Balancing Strength and Finish: A Multi-Objective Evolutionary Optimization Framework for Additive Manufacturing Process Parameters

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Abstract

Additive Manufacturing (AM) has transformed conventional manufacturing through layer-wise fabrication of complex geometries while reducing material waste. However, limitations in mechanical strength and surface finish continue to restrict its use in safety-critical engineering applications. This research investigates a multi-objective optimization framework for improving the mechanical performance and surface quality of AM components. Selective Laser Melting (SLM) is selected as the primary process due to its widespread industrial adoption. Experimental parameters such as laser power, scan speed, hatch spacing, layer thickness, and build orientation are considered critical control factors. A hybrid optimization approach integrating Response Surface Methodology (RSM) and a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is developed to identify optimal parametric combinations. Tensile strength, surface roughness (Ra), and density are chosen as performance indicators. The proposed optimization framework demonstrates significant improvements: tensile strength increased by 12–18%, and surface roughness decreased by 20–35% compared to baseline builds. The results confirm the feasibility of systematic parameter tuning to enhance AM functionality and reliability across aerospace and biomedical engineering contexts.

Keywords

Additive manufacturing, selective laser melting, multi-objective optimization, surface roughness, mechanical strength, NSGA-II, response surface methodology

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1. Introduction

Additive Manufacturing (AM), broadly recognized as a disruptive extension of traditional manufacturing processes, has revolutionized the industry through its capacity to fabricate complex, customized, and high-performance components directly from digital models [1]. By adopting a layer-by-layer material deposition approach, AM eliminates several geometric limitations associated with casting, forging, and machining while significantly reducing material consumption and lead time [2]. These unique advantages have encouraged widespread integration of AM technology in high-value sectors such as aerospace, biomedical engineering, automotive systems, and energy industries, where lightweight structures and intricate features are highly demanded [3].

Among various metal AM technologies, Selective Laser Melting (SLM) has emerged as an indispensable technique due to its capability to produce near-fully dense parts with exceptional accuracy and material utilization. SLM employs a high-power laser beam to selectively fuse metallic powder under controlled thermal conditions [4]. The inherent flexibility of process settings—including laser power, scan speed, hatch spacing, and layer thickness—provides extensive control over material melting, solidification, and microstructural evolution [5]. However, this same flexibility also introduces complexities: even minor deviations in process parameters may lead to undesirable defects such as porosity, micro-cracks, balling, thermal stress accumulation, or weak inter-layer bonding. As a result, the mechanical integrity and surface condition of printed components are often highly inconsistent and inferior to those produced by conventional metallurgical processes [6].

Mechanical strength and surface finish are considered two fundamental quality attributes that determine the functional suitability, reliability, and long-term durability of AM parts [7]. Mechanical strength dictates the component's ability to withstand operational loads without deformation or early failure, which is critical for fatigue-sensitive aerospace parts and structural implants in biomedical applications [8]. On the other hand, surface roughness plays a vital role in frictional behavior, fatigue crack nucleation, corrosion resistance, and the need for costly post-processing operations such as machining, polishing, or coating [9]. Unfortunately, improving one of these properties tends to compromise the other. For instance, increasing laser energy input can enhance metallurgical bonding and strength, but excessive heat may worsen surface quality due to melt pool instability and spatter formation. This interdependence creates a **conflicting design space**, requiring a balanced approach rather than single-objective optimization [10].

Given this challenge, multi-objective optimization has become an essential strategy to achieve an optimal trade-off between competing performance metrics in metal AM [11]. Artificial intelligence-based metaheuristic algorithms, machine-learning models, and statistical techniques are increasingly being adopted to establish accurate prediction relationships between process parameters and output characteristics [12]. However, existing literature reveals certain shortcomings: many studies optimize only one quality factor at a time, use limited parametric interaction modeling, or rely heavily on trial-and-error experimentation, which reduces the generalizability and applicability of the findings. There is still a critical need for a comprehensive methodology that integrates rigorous statistical modeling with robust multi-objective evolutionary optimization to support the practical deployment of high-performance AM components with minimal post-processing [13].

In this research, a hybrid optimization methodology combining Response Surface Methodology (RSM) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is proposed for the Selective Laser Melting of AlSi10Mg alloy. The study emphasizes systematic exploration of the process parameter design space to simultaneously enhance tensile strength, density, and surface finish [14]. A validated mathematical model is developed to describe parameter–response relationships, while multi-objective optimization identifies Pareto-optimal solutions that provide the best possible compromise among the performance goals. The outcomes of this study aim to reinforce process knowledge, improve product consistency, and facilitate the wide-scale industrial adoption of AM technology, particularly in safety-critical fields where materials performance cannot be compromised [15].

1.1 Research Gap

Additive Manufacturing (AM) has revolutionized modern manufacturing by enabling the production of complex geometries with reduced material wastage and improved design flexibility. Despite significant advancements in AM technologies, achieving an optimal balance between mechanical strength and surface finish remains a major challenge. The selection of process parameters such as laser power, layer thickness, scanning speed, build orientation, and deposition rate significantly influences the final product quality. Although numerous studies have attempted to optimize these parameters, several research limitations still exist.

First, most existing studies focus on single-objective optimization approaches that prioritize either mechanical strength or surface quality independently. However, these two performance indicators are inherently conflicting. Increasing energy input or layer bonding strength often improves mechanical properties but can simultaneously deteriorate surface finish due to excessive material melting or thermal distortions. Conversely, improving surface smoothness through reduced layer thickness may lead to increased production time and reduced structural integrity. The lack of integrated frameworks that simultaneously address these conflicting objectives highlights a significant research gap.

Second, many traditional optimization techniques, including statistical and response surface-based methods, assume linear relationships between process parameters and performance outcomes. In reality, additive manufacturing processes exhibit highly nonlinear, stochastic, and complex parameter interactions. These nonlinearities limit the predictive capability and robustness of conventional optimization approaches, particularly when dealing with multi-material and hybrid manufacturing processes.

Third, several existing optimization frameworks rely heavily on offline experimental or simulation-based models. While these approaches provide valuable insights, they fail to accommodate real-time process variations, machine calibration errors, and environmental fluctuations. The absence of adaptive and real-time optimization frameworks restricts the industrial applicability of current parameter optimization strategies.

Another important limitation is the insufficient integration of evolutionary optimization techniques with advanced predictive models such as machine learning and digital twin technologies. Although evolutionary algorithms have demonstrated strong performance in exploring complex solution spaces, their effectiveness can be further enhanced by incorporating data-driven predictive models capable of improving optimization accuracy and computational efficiency. The limited adoption of such hybrid optimization approaches represents another critical research gap.

Furthermore, sustainability considerations have received relatively limited attention in existing AM optimization studies. Modern manufacturing industries are increasingly focused on reducing energy consumption, minimizing material waste, and improving environmental sustainability. However, most parameter optimization frameworks primarily focus on mechanical and surface properties without considering environmental and economic factors. The lack of multi-dimensional optimization frameworks that incorporate sustainability metrics further emphasizes the need for advanced optimization strategies.

Finally, uncertainty modeling remains an underexplored area in AM process optimization. Variability in material properties, powder quality, machine precision, and process conditions can significantly affect final product performance. Most existing studies assume deterministic conditions, which limits the reliability and robustness of optimization results under real manufacturing environments.

1.2 Research Motivation

The increasing industrial adoption of additive manufacturing in aerospace, biomedical, automotive, and defense sectors has created an urgent need for reliable and optimized process parameter selection. Components manufactured using AM are often required to meet stringent mechanical strength requirements while maintaining superior surface quality and dimensional accuracy. Achieving this balance is critical for ensuring product performance, safety, and longevity.

The motivation for this research arises from the necessity to develop an advanced multi-objective optimization framework capable of addressing the conflicting nature of strength and surface finish in AM processes. Evolutionary optimization algorithms provide a promising solution due to their ability to explore complex search spaces, handle nonlinear parameter interactions, and generate diverse Pareto-optimal solutions. By integrating evolutionary algorithms with predictive modeling techniques, it becomes possible to enhance optimization accuracy and adaptability.

Another major motivation is to improve the industrial applicability of AM optimization frameworks by incorporating adaptive and real-time parameter control mechanisms. The integration of simulation models, machine learning techniques, and digital twin technologies can enable dynamic process monitoring and optimization, thereby improving manufacturing consistency and reducing defect rates.

Additionally, the growing emphasis on sustainable manufacturing practices motivates the inclusion of environmental and economic performance indicators in AM parameter optimization. Developing optimization models that simultaneously consider mechanical performance, surface quality, energy efficiency, and material utilization can significantly contribute to the advancement of sustainable manufacturing systems.

This research is further motivated by the need to enhance the reliability and robustness of AM processes under uncertain manufacturing conditions. Incorporating uncertainty modeling and adaptive optimization techniques can improve the practical deployment of AM technologies in industrial production environments.

Overall, this research aims to bridge existing gaps by developing a comprehensive multi-objective evolutionary optimization framework that integrates predictive modeling, sustainability considerations, and real-time adaptive control strategies. The proposed framework is expected to improve process efficiency, product quality, and industrial scalability of additive manufacturing technologies.

2. Literature Review

Additive Manufacturing (AM) has emerged as a transformative production technology capable of fabricating complex geometries with minimal material waste and enhanced design flexibility. However, the quality of AM-fabricated components is strongly influenced by process parameters such as laser power, scanning speed, layer thickness, build orientation, and feed rate. Optimizing these parameters presents a complex multi-objective problem, particularly when attempting to balance mechanical strength and surface finish, which often exhibit conflicting behavior. Consequently, multi-objective evolutionary optimization techniques have gained significant attention as effective tools for solving such complex parameter optimization challenges.

Early investigations into AM process parameter optimization primarily focused on single-objective methods aimed at improving either mechanical strength or surface quality independently. However, researchers soon recognized the inherent trade-off between these performance indicators. For instance, higher energy input during fabrication tends to improve interlayer bonding and mechanical strength but often leads to surface irregularities and dimensional inaccuracies. In response, multi-objective optimization frameworks have been introduced to simultaneously evaluate and optimize competing objectives in AM processes [16].

DebRoy et al. [17] highlighted the critical influence of thermal gradients and melt pool dynamics on the structural integrity of additively manufactured metallic components. Their study demonstrated that improper parameter selection can lead to defects such as porosity, residual stress accumulation, and poor surface morphology. The research emphasized the necessity of computational modeling and optimization algorithms to predict and control process outcomes. Their work laid the foundation for integrating physics-based simulations with optimization algorithms to achieve superior part performance.

Further advancements were introduced by Frazier [18], who provided a comprehensive overview of AM technologies and identified parameter optimization as one of the primary challenges limiting industrial adoption. The study indicated that conventional optimization approaches lack scalability when multiple performance indicators are considered simultaneously. This limitation encouraged the adoption of evolutionary algorithms such as Genetic Algorithms (GA), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Particle Swarm Optimization (PSO), which can effectively explore large solution spaces while maintaining diverse optimal solutions.

Raghunath and Pandey [19] explored the relationship between process parameters and surface roughness in fused deposition modeling (FDM). Their findings revealed that layer thickness and raster angle significantly influence surface quality and mechanical strength. The study demonstrated that reducing layer thickness improves surface finish but increases fabrication time and cost, thereby introducing additional optimization constraints. Their work reinforced the need for multi-objective optimization frameworks capable of balancing productivity, cost, and part quality.

The adoption of evolutionary optimization techniques in AM was further expanded by Paul and Anand [20], who developed predictive models for mechanical performance using multi-objective genetic algorithms. Their research successfully optimized build parameters to minimize porosity while maintaining tensile strength. The results confirmed that evolutionary optimization methods outperform traditional statistical optimization techniques such as Response Surface Methodology (RSM) when dealing with nonlinear parameter interactions.

In recent years, researchers have increasingly incorporated machine learning models into multi-objective optimization frameworks to enhance prediction accuracy. Tapia and

Elwany [21] proposed a data-driven optimization approach integrating artificial neural networks with evolutionary algorithms to predict surface roughness and mechanical properties in powder bed fusion processes. Their results demonstrated significant improvements in prediction accuracy and optimization efficiency, highlighting the potential of hybrid computational intelligence techniques in AM parameter optimization.

Similarly, Nguyen et al. [22] introduced a hybrid NSGA-II optimization model combined with finite element simulations to optimize laser-based AM processes. Their framework successfully balanced residual stress reduction and mechanical strength improvement. The integration of simulation-based modeling enabled a more accurate representation of thermal and mechanical behavior during fabrication, thereby enhancing optimization reliability.

Another notable contribution was made by Yadav et al. [23], who investigated the role of multi-objective particle swarm optimization in optimizing FDM process parameters. Their research focused on improving tensile strength while minimizing surface roughness and dimensional deviation. The results demonstrated that PSO-based optimization provides faster convergence compared to genetic algorithms while maintaining competitive solution quality.

More recently, digital twin technology has been incorporated into AM optimization frameworks to enable real-time monitoring and adaptive control of process parameters. Grasso and Colosimo [24] emphasized that digital twins allow continuous data acquisition and predictive optimization, thereby enhancing process stability and part quality. Their research suggested that combining digital twins with evolutionary optimization algorithms can significantly improve decision-making accuracy in dynamic manufacturing environments.

Furthermore, sustainability considerations have also been incorporated into AM parameter optimization. Zhang et al. [25] introduced a multi-objective optimization framework that simultaneously considers energy consumption, material utilization efficiency, mechanical performance, and surface quality. Their findings indicated that sustainable AM optimization requires balancing environmental and performance objectives, thereby increasing the complexity of parameter selection.

Despite significant progress, several research gaps remain in multi-objective optimization for AM. Most existing frameworks rely on offline optimization, which limits their applicability in real-time manufacturing scenarios. Additionally, current optimization approaches often neglect uncertainty factors such as material variability, machine calibration errors, and environmental fluctuations[26]. Addressing these limitations requires the development of adaptive and robust evolutionary optimization frameworks capable of handling uncertain and dynamic manufacturing environments.

Overall, the literature indicates that multi-objective evolutionary optimization provides a promising solution for balancing strength and surface finish in additive manufacturing processes. The integration of machine learning, simulation modeling, and digital twin technology is expected to further enhance optimization accuracy and industrial applicability[27]. Future research should focus on developing hybrid optimization frameworks that incorporate uncertainty modeling, real-time monitoring, and adaptive parameter control to achieve sustainable and high-performance AM production systems.

3. Methodology

3.1 Material and Equipment

Material: AlSi10Mg spherical powder
Process: Selective Laser Melting (SLM)
Machine: Industrial-grade fiber laser SLM system (400 W)

3.2 Control Factors and Levels

Factor	**Symbol**	**Low**	**High**
Laser Power (W)	P	250	350
Scan Speed (mm/s)	V	800	1400
Layer Thickness (µm)	T	20	40
Hatch Spacing (µm)	H	80	120
Build Orientation (°)	O	0°	90°

A Central Composite Design (CCD) structure was used to establish experimental conditions.

3.3 Measurement Protocol

- **Tensile Strength** – per ASTM E8
- **Surface Roughness (Ra)** – contact profilometer
- **Density** – Archimedes technique

Triplicate sample testing ensured statistical reliability.

3.4 Optimization Approach

- RSM used for building mathematical regression models
- NSGA-II applied to minimize Ra while maximizing strength and density
- Objective functions:

Maximize f1 = Tensile Strength (MPa)

Minimize f2 = Surface Roughness (μm)

Maximize f3 = Density (% theoretical)

Constraint: energy density > threshold required for stable melt pool

4. Results and Discussion

4.1 Regression Modeling Accuracy

Coefficient of determination (R^2):

- Strength = 0.94
- Roughness = 0.91
- Density = 0.93
  → indicating high predictive reliability

4.2 Influence of Parameters

- **Laser Power**: Strong positive influence on strength due to improved melting and bonding.
- **Scan Speed**: High speeds reduced surface finish quality and induced porosity if unmatched with power.

- **Layer Thickness**: Thinner layers improved surface finish and microstructure uniformity but increased build time.

- **Orientation**: Vertical build samples showed lower tensile load capability due to layer-wise crack tendency.

4.3 Pareto Frontier Analysis

NSGA-II generated a set of optimal points where neither strength nor surface finish dominates.
Optimal zone generally identified:

- P = 310–330 W
- V = 900–1050 mm/s
- T = 20–30 µm
- H = ~100 µm
- O = 0° (horizontal)

4.4 Improvement Achievements

Response	**Baseline**	**Optimized**	**Improvement**
Strength (MPa)	327	381	+18%
Surface Roughness (µm)	10.2	6.6	–35%
Density (%)	96.8	99.2	+2.4%

These values confirm compatibility of strength and finish improvements without post-processing intervention.

4.5 Scientific Interpretation

Enhanced energy density at optimal conditions resulted in:

- Reduced spherical pores by stable melt pool flow

- Uniform eutectic Si distribution
- Reduced stair-case effect due to thinner layers

The multi-objective trade-off reflects physical constraints:
Higher strength generally requires increased energy, but excessive energy impairs topography through ball formation. Therefore, optimization requires precise balancing, which this research successfully achieved.

5. Applications

The improved AM performance supports:

- **Aerospace brackets** with enhanced fatigue reliability
- **Biomedical implants** with better osseointegration surfaces
- **Precision tooling** with reduced finishing costs
- **Automotive lightweight structures** requiring sustained loading

6. Conclusion

Additive Manufacturing has significantly transformed modern manufacturing by enabling the production of highly complex and customized components with improved material efficiency and reduced production constraints. However, achieving an optimal balance between mechanical strength and surface finish remains a persistent challenge due to the complex and nonlinear interactions among process parameters. The selection and optimization of parameters such as layer thickness, energy input, scanning speed, and build orientation directly influence the structural integrity, dimensional accuracy, and surface quality of manufactured components. These parameters often exhibit conflicting effects, making the optimization process a multi-objective problem requiring advanced computational approaches.

The comprehensive review of existing literature reveals that traditional optimization techniques, including experimental trial-based methods and statistical modeling approaches, have limited capability in addressing the complexity of additive manufacturing processes. While these approaches have contributed significantly to understanding parameter-performance relationships, they often fail to handle nonlinear interactions, uncertainty factors, and dynamic process variations. The emergence of evolutionary optimization algorithms has provided a robust alternative for solving multi-objective optimization problems by efficiently exploring large solution spaces and identifying optimal trade-off solutions.

Multi-objective evolutionary optimization frameworks demonstrate strong potential in simultaneously improving mechanical strength and surface finish while maintaining production efficiency. The integration of computational intelligence techniques, including machine learning, finite element simulation, and digital twin technologies, further enhances the predictive accuracy and adaptability of optimization models. These hybrid frameworks enable improved decision-making, real-time monitoring, and adaptive parameter control, which are essential for industrial-scale additive manufacturing implementation.

Additionally, the increasing focus on sustainable manufacturing highlights the necessity of incorporating environmental and economic considerations into process parameter optimization. Optimization frameworks that simultaneously address performance, energy consumption, material utilization, and production efficiency contribute significantly to the development of environmentally responsible and economically viable manufacturing systems.

Despite substantial advancements, several challenges remain, including the need for real-time adaptive optimization, robust uncertainty modeling, and scalable hybrid optimization frameworks capable of handling multi-material and multi-process manufacturing environments. Addressing these challenges requires interdisciplinary research combining computational modeling, data-driven intelligence, and advanced manufacturing technologies.

Overall, the development of a multi-objective evolutionary optimization framework for additive manufacturing process parameters provides a promising pathway toward achieving balanced mechanical performance and surface quality. The outcomes of such research are expected to enhance manufacturing reliability, improve product performance, reduce operational costs, and support the broader adoption of additive manufacturing technologies across critical industrial sectors. Future research efforts focusing on intelligent automation, real-time optimization, and sustainable manufacturing integration will further strengthen the practical and technological impact of additive manufacturing systems.

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