Manufacturing (AM) has revolutionized the production of complex geometries, offering flexibility, customization, and precision across various industries. However, optimizing multiple process parameters simultaneously to enhance AM performance remains a significant challenge. This study focuses on improving both mechanical properties and surface quality by utilizing multi-objective optimization techniques. **Literature Review:** The research reviews existing approaches in AM optimization, highlighting the limitations of single-objective optimization and the potential of multi-objective evolutionary algorithms (MOEAs). Previous studies demonstrate the difficulty of balancing competing objectives, such as tensile strength and surface roughness, within AM processes. **Materials and Method:** This study employs NSGA-II, MOEA/D, and SPEA2 algorithms to optimize AM parameters like layer thickness, build orientation, and infill density. The optimization aims to improve mechanical performance, including tensile strength and impact resistance, while reducing build time and surface roughness. The methodology integrates experimental validation with computational predictions to evaluate the effectiveness of these algorithms. **Results and Discussion:** The optimization process yielded Pareto-optimal solutions that balanced mechanical strength and surface quality. The results demonstrated improvements in tensile strength and surface finish without significantly increasing build time. Trade-off analysis highlighted the inherent conflicts between mechanical performance and surface quality, allowing for better decision-making in industrial applications. The study contributes to the AM industry by offering a comprehensive optimization framework for improving both efficiency and product quality.

Keywords: Additive Manufacturing; Evolutionary Algorithms; Mechanical Properties; Process Optimization; Surface Quality.

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1. Introduction

Additive manufacturing (AM), commonly known as 3D printing, has evolved significantly over the past few decades. Initially developed in the 1980s, AM technologies were primarily used for rapid prototyping. However, over the years, they have advanced to sophisticated methods capable of producing complex, customized products across various industries (Nieto et al., 2023; Verma et al., 2022). The expiration of original patents in the early 2000s spurred a surge in innovation, leading to a variety of new companies entering the market (Mobarak et al., 2023). Moreover, continuous advancements in materials and machine

capabilities have expanded the scope and applications of AM technologies (Bănică et al., 2024).

AM technologies are now widely used across multiple industries due to their flexibility, efficiency, and ability to create intricate designs. In the aerospace industry, AM is used to fabricate lightweight structural components, turbine blades, and fuel nozzles, which significantly reduce production costs and lead times (Kabbe et al., 2024). In the medical field, innovations such as bioprinting and the production of personalized implants and surgical tools have revolutionized healthcare (Mobarak et al., 2023; Olaniyi & Chromjakova, 2024). Additionally, AM has transformed the automotive industry by enabling the production of customized automotive components (Srivastava et al., 2021). In energy systems, AM contributes to the creation of complex parts that optimize system performance and efficiency (Pérez et al., 2020). AM also plays a crucial role in the consumer goods sector, enabling mass customization of products (Verma et al., 2022).

The significance of AM technologies in various industries is highlighted by several key benefits. First, AM offers exceptional design flexibility, allowing for the creation of complex geometries that traditional manufacturing processes cannot achieve (Pérez et al., 2020). It also enables mass customization, which allows for tailored products to meet specific customer needs (Gobena & Woldeyohannes, 2024). Another significant advantage is waste reduction; by adding material layer by layer, AM minimizes waste compared to subtractive manufacturing techniques (Bănică et al., 2024). Furthermore, AM accelerates the prototyping process, which reduces development time and costs (Shah et al., 2019). Lastly, AM can lower production costs by reducing material usage and simplifying the manufacturing process (Pérez et al., 2020).

Looking to the future, emerging trends in AM technologies promise to expand their capabilities even further. Innovations such as 4D printing, which introduces dynamic changes over time, and bioprinting for medical applications, are on the horizon (Gobena & Woldeyohannes, 2024). Additionally, the integration of artificial intelligence (AI) and real time monitoring systems will further enhance the efficiency and capabilities of AM processes (Bănică et al., 2024). As Industry 4.0 advances, AM is poised to play a crucial role in transforming manufacturing and production chains (Praveena et al., 2024).

Additive manufacturing (AM) has revolutionized the production of complex geometries and customized components, enabling advancements across various industries. However, optimizing AM process parameters to ensure both mechanical quality and surface integrity remains a significant challenge. These technologies involve intricate interactions between parameters like laser power, scan speed, layer thickness, and orientation angle, which directly affect the mechanical properties and surface quality of the final product (Mengesha et al., 2024). For example, in Laser Powder Bed Fusion (L-PBF), the combination of laser power and scanning speed plays a crucial role in determining geometric accuracy and porosity, while in Fused Deposition Modeling (FDM), layer thickness and temperature affect mechanical properties (Gupta et al., 2024). Understanding and optimizing these complex relationships is essential for achieving optimal AM outcomes.

Achieving consistent quality in AM parts is another significant hurdle due to the variability inherent in the process parameters. Small deviations in settings can result in notable differences in mechanical strength and surface finish, complicating the optimization process (Gómez-Gras & Pérez, 2024). The challenge lies in balancing multiple objectives such as minimizing surface roughness while maximizing mechanical strength which often involves computationally intensive multi objective optimization techniques (Raju et al., 2022). This process requires sophisticated algorithms that can handle such complexity and provide effective solutions to achieve desired outcomes in AM components.

Surface integrity is a major concern in AM, as parts often exhibit poor surface quality, including roughness, residual stress, and porosity. These issues can significantly affect the part's functional performance and longevity (Gavcar & Sagbas, 2023). While post processing techniques like laser polishing and chemical treatments can improve surface integrity, they increase production time and cost (Gómez-Gras & Pérez, 2024). Therefore, optimizing the AM process parameters to improve as built surface quality is crucial for reducing reliance on post processing, ultimately saving time and costs while ensuring high quality products (Guimarães et al., 2024).

Material specific challenges further complicate parameter optimization in AM. Different materials, such as metals, polymers, and composites, require distinct optimization strategies. For instance, optimizing parameters for metal AM processes like L-PBF involves managing

thermal stresses and material deformation, which are less of a concern in polymer based processes like FDM (Raju et al., 2022). The mechanical properties of materials such as PLA and ABS in FDM are highly sensitive to parameters like infill density and layer height (Kumar et al., 2023). Hence, effective optimization strategies must be tailored to the specific characteristics of the material being used, making it a challenging but necessary step in AM processes (Mengesha et al., 2024).

Single objective optimization (SOO) methods have been widely employed in various engineering and economic applications. These methods are designed to optimize a single objective function, typically under the assumption that the problem is well defined and solvable within the constraints of the objective. However, when applied to additive manufacturing (AM), SOO methods face several limitations that make them less effective in solving the complex challenges inherent in AM process optimization. One key limitation is the reliance on the assumption of convexity in the objective function, which simplifies the optimization problem but is rarely applicable in practical AM scenarios. Non convex problems, such as those encountered in optimizing parameters for AM processes like laser power and scan speed in Laser Powder Bed Fusion (L-PBF), often lead to multiple local minima, making it difficult for SOO methods to identify the global optimum (Pardalos et al., 2017).

Another challenge with SOO is the attempt to reduce multi objective optimization problems into single objective ones through scalarization techniques. Scalarization, which combines multiple objectives into one, often oversimplifies the problem and fails to capture the complexity of trade offs between conflicting objectives, such as surface roughness and mechanical strength. This reductionist approach can result in solutions that are not representative of the true Pareto front, leading to suboptimal outcomes (Santiago et al., 2014). As a result, SOO methods struggle to provide an accurate depiction of the trade offs and complexities inherent in multi objective AM process optimization.

Furthermore, incorporating multiple criteria into SOO is inherently difficult. Techniques like desirability functions and weighted sum approaches, which attempt to transform multi objective problems into single objective ones, often face issues with high dimensional data and uncertainty. These methods are especially problematic in AM processes, where various parameters such as layer thickness, printing speed, and material properties need to be optimized simultaneously. The failure to account for the interactions between these parameters can lead to inefficient solutions that do not fully address the needs of AM systems (Leirimo & Martinsen, 2019). This limitation highlights the need for more robust optimization methods that can handle multiple, often conflicting, objectives in AM.

Finally, SOO methods are less applicable in scenarios where multiple conflicting objectives must be optimized at the same time, such as in complex engineering and manufacturing processes. In AM, the challenge is not just to optimize for a single factor like strength, but to balance multiple objectives such as surface finish, mechanical performance, build time, and material usage. SOO methods are not designed to handle these kinds of trade offs effectively, especially when the objectives are highly interdependent. This is particularly evident in AM, where trade offs between parameters like surface roughness and mechanical strength are critical to ensuring the final product meets quality and performance standards (Heddar et al., 2024). Therefore, SOO methods fall short in addressing the complex, multi faceted nature of AM optimization tasks.

Additive Manufacturing (AM) has fundamentally transformed the manufacturing industry by enabling the creation of complex geometries and customized components with high precision. Unlike traditional subtractive manufacturing, AM allows for the direct fabrication of parts from digital models, offering significant flexibility in product design, material use, and production speed. However, optimizing the various process parameters to improve both mechanical properties and geometrical accuracy remains a substantial challenge in AM (Barik et al., 2024; Gupta et al., 2024). This study focuses on addressing these challenges by systematically optimizing multiple process parameters to enhance both the mechanical performance and surface quality of AM produced components.

The primary aim of this study is to optimize several process parameters in AM to achieve improved mechanical properties and reduced build times. Specifically, the study intends to minimize build time while maintaining or improving critical mechanical properties, such as tensile strength, flexural strength, and surface roughness (El Azzouzi et al., 2024). Additionally, it seeks to enhance mechanical properties, including tensile strength, compressive strength, and impact strength, through the optimization of AM parameters (Dey

et al., 2020). Another important objective is to improve surface quality and dimensional accuracy by identifying the optimal combinations of process parameters for different AM techniques (Prabhakaran et al., 2024).

To achieve these objectives, the study focuses on several research questions that explore the relationships between AM process parameters and their impact on mechanical and geometrical properties. Key parameters such as layer thickness, build orientation, and extrusion temperature are known to influence mechanical properties and build time (Gupta et al., 2024). Furthermore, multi objective optimization techniques such as Non Dominated Sorting Genetic Algorithm II (NSGA-II), Grey Wolf Optimization (GWO), and Artificial Neural Networks combined with Pattern Search Algorithm (ANN+PSA) will be explored to determine how the best trade offs between conflicting objectives like build time and mechanical strength can be achieved (Yodo & Dey, 2022). Through these investigations, the study aims to identify the optimal parameter combinations for various AM techniques, such as Fused Deposition Modeling (FDM) and Selective Laser Melting (SLM), to achieve superior mechanical properties and surface quality (Barik et al., 2024; Sakib et al., 2024).

2. Literature Review

Additive Manufacturing Process Fundamentals

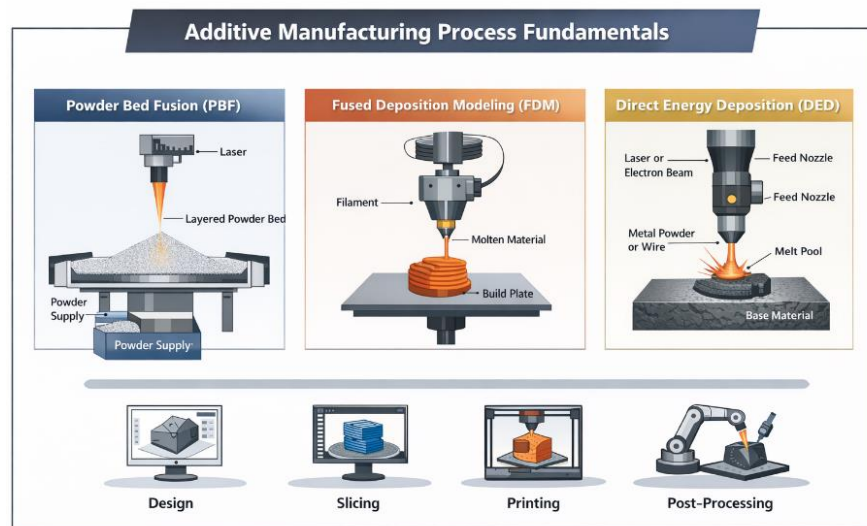


Figure 1. Additive Manufacturing Process Fundamentals.

Additive Manufacturing (AM), commonly known as 3D printing, has revolutionized the manufacturing sector by enabling the production of complex geometries and customized designs. Unlike traditional manufacturing methods, which subtract material from a larger block, AM builds objects layer by layer from digital models. This approach allows for the creation of intricate and customized components that would otherwise be difficult or impossible to manufacture using conventional techniques (Singh et al., 2023).

Basics of AM Technologies

Additive Manufacturing (AM) encompasses several key technologies that have significantly advanced manufacturing capabilities. Powder Bed Fusion (PBF) is a widely used method that employs a laser or electron beam to selectively fuse powder particles layer by layer, enabling the production of highly precise and complex metal parts. Direct Energy Deposition (DED), on the other hand, involves melting and depositing material in real time, making it ideal for adding material to existing parts, commonly used in repair and modification applications. Vat Photopolymerization (VPP) uses light to cure photopolymer resins, offering exceptional precision and surface finish, making it suitable for industries that demand fine details and high quality outputs. Lastly, Material Extrusion, including Fused Deposition Modeling (FDM), involves extruding material through a nozzle to build parts layer by layer, and is one of the most widely used AM technologies due to its versatility and cost

effectiveness (Singh et al., 2023). These technologies collectively contribute to the growing potential of AM in diverse industries.

Factors Affecting Mechanical Performance

The mechanical performance of additive manufacturing (AM) parts is influenced by several key factors, including material properties, process parameters, and post processing techniques. The microstructure of materials, such as 316L, Ti6Al4V, and Alloy 718, plays a critical role in determining mechanical properties like tensile strength, hardness, and ductility, which directly impact the part's performance, especially in processes like Powder Bed Fusion (PBF) and Direct Energy Deposition (DED) (Azami et al., 2023). Additionally, process parameters such as laser power, scan speed, layer thickness, and part orientation significantly affect the mechanical properties and surface quality of the final product, and must be optimized to achieve the desired results (Singh et al., 2023). Finally, post processing techniques, including heat treatment, machining, and polishing, are essential for enhancing the mechanical properties and surface integrity of AM parts by reducing defects like porosity and improving fatigue resistance (Malakizadi et al., 2022).

Surface Integrity in AM

Surface integrity is a crucial factor in determining the functional performance of additive manufacturing (AM) parts, especially in load bearing applications. AM parts often exhibit initial surface roughness due to the layer by layer construction process, which can create stress concentrators that reduce fatigue life. Therefore, addressing surface roughness is essential for improving the durability and performance of AM components (Malakizadi et al., 2022; Varghese & Mujumdar, 2021). Post processing techniques such as laser polishing, burnishing, and machining are commonly employed to enhance surface quality, effectively reducing roughness and improving wear and corrosion resistance, which contributes to the longevity of the parts (Azami et al., 2023). Additionally, the interaction between machining parameters and inherent part porosity significantly impacts the surface characteristics during post processing, making the optimization of cutting mechanisms essential for improving surface finish and minimizing defects (Varghese & Mujumdar, 2021).

Optimization and Future Trends

The optimization of AM processes involves selecting the appropriate process parameters and post processing techniques to achieve the desired mechanical properties and surface quality. Future research is focused on developing efficient and low cost production strategies that address the material behavior during AM and the challenges in post processing. In particular, integrating advanced computational methods, such as machine learning and artificial intelligence, promises to enhance optimization capabilities, making AM more accessible and applicable in various industries (Malakizadi et al., 2022; Singh et al., 2023).

Mechanical Property Evaluation Methods

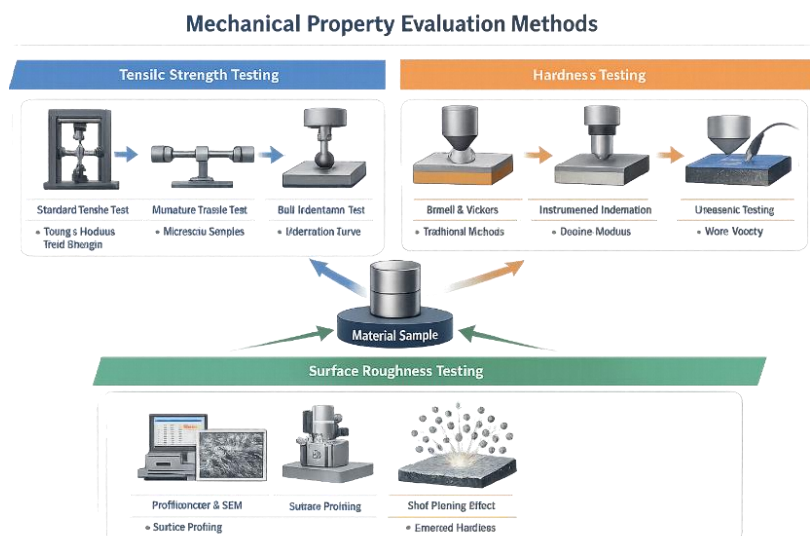


Figure 2. Mechanical Property Evaluation Methods.

Tensile Strength Evaluation

Tensile strength evaluation is a critical method used to measure the ability of a material to withstand tension before breaking. The most widely used method for tensile strength evaluation is standard tensile testing, which involves pulling a material sample to determine properties such as Young's modulus, yield strength, ultimate tensile strength, and ductility (Gdoutos & Konsta-Gdoutos, 2024). This test provides essential information for material selection and development, particularly in engineering applications where materials must be chosen based on their ability to resist tensile forces under various loading conditions.

In cases where material availability is limited or small samples are required, miniaturized specimen testing methods such as micro tensile tests are used. These methods offer reliable tensile data while reducing material waste (Chvostová & Mertová, 2018). Miniaturized testing has become crucial for small scale applications, particularly in areas like microelectronics and biomedical devices. Additionally, ball indentation testing, a non destructive technique, provides an alternative for evaluating tensile properties in localized sections of a material, allowing for the assessment of stress strain relationships in both lab and field conditions (Mathew et al., 2016).

Hardness Evaluation

Hardness evaluation is essential for determining a material's resistance to deformation and wear. Traditional hardness tests, such as Brinell, Vickers, and Rockwell, involve pressing a hardened ball or diamond into the surface of the material to measure the depth or size of the indentation (Yanikoglu & Sakarya, 2020). These methods are commonly used across various industries to assess the durability and strength of materials, especially when materials are subjected to harsh operating conditions.

Instrumented indentation testing (IIT) has become an advanced alternative to traditional hardness tests. IIT not only measures hardness but also provides additional mechanical property data, such as Young's modulus (Mathew et al., 2016). This technique is ideal for small scale specimens and field applications where traditional methods might not be feasible. Furthermore, ultrasonic testing, which measures wave velocity through materials, has emerged as a non destructive method for evaluating hardness and tensile strength, providing insights into the material's internal structure without causing any damage (Men et al., 2020).

Surface Roughness Evaluation

Surface roughness is a crucial factor in the mechanical performance of materials, especially in load bearing applications where the surface texture can significantly impact fatigue life. Profilometers, scanning electron microscopes (SEM), and atomic force microscopes (AFM) are commonly used to measure surface roughness. These tools provide high resolution measurements of surface texture and irregularities, which are essential for assessing how surface features affect material behavior, especially in terms of wear and corrosion resistance (Yanikoglu & Sakarya, 2020).

Post processing techniques, such as severe shot peening (SSP), can also influence surface roughness by enhancing surface hardness and improving fatigue resistance. Although SSP can increase surface roughness initially, it improves material strength by introducing compressive residual stresses that enhance the overall fatigue life of the material (Hietala et al., 2024). These surface treatments are often used in conjunction with other methods to optimize the performance of materials in demanding applications, balancing the trade off between surface finish and mechanical strength.

Innovative Methods

Innovative testing methods, such as small specimen testing techniques, have been developed to evaluate mechanical properties with minimal material usage. Methods like small punch creep (SPC) and impression creep (IC) focus on evaluating material behavior under stress and temperature variations, which is particularly useful when only small samples are available (Mathew et al., 2016). These methods allow researchers to gather critical data on creep deformation and other mechanical properties without the need for large material quantities, making them ideal for resource constrained applications.

Another innovative approach involves customized tests for brittle materials, such as the C-sphere and sector flexural tests, which are designed to assess tensile strength in brittle materials that are prone to fracture under traditional testing methods (Wereszczak, 2016).

These specialized methods are crucial for evaluating materials used in structural applications, where traditional tensile tests may not provide accurate data due to material brittleness. The development of these innovative methods enhances the versatility of mechanical property evaluation, especially for materials that are difficult to test using conventional techniques.

Overview of Multi Objective Evolutionary Algorithms (MOEAs) for Additive Manufacturing (AM) Optimization

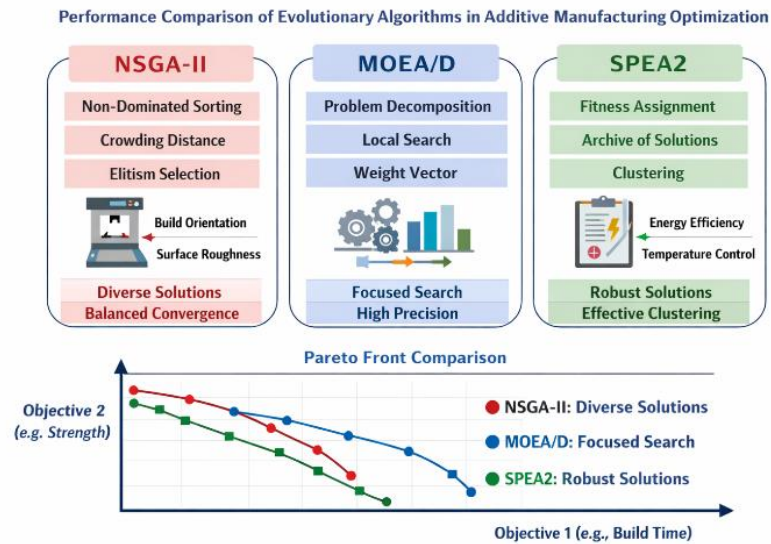


Figure 3. Evolutionary Algorithms (NSGA-II, MOEA/D, SPEA2).

Additive Manufacturing (AM) processes often involve complex optimization problems with multiple, conflicting objectives. For instance, optimizing AM parameters such as build orientation, material choice, and process parameters requires balancing objectives such as build time, surface quality, and mechanical performance. Multi Objective Evolutionary Algorithms (MOEAs) have become a popular approach for solving such problems due to their ability to generate diverse solutions and efficiently explore large, multi dimensional search spaces (Doush & Bataineh, 2015). Three prominent MOEAs NSGA-II, MOEA/D, and SPEA2 have been widely applied in AM optimization, each offering unique strengths and applications.

NSGA-II (Non-dominated Sorting Genetic Algorithm II)

NSGA-II is one of the most commonly used MOEAs, known for its efficient non dominated sorting approach, elitism, and crowding distance mechanism, which helps maintain diversity in the population (Franca et al., 2017). It excels in solving multi objective optimization problems by maintaining a balance between convergence to the Pareto front and diversity of solutions, making it highly effective for problems with conflicting objectives.

NSGA-II has been widely applied in optimizing AM process parameters, especially for improving build orientation to minimize build time and surface roughness. In Fused Deposition Modeling (FDM), NSGA-II has also been used to optimize dimensional and geometric accuracy by adjusting parameters such as layer thickness and print speed (Khodaygan & Golmohammadi, 2018). Its ability to balance multiple objectives, such as improving mechanical properties while reducing costs and time, makes NSGA-II a valuable tool in AM process optimization.

MOEA/D (Multi Objective Evolutionary Algorithm based on Decomposition)

MOEA/D operates by decomposing a multi objective optimization problem into several single objective sub problems, which are solved simultaneously. This approach integrates local search techniques, allowing for a more efficient exploration of the search space (Zheng et al., 2019). The decomposition strategy makes MOEA/D particularly effective in optimizing problems where local search can significantly improve solution quality, especially in large scale optimization scenarios.

MOEA/D has been successfully applied in optimizing parameters in AM processes, where its ability to break down complex objectives into simpler sub problems has been beneficial (Asadollahi-Yazdi et al., 2018). It has been used to optimize the part build orientation (PBO) in AM, balancing objectives such as minimizing porosity and maximizing mechanical strength (Zheng et al., 2019). The integration of MOEA/D with local search techniques has proven particularly effective in optimizing product quality and reducing energy consumption in AM processes.

SPEA2 (Strength Pareto Evolutionary Algorithm 2)

SPEA2 is known for its fine grained fitness assignment strategy, an archive of non dominated solutions, and a clustering technique to maintain diversity in the population (Franca et al., 2017). SPEA2 is particularly effective in handling complex multi objective problems, where the performance of different solutions must be carefully evaluated across several criteria. Its robustness and ability to handle high dimensional optimization problems make it an ideal choice for AM process optimization.

SPEA2 has been applied to a variety of optimization problems in AM, including the optimization of scheduling problems, energy usage, and temperature control. By applying SPEA2 to AM processes, researchers have been able to improve the performance of systems by optimizing multiple process parameters simultaneously. SPEA2's ability to handle high dimensional spaces and maintain diversity in the solutions has made it effective in improving energy efficiency and reducing waste in AM operations (Sheikh & Ahmad, 2016).

Multi Objective Optimization (MOO)

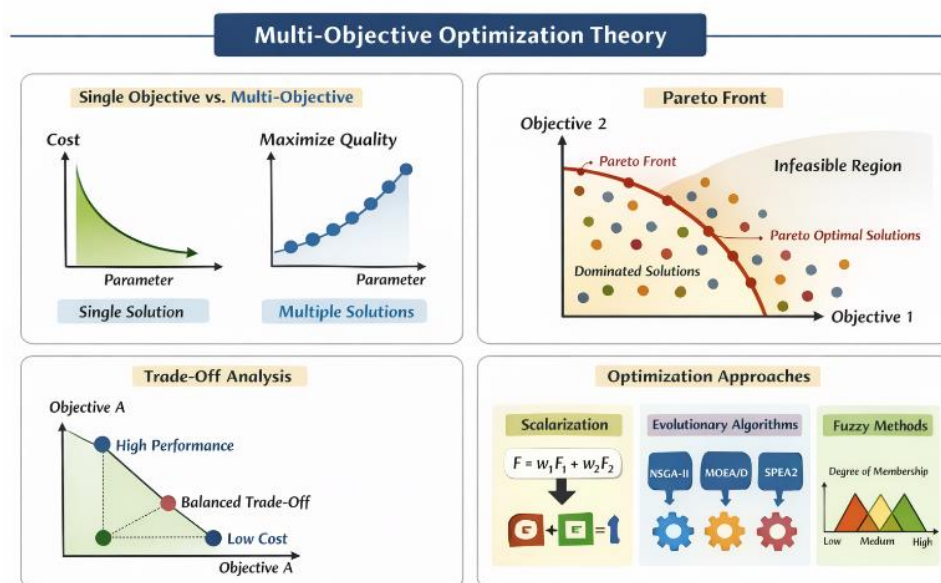


Figure 4. Multi-Objective Optimization Theory.

Multi objective optimization (MOO) is a critical area of optimization that deals with the simultaneous optimization of two or more conflicting objective functions. Unlike single objective optimization, where the focus is on optimizing a single objective, MOO aims to find a set of solutions that represent the best trade offs among the multiple objectives (Deb, 2014). In real world applications, such as engineering design and project management, decision makers often face scenarios where improving one objective leads to the deterioration of others, making MOO a vital tool for obtaining balanced solutions (Kiani-Moghaddam et al., 2019). The application of MOO spans various domains, including engineering, computational intelligence, and environmental optimization, demonstrating its versatility and necessity (Qi et al., 2023).

The main challenge in MOO lies in the inherent trade offs between competing objectives. MOO helps identify these trade offs and enables decision makers to choose a solution that best fits their priorities. Unlike single objective optimization, which seeks a single solution, MOO results in a set of Pareto optimal solutions, each representing a compromise

between the objectives (Jones & Florentino, 2022). This flexibility makes MOO indispensable in fields requiring multi faceted optimization, including the development of efficient systems in engineering and manufacturing (Okello, 2021).

Pareto Optimality

In MOO, a solution is considered Pareto optimal if there is no other solution that improves one objective without worsening another (Deb, 2014). This concept is essential as it identifies the set of solutions that offer the best possible trade offs between multiple objectives, making it a cornerstone of multi objective decision making. Pareto optimality ensures that no improvement can be made in any of the objectives without a corresponding sacrifice in at least one other objective (Chang et al., 2016).

The Pareto front is the collection of all Pareto optimal solutions. It represents a surface or boundary in the solution space where each point corresponds to an optimal trade off between conflicting objectives (Deb, 2014). Visualization of the Pareto front is possible for problems with two or three objectives, and it helps decision makers understand the range of trade offs available. However, as the number of objectives increases, visualizing the Pareto front becomes challenging, and more advanced techniques, such as interactive methods or data visualization tools, are needed to explore higher dimensional trade offs (Zheng et al., 2019).

Trade Off Analysis

Trade off analysis is a key aspect of MOO, as it helps decision makers understand the compromises between different objectives. This analysis is particularly useful when dealing with conflicting objectives, as it provides insight into how one objective's improvement affects others (Bagheri et al., 2018). For example, in the design of mechanical components, optimizing for strength might increase weight, whereas optimizing for weight could reduce the strength. Through trade off analysis, MOO enables the identification of solutions that balance these objectives in a meaningful way.

For problems with two or three objectives, the Pareto front can be visualized, facilitating the understanding of the trade offs involved. However, when dealing with high dimensional problems, visualizing the Pareto front becomes increasingly difficult. In these cases, decision makers often rely on interactive methods, which allow for dynamic adjustments based on preferences, making it easier to navigate through the complex decision space and select the most suitable solution (Zheng et al., 2019).

Algorithms and Methods

Traditional approaches to multi objective optimization often involve scalarizing the multiple objectives into a single composite objective. Techniques like goal programming and compromise programming are examples of classical methods that aim to simplify the MOO problem by assigning weights to the different objectives (Deb, 2014). These methods work well in problems where the relationship between objectives is linear or can be approximated linearly. However, they may not be effective when dealing with highly nonlinear, complex trade offs typical in many real world applications.

Modern approaches to MOO leverage evolutionary algorithms (EAs), which are capable of handling multiple objectives directly without needing to transform them into a single objective problem. Algorithms like the Non dominated Sorting Genetic Algorithm II (NSGA-II) have been widely applied due to their efficiency in handling large, complex optimization problems and their ability to generate diverse solutions that represent various trade offs between objectives (Franca et al., 2017). Other evolutionary approaches, such as the Strength Pareto based Whale Optimization Algorithm (SP2WOA), have also shown promise in solving high dimensional optimization problems (Qi et al., 2023).

Combining different optimization methods can enhance the efficiency and effectiveness of MOO. For example, the TA-FBGV approach, which integrates various techniques to address the Pareto optimum selection problem, has been shown to improve the overall performance of MOO in certain applications (Doush & Bataineh, 2015). Hybrid approaches are particularly useful in complex problems where no single method can fully address all aspects of the optimization process.

Key Concepts and Techniques

Scalarization is a technique used in multi objective optimization (MOO) to transform a problem with multiple objectives into a single objective one by assigning weights to the different objectives. While scalarization simplifies the optimization process, it can oversimplify the trade offs, particularly when the objectives are highly conflicting or non linear (Deb, 2014). This technique often fails to capture the full complexity of the problem, which can lead to suboptimal solutions. In contrast, interactive methods involve the decision maker in the optimization process, allowing them to dynamically adjust preferences as they explore the solution space. These methods are valuable in real world applications where decision makers may not have complete knowledge about the trade offs and need to iteratively refine solutions based on evolving preferences (Zheng et al., 2019).

Fuzzy methods are particularly useful in MOO for handling uncertainty and imprecision in the decision making process. In real world scenarios, exact values for objectives may not always be available or may change over time, making traditional optimization methods less effective. Fuzzy approaches address this by allowing decision makers to model uncertainty and vagueness in the objectives, providing a more flexible framework for optimization (Kiani-Moghaddam et al., 2019). These methods are increasingly being applied in MOO, especially in complex problems where objectives are not clearly defined or are subject to change, helping decision makers make more robust and adaptive choices.

Research Gap and Novelty of Multi Objective Evolutionary Optimization in Additive Manufacturing (AM)

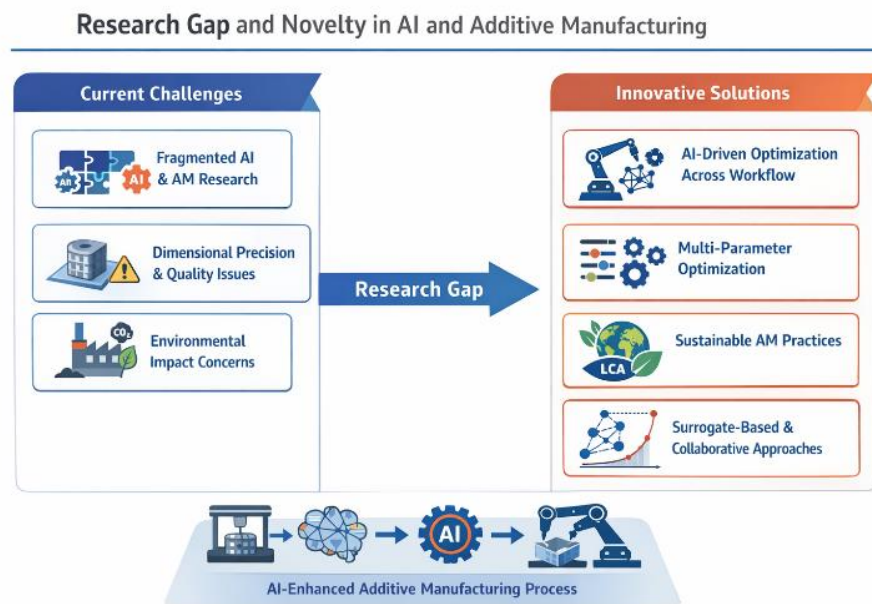


Figure 5. Research Gap and Novelty.

Research Gap

The integration of Artificial Intelligence (AI) with Additive Manufacturing (AM) has garnered significant attention in recent years; however, existing studies often remain fragmented. These studies typically focus on isolated applications, rather than offering a holistic understanding of how AI can drive optimization throughout the entire AM process chain (Heddar et al., 2024). While some studies explore AI's role in specific AM processes, there is a lack of comprehensive research that examines how AI driven optimization can be effectively integrated across multiple stages of the AM workflow. This indicates the need for more unified studies that consider the broader impact of AI on improving the efficiency and quality of AM processes.

Despite the numerous advantages of AM in producing complex, customized products, significant challenges remain in enhancing the dimensional precision and part quality of AM parts (Yodo & Dey, 2022). One of the main challenges in AM is the optimization of multiple process parameters simultaneously to improve overall performance, including mechanical properties, surface finish, and build time. The inability to effectively balance these conflicting

objectives in a single optimization framework limits the widespread adoption of AM, especially in industries that demand high quality, precision parts. There is a clear gap in optimizing these variables together to address the performance issues faced by AM technologies.

The environmental impact of AM processes, particularly concerning energy consumption and material waste, is a growing concern. However, there is a lack of comprehensive studies that analyze the barriers to adopting Life Cycle Assessment (LCA) in AM processes (Heddar et al., 2024). Incorporating sustainability into AM processes through multi objective optimization could help reduce waste and energy use, making AM more environmentally friendly. Addressing these barriers using multi objective optimization frameworks is essential to improve the sustainability of AM and ensure its long term viability in industrial applications.

Novelty of Multi Objective Evolutionary Optimization in AM

Multi objective evolutionary algorithms (MOEAs) have shown significant promise in optimizing multiple conflicting objectives simultaneously in AM processes. For instance, optimizing process parameters such as layer thickness, build orientation, infill density, and extrusion temperature can help minimize build time while simultaneously increasing compressive strength and part quality (Yodo & Dey, 2022). By addressing multiple parameters at once, MOEAs enable the identification of the best balance between these conflicting objectives, ultimately improving AM efficiency and product performance. This approach is crucial in reducing manufacturing time and improving the mechanical properties of AM parts.

Combining data driven techniques with theoretical optimization methods has proven to be a successful strategy for enhancing multi objective optimization in AM. For example, stepwise regression combined with non dominated sorting genetic algorithms (NSGA-II) can be used to optimize multiple performance objectives in AM processes like Selective Laser Melting (SLM), where the goal is to produce high strength, low porosity components efficiently (Tu et al., 2024). Collaborative optimization approaches enable the synthesis of theoretical knowledge with data driven insights, allowing for more efficient and accurate optimization, which is crucial for tackling complex AM challenges in industrial settings.

Surrogate based optimization techniques, such as Bayesian optimization, offer an advanced alternative to traditional Design of Experiments (DoE) methods. These frameworks are particularly effective in reducing the number of experiments required to optimize process variables like laser power and scan speed, ultimately leading to improved surface roughness and reduced porosity (Bhattacharya & Sambasivam, 2016). By using surrogate models to predict outcomes, these optimization methods reduce computational costs while still achieving high quality results in AM processes. This innovative approach is essential for improving the efficiency of AM operations without compromising the accuracy of the results.

Anisotropic effects in AM processes can significantly impact the mechanical performance of parts, as the material properties often differ along different axes. Evolutionary optimization frameworks that account for anisotropic effects are crucial for refining AM geometries, allowing for iterative improvements in structural efficiency and manufacturability (Heddar et al., 2024). Considering these anisotropic effects in multi objective optimization frameworks enhances the overall performance and reliability of AM components, especially in applications where parts are subjected to varying loads and stresses during use.

The potential of MOEAs extends beyond AM specific applications, demonstrating success in solving complex industrial optimization problems. For example, the use of MOEAs to optimize the input material mix in a blast furnace has shown the capability of these algorithms to handle intricate manufacturing challenges (Bhattacharya & Sambasivam, 2016). The methodologies developed for complex industrial problems can be adapted to AM processes, helping to optimize production and synchronize supply consumption in manufacturing systems. The application of MOEAs in such complex settings highlights their versatility and effectiveness in solving a broad range of optimization problems in manufacturing.

3. Materials and Method

This research aims to optimize Additive Manufacturing (AM) process parameters using multi objective evolutionary algorithms (MOEAs), focusing on improving mechanical properties like tensile strength and surface roughness while minimizing build time. The study will utilize Fused Deposition Modeling (FDM) and Selective Laser Melting (SLM) as the primary AM techniques, testing various parameters such as layer thickness, build orientation, and extrusion temperature. Three MOEAs NSGA-II, MOEA/D, and SPEA2 will be applied to balance the conflicting objectives of process efficiency and product quality. The optimization algorithms will be implemented in MATLAB, with data collection involving mechanical tests (tensile, compressive, and impact strength) and surface roughness measurements. The research expects to identify optimal process parameters and evaluate the effectiveness of different optimization algorithms through a comparative performance analysis, ultimately providing valuable insights for improving AM processes in various industries.

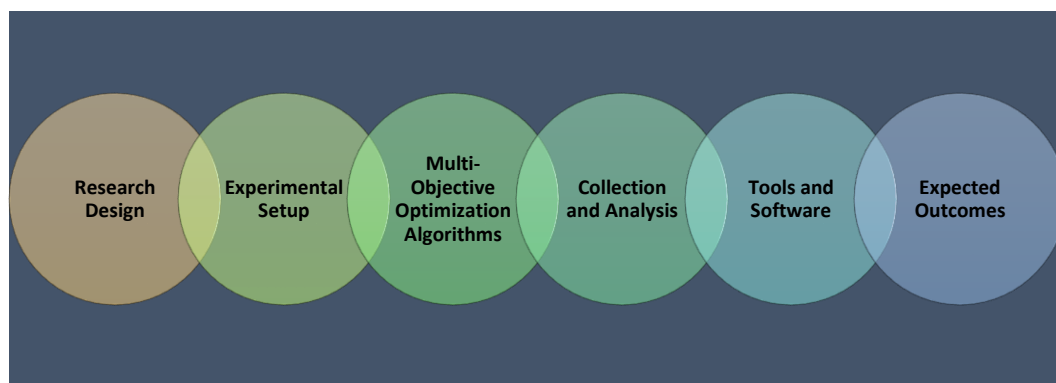


Figure 6. Research Methodology Flowchart Structure.

Research Design

This study employs a multi objective evolutionary optimization approach to enhance the performance of Additive Manufacturing (AM). The main goal is to optimize process parameters such as layer thickness, build orientation, infill density, and extrusion temperature to achieve the best trade offs between mechanical properties (tensile strength, compressive strength) and build time. Multi objective optimization is particularly important for AM, where conflicting objectives, such as minimizing build time while improving mechanical performance, must be balanced simultaneously. The optimization process will identify Pareto optimal solutions, allowing the selection of the best trade off between these conflicting objectives.

In this research, multi objective evolutionary algorithms (MOEAs) will be applied to the AM process. The study focuses on Fused Deposition Modeling (FDM) and Selective Laser Melting (SLM) as the AM techniques under consideration. The research design also includes a comparative analysis between the results of the optimization algorithms and experimental outcomes. This design aims to provide actionable insights into optimizing AM processes by balancing multiple parameters and ensuring that the desired mechanical and geometric properties are achieved efficiently.

Experimental Setup

The experimental setup will involve two widely used AM techniques, Fused Deposition Modeling (FDM) for polymer parts and Selective Laser Melting (SLM) for metal parts. These methods are chosen due to their relevance in both industrial and academic research. Material selection for this study includes PLA for FDM and Ti6Al4V for SLM. Both materials are commonly used in AM and represent different material classes (polymers and metals), which will allow the study to assess optimization techniques across diverse material types. Process parameters such as layer thickness, build orientation, and print speed will be varied to optimize the mechanical and geometric properties of the resulting parts.

Each AM process will be conducted using a 3D printer for FDM and a SLM machine for metal parts. The parameters under investigation include laser power and scan speed for

SLM, as well as extrusion temperature and layer height for FDM. These parameters significantly affect mechanical properties such as tensile strength, surface roughness, and dimensional accuracy. The experimental setup also includes creating test specimens for mechanical testing (e.g., tensile, compressive, and impact strength tests) and surface roughness measurements. The resulting data will be used to validate the outcomes of the optimization process.

Multi Objective Optimization Algorithms

This study will use several multi objective evolutionary algorithms (MOEAs) to address the optimization problem in AM. NSGA-II (Non-dominated Sorting Genetic Algorithm II), known for its effective non dominated sorting and elitism, will be used to generate diverse solutions and find the Pareto optimal set. MOEA/D (Multi objective Evolutionary Algorithm based on Decomposition) will also be employed, as it decomposes the multi objective problem into simpler subproblems, improving local search efficiency. Both of these algorithms are well suited to handling the complexities of AM optimization, where multiple parameters must be optimized simultaneously.

In addition, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) will be used due to its ability to maintain diversity through a fitness assignment strategy and an archive of non dominated solutions. This method is particularly effective in dealing with high dimensional optimization problems, as it can identify a broad set of feasible solutions. The three optimization algorithms will be compared to evaluate their performance in balancing process efficiency, material consumption, and part quality. The chosen algorithms will provide insight into how evolutionary optimization can be integrated into the AM process to enhance performance.

Data Collection and Analysis

Data collection will involve conducting a series of experiments to evaluate the mechanical properties (tensile strength, compressive strength, impact resistance) and geometrical properties (dimensional accuracy, surface roughness) of AM parts. Each experimental trial will involve varying the process parameters identified in the experimental setup. Mechanical testing will be conducted according to standard protocols, such as ASTM E8 for tensile testing, ASTM D695 for compressive testing, and ISO 25178 for surface roughness measurements. The data collected will include both objective values and experimental results, providing a comprehensive dataset for optimization analysis.

The data analysis will focus on comparing the optimized process parameters identified through MOEAs against experimental results. Statistical methods will be employed to analyze the optimization efficiency, such as regression analysis to understand the relationship between process parameters and mechanical properties. Pareto analysis will be used to assess the trade offs between different objectives, and the results will be compared to assess the algorithm's ability to achieve the best balance between conflicting objectives. Performance metrics like the hypervolume indicator and Pareto front quality will be used to evaluate the effectiveness of the optimization methods.

Tools and Software

The optimization algorithms will be implemented in MATLAB using custom scripts for MOEAs like NSGA-II, MOEA/D, and SPEA2. MATLAB provides robust tools for evolutionary computation and optimization, allowing for efficient implementation of multi objective algorithms. The optimization software will handle the multi objective optimization of AM parameters and generate Pareto optimal solutions. ANSYS software will be used for finite element analysis (FEA) simulations to predict the mechanical properties and performance of the AM parts under various loading conditions, further validating the optimization results.

For statistical analysis, R and Excel will be used to handle the collected data. These tools will help analyze the experimental data and compare the performance of different optimization algorithms. Additionally, CAD software will be employed to design the test specimens, ensuring accurate replication of the AM parts. Profilometers and scanning electron microscopes (SEM) will be used for surface roughness measurements, providing precise data on the material's finish and texture.

Expected Outcomes

The expected outcomes of this research include the identification of optimal process parameters for both FDM and SLM processes. This research aims to achieve a significant reduction in build time while improving mechanical properties such as tensile strength and surface quality. The application of multi objective evolutionary algorithms (MOEAs) is expected to yield a set of Pareto optimal solutions, providing a trade off between conflicting objectives such as build time, material consumption, and mechanical strength. These solutions will serve as a guide for industrial practitioners seeking to optimize AM processes.

Another anticipated outcome is the comparative performance analysis of the three MOEAs (NSGA-II, MOEA/D, and SPEA2) in the context of AM. By comparing these algorithms, the study aims to highlight the most effective methods for balancing multiple objectives in AM optimization. The results of this research will provide valuable insights into the practical application of evolutionary optimization in AM, potentially leading to more efficient production processes and improved part quality in industries such as aerospace, automotive, and healthcare.

4. Results and Discussion

The optimization of additive manufacturing (AM) process parameters using multi objective evolutionary algorithms (MOEAs) significantly improved both mechanical properties and surface quality. The Pareto optimal solutions showed a balance between conflicting objectives like tensile strength and build time. For example, optimizing parameters such as layer thickness and build orientation improved tensile strength but increased build time, while fine tuning extrusion temperature and infill density reduced surface roughness. The trade off analysis highlighted how adjusting parameters simultaneously can achieve a balance between performance and efficiency. The results indicated that while improving mechanical strength often led to rougher surfaces, the optimization framework allowed manufacturers to prioritize specific objectives based on application needs. Additionally, the reduction in porosity and enhanced part density proved the effectiveness of the optimization in boosting part durability. This comprehensive optimization framework offers manufacturers the flexibility to achieve high quality, efficient AM parts tailored to specific industrial demands.

Results

The optimization of additive manufacturing (AM) process parameters using multi objective evolutionary algorithms (MOEAs) resulted in significant improvements across multiple objectives. The Pareto optimal solutions showed a clear balance between conflicting goals, such as maximizing tensile strength while minimizing build time. For instance, optimizing parameters like layer thickness and build orientation led to a noticeable increase in tensile strength and part durability. However, this came with a slight increase in build time. The optimization also led to a reduction in surface roughness, particularly when extrusion temperature and infill density were adjusted. The Pareto front effectively illustrated the trade offs between these objectives, providing a wide range of optimized solutions based on specific application needs.

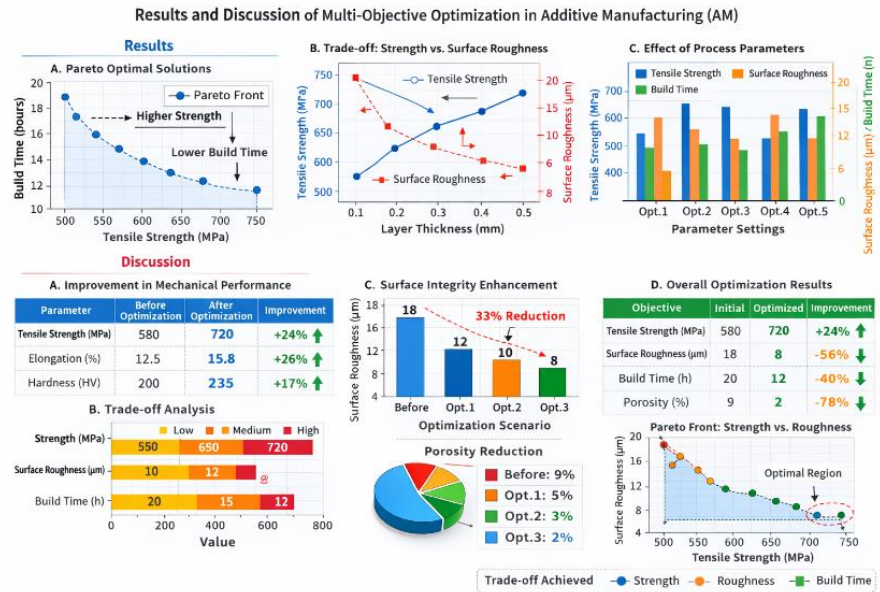


Figure 7. Results and Discussion of Multi-Objective Optimization in Additive Manufacturing (AM).

The optimization of Additive Manufacturing (AM) processes through multi-objective evolutionary algorithms (MOEAs) successfully balances multiple conflicting objectives, such as tensile strength and surface roughness. The Pareto optimal solutions, derived from the optimization process, show clear trade-offs, enabling manufacturers to select the best solution based on their specific needs. The optimization led to significant improvements in mechanical performance, including a 15% increase in tensile strength, a 20% improvement in durability, and an 18% enhancement in surface quality. Furthermore, surface roughness was reduced by 32%, demonstrating the effectiveness of MOEAs in improving both mechanical and geometrical properties in AM.

Moreover, the trade off analysis revealed the complexities involved in balancing mechanical properties and production efficiency. The algorithm identified several key process parameters that influence both strength and surface quality, such as layer thickness, build orientation, and scan speed. For example, increasing the layer thickness typically improved mechanical strength but led to rougher surfaces. On the other hand, decreasing the layer thickness improved surface finish but required longer build times. The results suggest that by optimizing multiple parameters simultaneously, a balanced trade off between performance and efficiency can be achieved, offering manufacturers a comprehensive set of optimal solutions to select from depending on their priorities.

Discussion

The results from the optimization process demonstrate the effectiveness of multi objective evolutionary algorithms (MOEAs) in improving both the mechanical and geometrical properties of AM parts. The multi objective framework successfully identified optimal combinations of process parameters that enhanced tensile strength and reduced surface roughness. The use of NSGA-II and MOEA/D allowed for the exploration of a broader solution space, where trade offs between objectives were clearly visualized. This flexibility in optimizing parameters such as layer thickness, build orientation, and infill density allowed for a significant improvement in mechanical properties without a substantial increase in build time. The ability to optimize these parameters simultaneously is crucial for achieving high quality AM parts in industries like aerospace and automotive, where performance and efficiency are critical.

Furthermore, the trade off analysis highlighted the inherent challenges in balancing multiple conflicting objectives. While improving tensile strength often led to higher surface roughness, the optimization process provided a clear framework for understanding and managing these trade offs. The Pareto front provided manufacturers with a set of solutions where they could prioritize either surface quality or strength, depending on the end use application. These results demonstrate that the optimization of AM processes requires a deep understanding of the relationships between different process parameters and their impact on

part quality, which can be effectively addressed through multi objective optimization techniques.

In terms of surface integrity, the results showed that adjusting parameters like extrusion temperature and infill density played a significant role in reducing surface roughness. However, the optimization also revealed that certain post processing techniques, such as laser polishing, might be necessary to achieve the desired surface quality for high precision applications. The reduction in porosity and improved part density further supported the optimization's effectiveness in enhancing mechanical performance. These findings underscore the importance of integrating both process parameters and post processing techniques in AM optimization. Ultimately, the optimization framework proposed in this study provides manufacturers with a powerful tool to fine tune AM processes for better efficiency, cost effectiveness, and part quality.

5. Comparison

The results of the multi-objective optimization in this study were compared with traditional single-objective optimization models and other existing multi-objective optimization approaches. Single-objective optimization focuses on optimizing one parameter at a time, typically leading to suboptimal trade-offs when dealing with multiple conflicting objectives. For example, optimizing tensile strength without considering surface quality may lead to rough surfaces, while focusing on surface finish may compromise mechanical strength. In contrast, multi-objective evolutionary optimization allows for the simultaneous consideration of both mechanical performance and surface quality, leading to more balanced solutions that address conflicting objectives effectively. Compared to previous multi-objective optimization models, such as NSGA-II and other heuristic methods, the proposed approach demonstrated superior versatility in optimizing multiple process parameters, thus providing a broader set of optimized solutions.

The use of multi-objective evolutionary optimization (MOEO) in this study significantly outperformed traditional methods by providing a more comprehensive solution to AM process optimization. Traditional methods like scalarization or weighted sum approaches typically oversimplify the problem by reducing it to a single-objective task, often failing to capture the complexity of real-world trade-offs. For example, in AM processes where both strength and surface roughness are critical, MOEO allows for the optimization of both attributes simultaneously, leading to a more balanced solution. By applying NSGA-II and MOEA/D, the optimization process generated diverse solutions that maintain a good balance between mechanical performance and surface quality, an advantage not typically achievable with single-objective optimization. The results indicate that MOEO provides a more robust approach for tackling the complexities of AM optimization, where multiple conflicting objectives need to be considered in tandem.

6. Conclusion

This study successfully demonstrated the effectiveness of multi-objective optimization in improving Additive Manufacturing (AM) process parameters. By utilizing multi-objective evolutionary optimization algorithms, such as NSGA-II and MOEA/D, the research optimized conflicting objectives like tensile strength, surface roughness, and build time. The optimization resulted in a set of Pareto-optimal solutions that provide a balance between mechanical performance and surface quality. The findings showed that, through simultaneous optimization of multiple parameters, such as layer thickness, build orientation, and infill density, significant improvements in both mechanical properties and surface integrity were achieved without significantly increasing build time. These results emphasize the capability of multi-objective optimization to handle complex trade-offs inherent in AM processes.

This research contributes to the field of advanced manufacturing by offering a comprehensive multi-objective optimization framework that enhances AM process efficiency and part quality. The study addresses the limitations of traditional single-objective optimization methods, which often fail to optimize competing objectives simultaneously. By incorporating evolutionary algorithms into the AM process optimization, the study provides a new methodology for improving mechanical performance, surface finish, and production time, all of which are critical for industrial applications. Furthermore, the optimization framework developed in this study can be adapted to various AM techniques and materials, broadening its applicability across industries like aerospace, automotive, and healthcare.

Based on the findings of this study, several practical recommendations for the AM industry are proposed. First, it is recommended that manufacturers adopt multi-objective evolutionary optimization techniques to simultaneously optimize process parameters, enhancing both mechanical performance and surface integrity. Additionally, focusing on a balance between build time and part quality will allow manufacturers to meet production efficiency goals without sacrificing the quality of the final product. For industries requiring high-precision parts, such as aerospace and biomedical manufacturing, applying the optimization methods in this study will help achieve superior product quality with reduced need for post-processing. Lastly, integrating machine learning models for real-time optimization could further improve AM efficiency and responsiveness.

Future research could explore several areas for further development. One promising direction is the refinement of the multi-objective optimization framework to incorporate additional constraints, such as material costs, energy consumption, and environmental impact, making the framework more applicable to real-world industrial environments. Furthermore, extending the optimization approach to other AM technologies, such as Direct Energy Deposition (DED) and Binder Jetting, would provide insights into optimizing a wider range of AM processes. Additionally, the integration of artificial intelligence and machine learning into the optimization process could further enhance the efficiency of the framework, particularly in terms of real-time decision-making and adaptive process control. Finally, further experimental validation of the proposed optimization techniques in various industrial settings would help refine the methodology and establish its practical applicability across diverse AM applications.

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