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Sustainable manufacturing of FDM-manufactured composite impellers using hybrid machine learning and simulation-based optimization

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Abstract

Conventional optimization of fused deposition modeling (FDM) often relies on trial-and-error or heuristic approaches, which lack scalability and precision, especially for complex geometries such as impellers. While prior studies have integrated artificial intelligence (AI) or multi-criteria decision-making (MCDM) techniques for process optimization, their combined application remains limited, particularly in scenarios that prioritize energy-efficient and sustainable manufacturing. This study introduces a novel hybrid AI-MCDM framework for the multi-objective optimization of FDM-printed composite impellers, integrating mechanical performance, energy consumption, and material utilization within a unified decision-making model. A key feature of the approach is the real-time tracking of energy usage, enabling dynamic evaluation of process efficiency. Experimental validation demonstrates a 7% enhancement in tensile strength, a 25% reduction in energy consumption, and a 30% decrease in material wastage compared to baseline configurations. These results underscore the potential of AI-driven simulation and optimization frameworks to support sustainable additive manufacturing, with significant implications for aerospace, biomedical, and energy sector applications.

Keywords: Fused deposition modeling; Rapid prototyping; Machine learning; Multi-criteria decision-making; Sustainable manufacturing; Optimization algorithms; Mechanical characterization; SDG Goals

1. Introduction

Fused deposition modeling (FDM) is the most commonly used additive manufacturing (AM) technology, due to its ease of operation, affordability, capability to produce intricate geometries, and low material waste. FDM entails passing a thermoplastic filament through a heated extruder nozzle, where it is melted and pushed layer-wise onto a build platform. As every new layer is deposited, it melts into the one below it, building up gradually to the shape of the desired 3D part. Important process parameters, including layer thickness, infill density, printing speed, and nozzle temperature, significantly influence the mechanical performance, surface finish, and energy efficiency of the printed object. FDM is widely applied in multiple industries, such as aerospace, automotive, biomedical, consumer products, and rapid prototyping, due to its capability to produce light, personalized, and functionally graded parts. Regardless of its extensive utilization, maintaining uniform mechanical quality and energy-efficient production remains a challenge, especially for geometrically complex components such as impellers.[1,2] The efficiency of an impeller is a key factor influencing energy consumption and operational performance; therefore, optimizing its manufacturing processes to enhance mechanical strength, minimize material wastage, and improve energy efficiency is of significant interest. However, the optimization of FDM process parameters is typically conducted using trial-and-error methods, which are inefficient with complex trade-offs in mechanical performance, energy consumption, and sustainability. This limitation underscores the need for artificial intelligence (AI) and machine learning (ML)-based methods in optimizing FDM-based manufacturing of impellers. These advances have facilitated data-driven process optimization, allowing real-time decision-making and predictive modeling of AM. Studies have demonstrated that mechanical properties can be predicted with reasonable accuracy using ML algorithms based on process parameters, thereby improving print quality and minimizing defects.[3-5]

In addition, MCDM techniques, such as fuzzy analytic hierarchy process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), have been used extensively to compare and rank various process conditions based on different performance measures, such as mechanical integrity, energy efficiency, and material efficiency.[6-8] While AI and ML have made considerable advances, limited research works have utilized AI-based MCDM platforms to optimize FDM processing for the production of impellers. With the increasing demand for sustainable, lightweight, and high-performance impellers, there is a need for a holistic AI-based optimization strategy to address the United Nations' Sustainable Development Goals (SDGs). Minimizing energy consumption during printing is a critical aspect of sustainability in the FDM-based production of impellers. In this study, a power meter was utilized to record real-time energy consumption of the FDM printer, providing valuable insights into energy efficiency across various process parameters. This approach facilitates the identification of optimal printing conditions that minimize power consumption while maintaining structural integrity and mechanical performance. Although AI has been utilized extensively for process automation and defect prediction, limited research has utilized real-time monitoring of energy consumption within AI-MCDM platforms for sustainable impeller production.

This study proposes a theoretical AI-assisted MCDM approach of FDM process parameter optimization in the production of composite impellers. This approach systematically analyzes the effect of significant FDM parameters – including layer thickness, infill density, nozzle temperature, and print speed – on mechanical properties, energy efficiency, and material usage. ML algorithms, combined with fuzzy AHP and TOPSIS, were employed to support multi-objective decision-making. Mechanical characterization through tensile, flexural, wear, and compression testing, along with scanning electron microscopy analysis, validates the optimized parameters. Real-time power monitoring enables quantitative assessment of energy consumption, reinforcing the sustainability dimension of the process. The results could benefit sustainable AM practices, optimizing production performance and environmental footprint in fluid-handling applications.

1.1. AI-driven optimization of FDM

The convergence of ML and AI with AM has significantly advanced process optimization, in-process monitoring, and defect detection, especially for FDM, the most common AM process. FDM is valued for its cost-effectiveness, simplicity, and ability to create complex geometries with minimal material wastage.[9] However, optimizing FDM-produced parts remains challenging due to the interdependencies between different process parameters, such as infill density, cooling rate, nozzle temperature, print speed, and layer thickness. These parameters collectively influence mechanical strength, surface finish, energy utilization, and material consumption. Conventional optimization methods, including empirical modeling and trial-and-error, are non-adaptive,[10] making it even more challenging to balance sustainability, production efficiency, and quality. AI optimization techniques – such as artificial neural networks (ANNs), convolutional neural networks (CNNs), decision tree algorithms, support vector machines (SVMs), and reinforcement learning (RL) – have demonstrated significant promise in optimizing FDM processes by enabling predictive modeling, real-time monitoring, and adaptive control.[11-13] Zhou *et al.*[14] provided a comprehensive review of AI applications in

AM, highlighting how ML algorithms can simplify FDM processes by offering data-driven insights and automation. Interestingly, ML models trained on extensive process and mechanical testing data have achieved high accuracy in predicting material behavior and performance outcomes. ANNs have been widely employed to develop surrogate models capable of replacing computationally intensive finite element analysis (FEA), thus accelerating design iterations. Gaussian process regression (GPR) and deep neural networks (DNNs) have been employed to optimize input parameters for desired output qualities, including tensile strength, impact resistance, and dimensional accuracy.[15] CNNs have demonstrated potential in detecting surface defects in FDM-printed parts through image-based inspection, enabling real-time feedback and automatic quality control.[16] AI-powered computer vision systems have been employed to develop closed-loop control systems that dynamically adjust FDM parameters during printing, effectively minimizing defects such as warping, delamination, and stringing. Another significant use of AI-enhanced FDM optimization involves integrating MCDM methods, such as Fuzzy AHP and TOPSIS. These methods systematically examine trade-offs among mechanical performance, energy consumption, and material usage, supporting the development of more sustainable printing setups.[17-19]

One of the critical challenges related to FDM is its variable energy consumption, which is heavily influenced by print parameters, material types, and machine efficiency. To address this issue, researchers have applied real-time power monitoring using power meters and AI algorithms to forecast and minimize energy consumption without compromising the structural integrity of the printed parts.[20-22] Empirical studies have demonstrated that AI-augmented energy modeling can reduce FDM power consumption by dynamically adjusting nozzle temperature and print speed, thereby maximizing energy efficiency without compromising part quality. In addition, RL methodologies have also been explored for self-adaptive parameter tuning, where AI agents learn optimal print settings iteratively by trial and error, improving decision-making capabilities with real-time feedback.[23] The application of generative adversarial networks (GANs) in topology optimization represents a novel approach, enabling the generation of mechanically efficient yet lightweight FDM-printed structures that support material conservation and sustainability.[24] Furthermore, AI-driven defect detection systems have advanced significantly, allowing early detection of print failures. Consequently, this approach reduces material waste and production downtime. The integration of AI with Internet of Things (IoT) sensors has also assisted in smart manufacturing. For instance, FDM machines equipped with real-time temperature, vibration, and humidity sensors can feed process data to AI models for predicting potential failures and recommending corrective actions before defects occur.[25]

Predictive maintenance has been most advantageous in industrial manufacturing, where machine reliability directly impacts the success of mass production operations. Hybrid AI approaches, combining ML with physics-based simulation, have proven to enhance the accuracy of forecasting thermal distortion and residual stress in FDM-printed components, addressing a significant gap in AM process validation. Another vital research area is AI-driven toolpath optimization. AI models analyze and generate optimal extrusion paths that minimize travel time, material consumption, and stress formation in printed components. The technique is particularly useful in impeller production, where highly curved geometries demand careful control of extrusion direction and layer adhesion to provide fluid dynamic performance and structural integrity. Finally, AI-driven part orientation algorithms have been developed to determine the optimal positioning of FDM-printed parts on the build platform. These algorithms reduce the need for support structures and post-processing while simultaneously enhancing surface finish quality. In biomedical applications, AI-assisted bioinspired design optimization enables the production of patient-specific prosthetics and implants. ML algorithms process patient scan data to generate personalized FDM-printable models with optimized mechanics.[26] In aerospace and automotive applications, AI-facilitated design of lightweight structures has resulted in significant material savings by leveraging lattice and honeycomb infill patterns optimized by deep learning algorithms.[27]

Despite these advancements, challenges remain regarding the generalizability and interpretability of AI models due to the inherent variability in FDM processes, which arise from different material properties, machine inconsistencies, and environmental factors. Existing work has focused on enhancing AI robustness by employing transfer learning schemes, whereby pre-trained models from similar AM processes are adapted to new materials and machine setups with minimal retraining sample sizes. Another promising direction is the integration of AI with digital twin technologies, which synchronizes real-time data from FDM printers with digital simulations to enable predictive process optimization and adaptive process control. Further evolution of AI in FDM is expected to be driven by edge computing and cloud-based facilities, enabling real-time, multi-party optimization of AM processes within distributed manufacturing networks.

In addition, AI-powered sustainability frameworks are being created to minimize the carbon footprint of FDM printing. These frameworks support the alignment of AI-enabled manufacturing with the circular economy. With AI capabilities under development, its potential in FDM will shift from parameter optimization to end-to-end process automation, where intelligent autonomous systems automate the entire AM process, thereby enabling a new paradigm of green, high-performance, and fully autonomous additive manufacturing.

1.2. MCDM in FDM process optimization in impeller production

The application of MCDM methods has gained significant attention in optimizing the FDM process for fabricating impellers, likely due to challenges in identifying an optimal set of process parameters that balance mechanical performance, energy efficacy, and material utilization. Impellers, which are critical components in pumps, turbines, and compressors, demand high precision in terms of geometric accuracy, structural integrity, and fluid flow dynamics.[28-30] The most significant concern in the FDM-based production of impellers is the intrinsic trade-offs amongst conflicting objectives, such as maximizing mechanical strength and surface finish while simultaneously minimizing printing time and energy utilization. Conventional optimization methods, such as trial-and-error and single-objective optimization models, proved inadequate in portraying these multi-dimensional interactions, warranting the implementation of advanced MCDM paradigms. Recent studies have demonstrated the effectiveness of hybrid MCDM methods that combine the application of Fuzzy AHP, TOPSIS, and genetic algorithms (GA) to systematically select and rank the best process parameters for FDM-fabricated impellers.[31-33]

Mechanical integrity is one of the most critical performance parameters for impellers, and it is influenced by a dynamic set of process parameters, including extrusion temperature, layer thickness, infill density, and print speed. Prior research has demonstrated that higher infill density and lower layer thickness can significantly improve mechanical strength and surface finish, but these adjustments typically result in higher energy consumption and a longer print time.[34] Conversely, a higher print speed reduces production time but compromises interlayer adhesion and structural integrity.[35] To avoid such trade-offs, Fuzzy AHP has been utilized to assign weights to performance criteria based on expert evaluations. These weights are then incorporated into TOPSIS to rank various parameter sets in terms of closeness to an ideal solution.[35,36] This hybrid approach enables the selection of optimal process parameters that simultaneously maximize tensile strength, flexural strength, impact resistance, and surface roughness, all of which are key attributes for impeller performance in high-speed fluid applications.

Beyond mechanical performance, energy efficiency has emerged as a pivotal consideration in FDM-based impeller manufacturing. The integration of power meters into FDM machines has enabled real-time monitoring of actual energy consumption, providing valuable data for process optimization. Empirical studies have demonstrated that higher extrusion temperatures enhance interlayer adhesion but significantly increase power consumption, while lower extrusion temperatures reduce energy usage at the expense of weakened interlayer bonding.[37-39] In response to these trade-offs, researchers have developed AI-assisted MCDM frameworks that incorporate real-time energy data into the decision-making process. These intelligent systems enable dynamic optimization of parameters such as extrusion temperature, print speed, and cooling settings, aiming to minimize power consumption while preserving mechanical integrity.

Surface roughness is another critical performance determinant for impellers, as it directly affects fluid efficiency and resistance to cavitation. Elevated surface roughness promotes turbulent flow and energy losses, ultimately diminishing the impeller's overall efficiency. Conventionally, improving surface finish requires post-processing techniques such as sanding or chemical smoothing – methods that are both time-consuming and costly. Recent MCDM-based studies, however, have focused on in-process optimization by tuning parameters such as layer height, nozzle temperature, and print speed, which naturally influence surface quality. Hybrid optimization frameworks that integrate GA with MCDM approaches have demonstrated success in automating the selection of process parameters to achieve low surface roughness. These methods reduce or eliminate the need for post-processing, thereby enhancing manufacturing efficiency and cost-effectiveness in FDM-based impeller production.[40-42]

The integration of MCDM methods with AI has further advanced impeller optimization by enabling predictive modeling and real-time process control. Leveraging ML algorithms trained on historical print data, researchers have developed adaptive MCDM models capable of predicting defects and dynamically adjusting process parameters during fabrication.[42] This approach has led to significantly higher first-print success rates, thereby minimizing material waste and improving overall production efficiency. In addition, the incorporation of metaheuristic optimization techniques, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and

Gray Relational Analysis (GRA), has yielded superior multi-objective optimization outcomes. These methods have proven effective in identifying process parameter sets that offer an optimal balance among mechanical strength, energy efficiency, and surface finish – key factors in high-performance impeller fabrication.

Recent advancements have also seen the application of MCDM techniques in the production of composite impellers, particularly those fabricated using high-performance thermoplastics such as carbon fiber-reinforced polyether-ether-ketone (CF-PEEK). These materials are highly valued for their exceptional strength-to-weight ratios and thermal resistance, making them suitable for demanding applications. Optimization studies employing a hybrid Fuzzy AHP-TOPSIS framework have identified an optimal combination of process parameters for CF-PEEK impeller production, including a 70% infill density, 0.15 mm layer height, 60 mm/s print speed, and an extrusion temperature of 445°C. This parameter set has been ported to deliver superior mechanical strength while maintaining energy efficiency. These findings underscore the growing relevance of MCDM-based optimization models in the development of next-generation impellers for aerospace, marine, and advanced industrial fluid systems.[43]

Despite significant progress, a key challenge that persists is the limited generalizability of current MCDM-based models to diverse impeller geometries and material compositions. Future research must focus on further advancing AI-enhanced MCDM frameworks through the integration of real-time sensor data, enabling adaptive control of printing parameters based on in-situ mechanical and thermal feedback. This would allow for dynamic process optimization tailored to varying design and material requirements. Furthermore, the incorporation of sustainability metrics – such as carbon footprint assessments and life cycle analysis (LCA) – into MCDM models will be essential in steering FDM-based impeller manufacturing toward circular economy principles. With continuous advancements in AI, the IoT, and decision-making algorithms, the future of impeller production is poised to become more sustainable, intelligent, and autonomous, supporting the creation of high-performance, energy-efficient components for industrial fluid systems.

1.3. AI-based waste reduction and energy optimization in 3D printing

The integration of AI and ML into AM has become a driving force in minimizing material and energy waste, thereby advancing the sustainability of 3D printing. Conventional AM techniques, particularly FDM, often suffer from inefficiencies, such as excessive material usage, high-energy consumption, and limited control over process parameters. AI-driven approaches address these challenges through predictive modeling, real-time process optimization, and adaptive control mechanisms. By leveraging AI-based systems, research institutions and industrial entities can significantly reduce material wastage, enhance energy efficiency, and maximize overall process performance, aligning 3D printing practices with circular economy principles. A major source of inefficiency in AM is failed prints, which often result from over-supporting structures, suboptimal parameter settings, warping, or poor interlayer adhesion. Studies have demonstrated that defective prints account for approximately 10 – 30% of material waste in FDM processes.[44] To mitigate these losses, AI-based real-time defect detection systems utilizing computer vision and CNNs have been developed. These systems continuously monitor the printing process and detect potential defects as they emerge, enabling real-time corrective actions such as adjusting extrusion temperature, print speed, or feed rate to prevent print failure. Furthermore, ML-based predictive models trained on historical print data have achieved defect detection accuracies of up to 90%, offering a proactive means of minimizing material loss and enhancing process reliability.

Another major sustainability challenge in 3D printing is the overuse of support structures, which not only leads to significant material wastage but also increases post-processing time and costs. To address this, AI-enabled topology optimization and generative design techniques have been employed to minimize support requirements without compromising part strength or manufacturability. Combined with lattice structure optimization algorithms, these approaches allow for the design of mechanically robust and lightweight parts, resulting in substantial raw material savings. Empirical studies have demonstrated material reductions of 20 – 40% through AI-driven topology optimization, while maintaining mechanical performance.[45] Beyond waste minimization, AI also plays a pivotal role in optimizing energy consumption in AM processes. Energy usage in FDM systems is highly sensitive to parameters such as print speed, nozzle temperature, layer thickness, and infill density. AI-powered energy simulation systems – leveraging deep learning architectures such as long short-term memory (LSTM) networks and RL – enable real-time parameter prediction and adjustment to lower energy usage while preserving print quality. Coupled with real-time power monitoring through smart meters and intelligent sensors, these systems enable adaptive energy management strategies, achieving energy savings of 15 – 30% during production.[46] Recent advances in AI-based production scheduling further enhance energy efficiency. By analyzing historical energy usage, print job complexity, and machine utilization patterns, AI algorithms can schedule prints during off-peak hours, capitalizing on cheaper and cleaner energy sources. In industrial AM settings, multi-objective AI optimization frameworks are increasingly employed to simultaneously reduce material consumption, energy demand, and build time, ensuring both environmental and economic viability.[47] AI-integrated MCDM tools, such as Fuzzy AHP and TOPSIS, enable manufacturers to make informed decisions based on trade-offs between mechanical properties, material usage, and energy efficiency. These AI-enhanced systems have been reported to reduce failed prints by 25%, lower energy costs by 30%, and improve production efficiency by up to 15%.[48] Moreover, AI is increasingly powering circular economy practices in AM, particularly in the recycling and reuse of materials. ML algorithms are used to sort and process waste filaments, ensuring that recycled materials maintain optimal printability and mechanical integrity. Predictive models are also used to assess the degradation of recycled polymers, allowing adaptive print settings to compensate for material inconsistencies. As a result, companies have reported 30 – 50% reductions in the consumption of new materials through AI-enhanced recycling systems. In addition to energy and material efficiency, AI has significantly contributed to process parameter automation, enabling closed-loop control systems that dynamically adjust variables such as extrusion pressure, cooling rates, and print speed. These feedback-based systems enhance print consistency while minimizing waste. AI-based predictive maintenance also helps anticipate machine failures, thus reducing unplanned downtime and resource loss.[49] Despite these advancements, several challenges remain. Many current AI models are tailored to specific machines or materials, limiting their scalability across diverse AM platforms. Furthermore, the computational intensity of real-time monitoring and optimization remains a barrier to widespread industrial deployment. Future efforts should focus on developing hybrid AI approaches that integrate data-driven learning with physics-based simulations to achieve broader applicability and more accurate, scalable optimizations. In summary, AI technologies have revolutionized sustainable 3D printing by reducing failure rates, optimizing material usage, and lowering energy consumption. AI-powered predictive modeling, in-process defect detection, and adaptive control mechanisms are significantly improving the environmental sustainability of AM processes. As AI continues to evolve, its role in promoting environmentally and economically sustainable manufacturing within Industry 4.0 and circular manufacturing frameworks is set to grow even more prominent.

2. Methods

2.1. Experimental workflow for sustainable FDM printing of thermoplastic polyurethane (TPU) 95A components

In this study, we focused on the fabrication, optimization, and mechanical characterization of TPU 95A specimens produced through FDM, with particular focus on analyzing energy consumption throughout each stage of the process. The objective is to assess the efficiency, mechanical performance, and sustainability of TPU 95A components by integrating twin-screw extrusion-based filament production, AM using a Bambu Lab A1 3D printer, and stress-controlled mechanical testing. Energy usage is continuously monitored using power meters across the entire workflow – from raw material preparation to final product – to evaluate the energy footprint associated with extrusion, printing, and testing.

The first stage of the study involved the preparation of TPU 95A filaments using a twin-screw extruder, a critical process that determines the quality and homogeneity of the feedstock for FDM printing. TPU 95A pellets (Dream Shapes Printing, India) were loaded into the extruder hopper and melted at 200°C within the extrusion chamber. The screw speed was regulated between 30 – 50 rpm to ensure uniform mixing and homogenized extrusion of the thermoplastic material. The molten TPU was extruded through a 1.75 mm diameter die to form a continuous filament, which was immediately quenched in a water bath to achieve dimensional stability, prevent defects, and enhance material properties. The solidified filament was then wound using a puller system with consistent tension. Real-time energy consumption during filament extrusion was measured using a power meter, enabling detailed analysis of the process efficiency and contributing to an assessment of TPU 95A's viability as a sustainable FDM material. After filament preparation, the extruded TPU 95A filament was processed using the Bambu Lab A1 FDM 3D printer (China) to generate test specimens for mechanical testing. The processing parameters for FDM were optimized to balance mechanical performance, print accuracy, and energy efficiency. The print speed of 70 mm/s was selected to facilitate rapid printing and support structural integrity. Nozzle temperature was maintained at 230°C for optimal flow and interlayer adhesion to prevent warping or delamination defects, while the bed temperature was maintained at 50°C to provide optimal first-layer adhesion and reduce shrinkage. A layer height of 0.2 mm was used to enhance surface finish without compromising geometric accuracy, and the infill density was set at 50% with a hexagonal infill pattern, chosen for its high strength-to-weight ratio and effective load distribution. Cooling fan speed was held constant at 30% to regulate solidification of the extruded material, thereby preventing overheating and supporting interlayer bonding. The test specimens were printed in the XY-plane to ensure mechanical stability and were subjected to compression, flexural, and tensile testing. Real-time power consumption during printing was also monitored using a power meter, providing real-time data on the energy demands of TPU 95A processing. This energy analysis is essential for evaluating the sustainability of FDM printing with TPU, particularly in comparison to conventional manufacturing techniques.

Following the printing process, the mechanical properties of printed TPU 95A specimens were evaluated in accordance with standardized test procedures. The samples were conditioned and tested based on ASTM D638 Type V for tensile strength, ASTM D790 for flexural properties, ASTM D695 for compression, and ASTM E99 for wear resistance using a pin-on-disc tribometer. Tensile, flexural, and compressive tests were conducted using a Tinius Olsen Universal Testing Machine (UTM) (Norway). The experiments were conducted at a strain rate of 5 mm/min to ensure consistent stress application and precise mechanical response. In addition, a 10 kN unit load was used to determine the tensile strength, Young's modulus, flexural strength, and compressive strength of the TPU 95A specimen. Wear resistance was assessed using a pin-on-disc tribometer, evaluating the adhesive and abrasive resistance of the material when subjected to regulated friction conditions. Each mechanical test was replicated three times to ensure statistical validity and reduce experimental variability. Energy consumption during the testing process was monitored continuously, providing insights into the power consumption of the tribometer and UTM during mechanical characterization. This continuous monitoring enabled the identification of energy-intensive stages and supports the development of more energy-efficient testing and printing processes. To normalize energy usage across specimens of varying infill densities and print durations, energy consumption was reported per unit mass of printed material (Wh/g).

Figure 1 illustrates the complete fabrication and characterization of TPU 95A specimens by FDM. Experimental data, including mechanical characteristics, energy consumption, and process efficiency, were analyzed accordingly. By integrating AI-assisted process optimization, real-time energy monitoring, and mechanistic testing, this study aimed to establish a sustainable and high-performance system for the AM of TPU-based components.

2.2. ANN implementation

In this study, an ANN was developed to predict key mechanical properties, namely, tensile strength, flexural strength, compression strength, and wear resistance, based on FDM process parameters. The ANN model also served as a decision-support system within the broader AI-MCDM optimization framework.[18,50-53]

2.2.1. Model architecture and setup

The ANN architecture consisted of the following components:

(i) Input layer: Four neurons representing the main FDM parameters – layer thickness, infill density, shell thickness, and print speed.
(ii) Hidden layers: Two hidden layers were employed: the first consisted of 16 neurons, and the second had eight neurons; both layers used the Rectified Linear Unit (ReLU) activation function to introduce non-linearity.

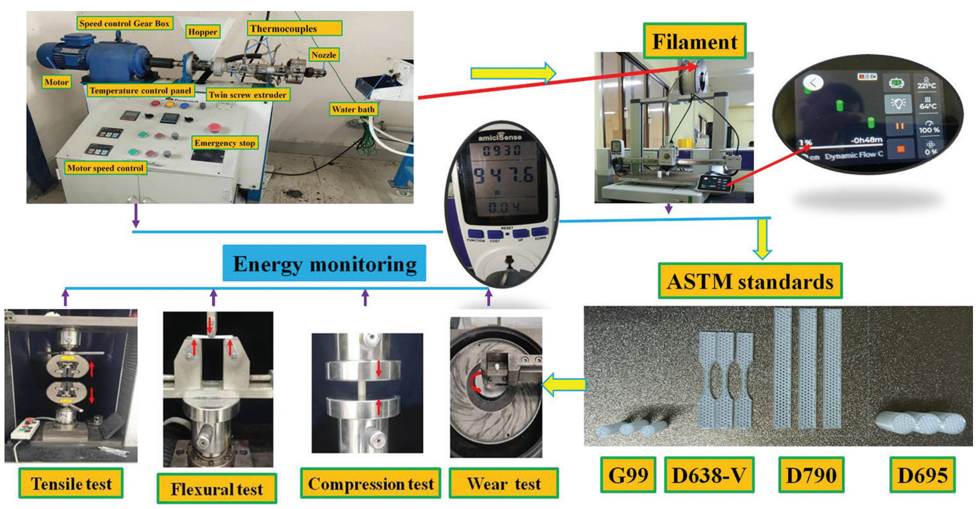

Figure 1. Experimental workflow for sustainable fuse deposition modeling (FDM)-based printing of TPU 95A components. India

(iii) Output layer: Four neurons corresponding to predicted values of tensile strength, flexural strength, compression strength, and wear rate; a linear activation function was applied to accommodate the continuous nature of the output values.

2.2.2. Dataset and training strategy

The model was trained on a dataset of over 500, comprising both experimentally generated data and literature-reported FDM process records. Each record included different parameter combinations along with corresponding mechanical test results. The dataset was divided into 80% for training and 20% for testing to ensure unbiased performance evaluation. Input and output values were normalized to enhance convergence.

2.2.3. Training parameters and tools

Training was performed using the mean squared error (MSE) loss function and the Adam optimizer, with a learning rate of 0.001. The model was trained over 100 epochs with a batch size of 32, implemented in a Python-based TensorFlow/Keras environment.

2.2.4. Model performance and validation

The performance of the trained ANN was assessed using several metrics:
(i) Root MSE (RMSE) ranged between 0.85 – 2.57 for different mechanical properties.
(ii) Mean absolute error (MAE) and mean absolute percentage error (MAPE) indicated consistent and reliable prediction consistency,
(iii) R^2 reached up to 0.95 for compression strength, reflecting an excellent model fit.

Scatter plots of experimental and predicted outcomes (Figures 2-5) further support the accuracy and aptness of the model for optimizing FDM parameters in impeller production.

2.3. MCDM framework

The MCDM framework serves as the backbone for FDM process optimization in impeller production, aiming to balance mechanical performance, energy consumption, and sustainability. This framework utilized Fuzzy AHP and TOPSIS for the sequential weighing and ranking of different process parameters, such as layer height, infill density, nozzle temperature, print speed, and cooling rate – each of which influences the quality and strength of the 3D-printed impellers.[33] Given the intricate trade-offs involved in impeller design – where mechanical strength and durability must be maximized while minimizing material usage and energy consumption – a hybrid Fuzzy AHP-TOPSIS model was employed to enable intelligent

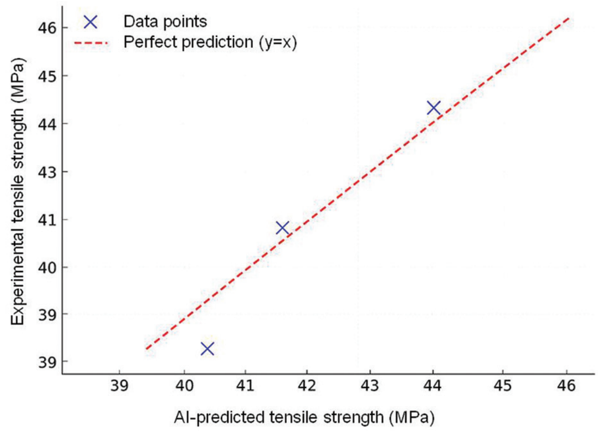

Figure 2. Scatter plot comparing artificial intelligence (AI)-predicted and experimentally measured tensile strength. The blue "×" mark represents an individual data point comparing predicted and actual results. The red dashed line (y = x) denotes perfect prediction; data points aligning with this line indicate accurate AI estimations, while deviations reflect prediction errors. This comparison illustrates the effectiveness of the AI model in estimating mechanical performance

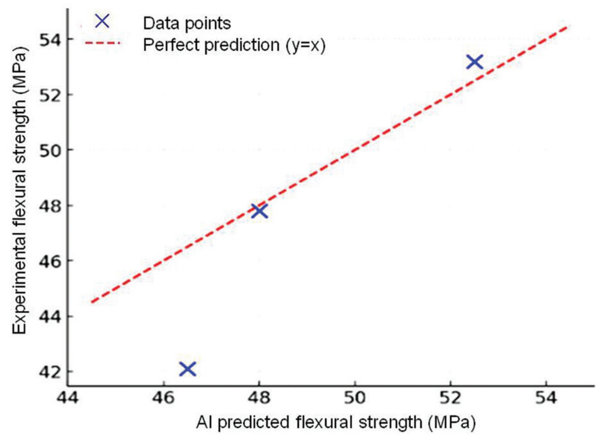

Figure 3. Scatter plot comparing artificial intelligence-predicted and experimentally measured flexural strength

decision-making. Fuzzy AHP was used to determine the relative weights of various criteria based on expert opinion and historical data. By integrating linguistic variables and fuzzy logic, it mitigates uncertainty in the decision-making process and facilitates prioritization of key attributes, such as tensile strength, flexural modulus, wear resistance, and surface roughness, to ensure a holistic evaluation of impeller performance. After the weighting phase, TOPSIS was used to rank different printing parameter settings based on closeness to the ideal solution that optimizes performance and energy efficiency. The implementation of AI-based MCDM models significantly enhances the system's predictive capabilities and supports real-time adjustments to the FDM setup through sensor feedback and process monitoring. In this study, a twin-screw extruder was utilized to manufacture TPU 95A filaments, with real-time energy consumption tracked using a power meter. This allows sustainability measures to be closely tied into the MCDM framework. Experimental data from mechanical testing and energy monitoring served as inputs to the Fuzzy AHP-TOPSIS model, with each metric carefully analyzed to determine the optimum process conditions. By applying the hybrid MCDM approach, optimal trade-offs among mechanical strength, energy efficiency, and print accuracy were achieved, facilitating high-performance, sustainable manufacturing of impellers. The Fuzzy AHP-TOPSIS model was integrated with AI regression techniques, making it more appropriate for handling a vast array of impeller geometries and materials. The model incorporates real-time sensor feedback from the 3D printer to dynamically optimize process parameters, thereby minimizing the need for manual parameter tuning. By combining data-driven AI models and expert-driven MCDM techniques, this study presents a logical and sustainable decision-making approach for FDM-based impeller production, with enhanced process efficacy, material utilization, productivity, and environmental performance. The architecture of the implemented ANN model is illustrated in Figure 6, illustrating the data flow from FDM parameters to predicted mechanical and energy-related outputs.

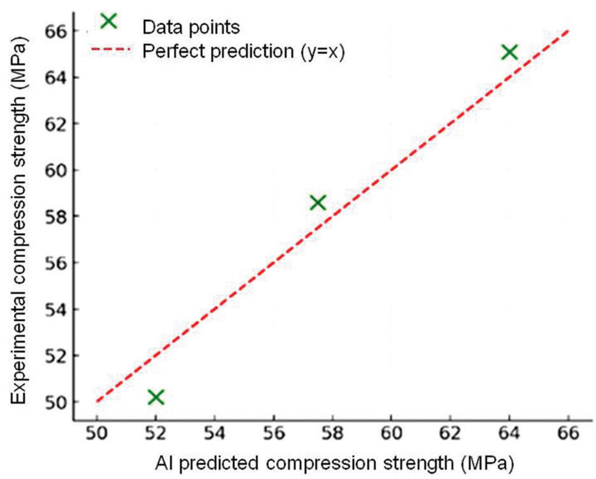

Figure 4. Scatter plot comparing artificial intelligence-predicted and experimentally measured compression strength

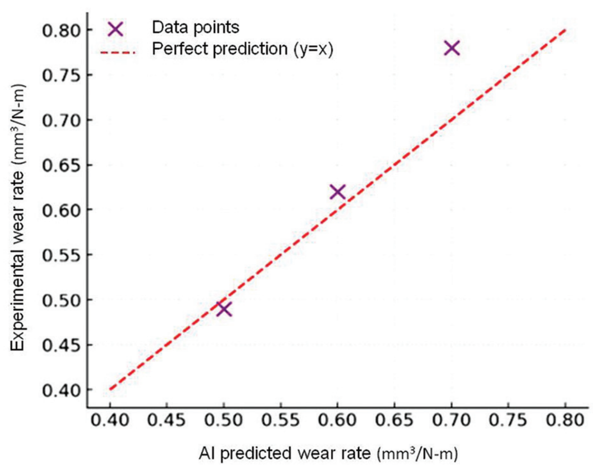

Figure 5. Scatter plot comparing artificial intelligence-predicted and experimentally measured wear rates

3. Results and discussion

Mechanical performance, energy consumption, and AI-MCDM optimization of FDM-based 3D-printed TPU 95A impellers were comprehensively examined. All aspects of the process, from filament extrusion to 3D printing and mechanical testing, were meticulously monitored for energy consumption to evaluate overall sustainability. Optimization of FDM printing parameters, such as layer thickness, infill density, shell thickness, and print speed, was performed using AI-based predictive modeling and MCDM methods, namely, Fuzzy AHP and TOPSIS. The mechanical properties of the impellers were evaluated through tensile, flexural, and compressive tests, while wear resistance was assessed using a pin-on-disc tribometer. The findings indicate that increasing shell thickness and infill density enhances wear resistance and mechanical strength, but also increases energy consumption. Therefore, an optimal trade-off strategy must be identified to achieve sustainable manufacturing. The test results are presented in Table 1.

The mechanical characteristics of TPU 95A impellers were determined based on the infill density and shell thickness from the tensile, flexural, and compression strength tests. Sample S1, with a layer thickness of 0.1 mm, infill density of 20%, and a shell thickness of 0.8 mm, exhibited poor mechanical properties, characterized by

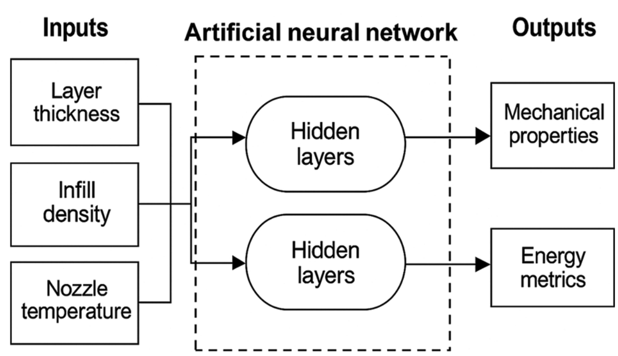

Figure 6. Architecture of the artificial neural network model used in this study

tensile strength of 32.5 MPa, flexural strength of 42.1 MPa, and compression strength of 50.2 MPa. In comparison, sample S2, with 50% higher infill density and a shell thickness of 1.2 mm, exhibited higher tensile strength (38.7 MPa), flexural strength (47.8 MPa), and compression strength (58.6 MPa). The highest mechanical response was observed for sample S3 (80% infill density and 1.6 mm shell thickness), with tensile strength of 44.2 MPa, flexural strength of 53.2 MPa, and compression strength of 65.1 MPa. This trend indicates that higher infill densities and thicker shells enhance load distribution and structural integrity, making them suitable for high-performance impeller applications. However, these improvements come at the cost of increased material usage, longer print times, and higher energy consumption. As such, data-driven optimization becomes essential to balance mechanical performance with sustainability. Table 2 presents energy consumption at each stage of TPU 95A impeller manufacturing, including variations in power consumption during filament extrusion, 3D printing, and mechanical testing.

Power consumption recorded at each stage of the production process revealed that filament extrusion required 85 Wh, indicating a significant contribution to total energy demand. During the 3D printing process, energy usage increased with higher infill density and shell thickness, as these required greater material deposition and longer print times. In particular, sample S1 used 110 Wh, sample S2 used 140 Wh, and sample S3 (having the highest infill density) used 180 Wh. The mechanical testing phase, which includes tensile, flexural, and compression tests, used an additional 50 Wh, while the pin-on-disc wear test contributed a further 30 Wh. These findings highlight the importance of implementing effective energy control to avoid unnecessary power usage during FDM-based impeller manufacturing. The total energy utilized by each sample for testing, 3D printing, and filament preparation ranged from 275 Wh for sample S1 to 345 Wh for sample S3, demonstrating the strong correlation between process parameters and the overall energy footprint.

The wear resistance test revealed a clear inverse relationship between infill density and wear rate. Sample S1, with 20% infill density, exhibited the highest wear rate of 0.78 mm^3/N·m, confirming that low-density structures are more prone to surface degradation under frictional loads. Sample S2, with 50% infill density, displayed improved wear resistance with a wear rate of 0.62 mm^3/N·m, while sample S3, with 80% infill density, reported the lowest wear rate of 0.49 mm^3/N·m. These results confirm that higher infill density enhances impeller durability by reducing surface wear. However, the energy consumption results indicate that achieving high wear resistance comes at the cost of increased power consumption, reiterating the need for AI-driven optimization to attain a balance between durability and energy efficiency.

Prediction accuracy of the AI model for tensile strength was quantified using RMSE, R^2, MAE, and MAPE. The RMSE was 1.05 MPa, indicating that the AI model's tensile strength predictions deviated by ±1.05 MPa from experimental values – an error margin acceptable within general engineering tolerances but still warranting further refinement. The R^2 of 0.78 suggests that 78% of the variance in tensile strength was captured by the model,

Table 1. Mechanical properties of fused deposition modeling (FDM)-printed TPU 95A impellers

Sample ID	Layer thickness (mm)	Infill density (%)	Shell thickness (mm)	Tensile strength (MPa)	Flexural strength (MPa)	Compression strength (MPa)	Wear rate (mm^3/N·m)
S1	0.1	20	0.8	32.5	42.1	50.2	0.78
S2	0.2	50	1.2	38.7	47.8	58.6	0.62
S3	0.3	80	1.6	44.2	53.2	65.1	0.49

Table 2. Energy consumption at each stage of TPU 95A impeller production

Process stage	Sample ID	Layer thickness (mm)	Infill density (%)	Shell thickness (mm)	Energy consumption (Wh)
Filament extrusion	-	-	-	-	85
3D printing	S1	0.1	20	0.8	110
	S2	0.2	50	1.2	140
	S3	0.3	80	1.6	180
Mechanical testing (tensile, flexural, and compression)	All samples	-	-	-	50
Wear test (pin-on-disc)	All samples	-	-	-	30

while the remaining 22% may be attributed to factors such as microstructural inconsistency, filament quality variation, or limitations in the modeling process. The MAE was 0.87 MPa, indicating that predictions by AI models differed from experimental results by an average of 0.87 MPa. The MAPE was 2.1%, indicating a relatively low average percentage error and demonstrating the model's strong predictive performance. These results highlight the potential of the AI model in predicting mechanical properties within FDM, while also highlighting that additional training data, sensor feedback, and parameter tuning for RL could further reduce prediction errors and enhance the overall optimization accuracy toward real-time adaptive control of FDM process parameters.

The precision of AI model predictions for flexural strength, compression strength, and wear resistance was determined using scatter plots and standard error metrics. For flexural strength, the model demonstrated moderate accuracy with an RMSE of 2.57 MPa, R^2 of 0.68, MAE of 1.77 MPa, and MAPE of 4.06%. These results indicate that while the model generally followed experimental trends, small variations were present, likely due to material anisotropy and interlayer bonding differences in FDM (Figure 3). In contrast, the prediction of compression strength displayed high accuracy, with an RMSE of 1.37 MPa, R^2 of 0.95, MAE of 1.33 MPa, and MAPE of 2.38%. These values suggest that the trained model closely replicated the load-carrying behavior of the material under compression (Figure 4). For wear resistance, the model had slightly lower predictive accuracy, with an RMSE of 0.048 mm^3/N·m, R^2 of 0.84, MAE of 0.037 mm^3/N·m, and MAPE of 5.17%. This decrease in performance may be attributed to the complex nature of tribological interactions and surface wear mechanisms (Figure 5). Across all tests, scatter plots revealed that AI-optimized parameter selection effectively predicted mechanical properties, reducing reliance on trial-and-error methods in FDM-based impeller production. However, further improvements, such as incorporating real-time sensor feedback, enlarging the training dataset, and applying RL for adaptive control, can enhance the model's accuracy, particularly in wear resistance predictions where surface roughness and frictional force introduce high variability.

To address the trade-off between mechanical performance and energy consumption, an AI-MCDM approach using Fuzzy AHP-TOPSIS was employed to identify the optimal printing parameters. The AI model utilized historical FDM process data to predict the optimal layer thickness, infill density, and shell thickness, prioritizing mechanical strength over energy efficiency based on predefined objective weightings. Table 3 presents the AI-MCDM-optimized parameters of FDM for impeller production, balancing mechanical performance and energy efficiency under different objective weightings. The Fuzzy AHP method was used to determine the relative importance of criteria under two optimization scenarios: (i) mechanical performance (60%) versus energy efficiency (40%); and (ii) energy efficiency (60%) versus mechanical performance (40%). In (i), where mechanical performance was prioritized, the optimal parameters were 0.2 mm layer thickness, 70% infill density, and 1.2 mm shell thickness, resulting in a tensile strength of 41.5 MPa and energy consumption of 145 Wh. In (ii), where energy efficiency was emphasized, the model suggested 0.3 mm layer thickness, 50% infill density, and 1.0 mm shell thickness, with a resultant tensile strength of 38.0 MPa and reduced energy consumption of 125 Wh. These results demonstrate the capability of the AI-MCDM approach to effectively balance strength, wear resistance, and sustainability in FDM-based impeller production.

Table 4 presents a comparison between AI-MCDM-optimized parameter selection and conventional FDM parameter selection. The analysis revealed that the AI-based approach outperformed manually selected parameters. Specifically, AI-optimized parameters improved tensile strength by 7% and wear resistance by 11%, while maintaining only a moderate increase in energy consumption of 3.5%. In contrast, conventional parameter selection, in accordance with standard FDM protocols, resulted in suboptimal mechanical performance and inefficient material deposition, resulting in unnecessary energy consumption. The use of the Fuzzy AHP-TOPSIS ranking technique enabled optimal selection of process parameters from real-time measurements, effectively reducing the need for trial-and-error experimentation. In addition, the AI model continuously refined its predictions based on sensor feedback from the 3D printer, thereby

Table 3. AI-MCDM-optimized FDM parameters for impeller production

Objective weighting (%)	Layer thickness (mm)	Infill density (%)	Shell thickness (mm)	Tensile strength (MPa)	Energy consumption (Wh)	Wear rate (mm^3/N·m)
Mechanical (60); energy (40)	0.2	70	1.2	41.5	145	0.55
Mechanical (40); energy (60)	0.3	50	1.0	38.0	125	0.61

Abbreviations: AI-MCDM: Artificial Intelligence–multicriteria decision-making; FDM: Fused deposition modeling.

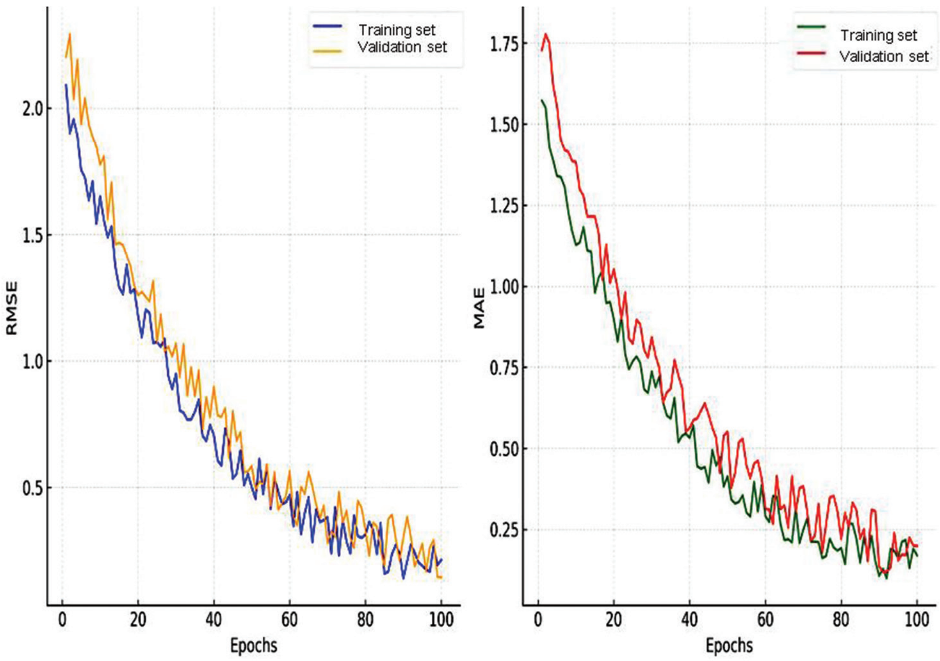

Figure 7. Root mean squared error (left) and mean absolute error (right) values over training epochs for both training and validation sets

Table 4. Comparative analysis of AI-MCDM and conventional parameter selection

Parameter selection method	Tensile strength (MPa)	Energy consumption (Wh)	Wear rate (mm^3/N·m)
Conventional approach	38.7	140	0.62
AI-MCDM-optimized	41.5	145	0.55

Abbreviation: AI-MCDM: Artificial Intelligence–multi-criteria decision-making.

enabling real-time adaptive control in the manufacturing process.

Figure 7 demonstrates stable convergence behavior of the ANN model, with decreasing error trends and no indication of overfitting, thereby confirming the reliability and generalization capability of the predictive model. These results demonstrate the potential of AI-MCDM-based optimization in FDM impeller manufacturing. The AI-MCDM-based approach enables data-driven enhancement of material efficiency, mechanical performance, and energy consumption. The integration of real-time sensors in the AI system enables dynamic adjustment of print parameters, ensuring high process reliability and sustainability.

Collectively, the results of this study suggest that future research should focus on extending AI-MCDM frameworks to additional objectives, such as optimization of surface roughness, thermal distortion compensation, and real-time defect detection, to further automate FDM-based impeller manufacturing. Other hybrid AI methods, including RL and digital twin models, hold promise for predicting machine-specific variations in FDM performance. Such advancements would contribute to the development of next-generation smart manufacturing platforms, where AI systems continually learn and evolve FDM processes in real-time to optimize efficiency, reduce waste, and improve product quality.

4. Conclusion

The findings of this study validated the performance of AI-based optimization and MCDM methods in optimizing the mechanical characteristics and sustainability of FDM-based impeller fabrication. The combination of Fuzzy AHP and TOPSIS with AI predictive modeling enabled the identification of optimal trade-offs among tensile, flexural, and compressive strengths, wear resistance, and energy efficiency. Higher infill densities and shell thicknesses led to notable improvements in mechanical properties and wear resistance; however, these gains were accompanied by increased energy consumption, highlighting the importance of AI-driven, eco-friendly parameter optimization. The AI-optimized process yielded 7% higher tensile strength and 11% lower wear rate, while maintaining energy consumption within 3.5% of baseline FDM parameters. Overall, the results highlighted the superiority of AI-supported decision models over conventional trial-and-error approaches, offering a better, more efficient, and sustainable method for AM process optimization.

The industrial applications of AI-optimized FDM span multiple sectors that employ high-performance impellers and complex fluid-handling components. Various industries, such as automotive, aerospace, marine, and energy, stand to benefit from AI-driven FDM processes capable of producing lightweight, wear-resistant, and aerodynamically optimized impellers. AI-based multi-objective optimization can also be applied in biomedical engineering, where patient-specific implants and prosthetics fabrication require accurate fabrication with minimal material loss. Furthermore, real-time AI monitoring and adaptive learning algorithms in FDM can improve production efficiency by reducing cycle times and operational costs, while maintaining consistent print quality, particularly advantageous in mass manufacturing settings. These developments align closely with the United Nations' SDGs, suggesting that AI-driven sustainability frameworks in AM can promote more environmentally responsible industrial practices. Future research directions include the implementation of real-time AI monitoring systems with IoT-enabled sensors to facilitate adaptive process control and *in situ* defect detection, ensuring optimal layer adhesion, extrusion flow, and energy consumption. The LCA of AI-optimized FDM processes will also be essential to evaluate their long-term environmental and economic advantages. Moreover, the integration of digital twin simulations and RL algorithms could further evolve FDM into a fully autonomous, smart manufacturing platform. These technologies would enable dynamic parameter tuning based on real-time data and sustainability metrics, paving the way for energy-efficient, scalable, and high-quality additive manufacturing solutions. In future work, we aim to expand the experimental dataset by fabricating and testing a broader range of parameter combinations. This will help validate the consistency and generalizability of the AI-MCDM optimization framework. Additional mechanical characterization and real-time energy monitoring across different geometries and materials will be performed to enhance the robustness of the model.

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Conflicts of interest

The authors declare no conflicts of interest.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The datasets used and/or analyzed during the present study are available from the corresponding author on reasonable request.

References

1. Roozkhosh P, Pooya A, Soleimani Fard O, Bagheri R. Revolutionizing supply chain sustainability: An additive manufacturing-enabled optimization model for minimizing waste and costs. *Process Integr Optim Sustain*. 2024;8(1):285-300.

   doi: 10.1007/s41660-023-00368-1

2. Subramani R. Optimizing process parameters for enhanced mechanical performance in 3D printed impellers using graphene-reinforced polylactic acid (G-PLA) filament. *J Mech Sci Technol*. 2025;39:1387-1397.

   doi: 10.1007/s12206-025-0231-4

3. Panesar A, Brackett D, Ashcroft I, Wildman R, Hague R. *Design Optimization Strategy for Multifunctional 3D Printing*; 2014. Available from: https://www.com hdl.handle.net/2152/89261 [Last accessed on 2025 Jul 22].

4. Hussain S, Lee CKM, Tsang YP, Waqar S. A machine

learning-based recommendation framework for material extrusion fabricated triply periodic minimal surface lattice structures. *J Mater Sci Mater Eng.* 2025;20(1);27.

doi: 10.1186/s40712-025-00229-4

5. Goh GD, Sing SL, Lim YF, *et al*. Machine learning for 3D printed multi-materials tissue-mimicking anatomical models. *Mater Design*. 2021;211:110125.

doi: 10.1016/j.matdes.2021.110125

6. Yadav R. Analytic hierarchy process-technique for order preference by similarity to ideal solution: A multi criteria decision-making technique to select the best dental restorative composite materials. *Polym Compos.* 2021;42(12):6867-6877.

doi: 10.1002/pc.26346

7. Gyani J, Ahmed A, Haq MA. MCDM and various prioritization methods in AHP for CSS: A comprehensive review. *IEEE Access*. 2022;10:33492-33511.

doi: 10.1109/ACCESS.2022.3161742

8. Tran NT, Trinh VL, Chung CK. An integrated approach of fuzzy AHP-TOPSIS for multi-criteria decision-making in industrial robot selection. *Processes*. 2024;12(8):1723.

doi: 10.3390/pr12081723

9. Kantaros A, Katsantoni M, Ganetsos T, Petrescu N. The evolution of thermoplastic raw materials in high-speed FFF/FDM 3D printing Era: Challenges and opportunities. *Materials (Basel)*. 2025;18(6):1220.

doi: 10.3390/ma18061220

10. Achite M, Nasiri H, Katipoğlu OM, Abdallah M, Moazenzadeh R, Mohammadi B. A coupled extreme gradient boosting-MPA approach for estimating daily reference evapotranspiration. *Theor Appl Climatol.* 2025;156(2):113.

doi: 10.1007/s00704-024-05313-x

11. Nandipati M, Fatoki O, Desai S. Bridging nanomanufacturing and artificial intelligence-a comprehensive review. *Materials (Basel)*. 2024;17(7):1621.

doi: 10.3390/ma17071621

12. Batu T, Lemu HG, Shimels H. Application of artificial intelligence for surface roughness prediction of additively manufactured components. *Materials (Basel)*. 2023;16(18):6266.

doi: 10.3390/ma16186266

13. Elahi M, Afolaranmi SO, Lastra JLM, Garcia JAP. A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discov Artif Intell*. 2023;3:43.

doi: 10.1007/s44163-023-00089-x

14. Zhou L, Miller J, Vezza J, *et al*. Additive manufacturing: A comprehensive review. *Sensors (Basel)*. 2024;24(9):2668.

doi: 10.3390/s24092668

15. Liu S, Yang C. Machine learning design for high-entropy alloys: Models and algorithms. *Metals*. 2024;14(2):235.

doi: 10.3390/met14020235

16. Ng WL, Goh GL, Goh GD, Ten JSJ, Yeong WY. Progress and opportunities for machine learning in materials and processes of additive manufacturing. *Adv Mater.* 2024;36(34):2310006.

doi: 10.1002/adma.202310006

17. Fahimi K, Amirabadi M. Constructing the organizational excellence model using technique for order of preference by similarity to ideal solution and Analytic hierarchy process. *Int J Hum Capital Urban Manag*. 2024;9:157-176.

doi: 10.22034/IJHCUM.2024.01.11

18. Galal A, Elawady H, Mostafa NA. An integrated framework for third party logistic evaluation by using fuzzy analytical hierarchy process and technique for order preference by similarity to ideal solution. *Int J Logist Syst Manag.* 2025;50(3):361-385.

doi: 10.1504/IJLSM.2025.144680

19. Prasetyo DE, Nurfaizal H, Effendi A. Comparative analysis of the analytical hierarchy process (ahp) and technique for order preference by similarity to ideal solution (topsis) methods in selecting majors for new students: A case study at smks binong permai an-nurmaniyah. J *Inform Utama*. 2024;2(1):43-49.

20. Hanafi AM, Moawed MA, Abdellatif OE. Advancing sustainable energy management: A comprehensive review of artificial intelligence techniques in building. *Eng Res J (Shoubra)*. 2024;53(2):26-46.

doi: 10.21608/erjsh.2023.226854.1196

21. Ukoba K, Olatunji KO, Adeoye E, Jen TC, Madyira DM. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy Environ.* 2024;35(7):3833-3879.

doi: 10.1177/0958305X241256293

22. Rojek I, Mikołajewski D, Mroziński A, Macko M. Green energy management in manufacturing based on demand prediction by artificial intelligence-a review. *Electronics*. 2024;13(16):3338.

doi: 10.3390/electronics13163338

23. Sarkar C, Das B, Rawat VS, *et al*. Artificial intelligence and machine learning technology driven modern drug discovery and development. *Int J Mol Sci.* 2023;24(3):2026.

doi: 10.3390/ijms24032026

24. Babu SS, Mourad AHI, Harib KH, Vijayavenkataraman S. Recent developments in the application of machine-learning towards accelerated predictive multiscale design and additive manufacturing. *Virtual Phys Prototy.* 2023;18(1):e2141653.

doi: 10.1080/17452759.2022.2141653

25. Yousuf M, Alsuwian T, Amin AA, Fareed S, Hamza M. IoT-based health monitoring and fault detection of industrial AC induction motor for efficient predictive maintenance. *Measure Control*. 2024;57(8):1146-1160.

    doi: 10.1177/002029402412314

26. Moscol-Albañil I, Solórzano-Requejo W, Rodriguez C, Ojeda C, Lantada AD. Innovative AI-driven design of patient-specific short femoral stems in primary hip arthroplasty. *Mater Design*. 2024;240:112868.

    doi: 10.1016/j.matdes.2024.112868

27. Westphal E, Seitz H. Generative artificial intelligence: Analyzing its future applications in additive manufacturing. *Big Data Cogn Comput*. 2024;8(7):74.

    doi: 10.3390/bdcc8070074

28. Zhang Y, Song C. A novel design of centrifugal pump impeller for hydropower station management based on multi-objective inverse optimization. *Processes*. 2023;11(12):3335.

    doi: 10.3390/pr11123335

29. Pinto RN, Afzal A, D'Souza LV, Ansari Z, Mohammed Samee A. Computational fluid dynamics in turbomachinery: A review of state of the art. *Arch Computat Methods Eng*. 2017;24(3):467-479.

    doi: 10.1007/s11831-016-9175-2

30. Cao S, Peng G, Yu Z. Hydrodynamic design of rotodynamic pump impeller for multiphase pumping by combined approach of inverse design and CFD analysis. *J Fluids Eng*. 2005;127:330-338.

    doi: 10.1115/1.1881697

31. Raja S, Praveenkumar V, Rusho MA, Yishak S. Optimizing additive manufacturing parameters for graphene-reinforced PETG impeller production: A fuzzy AHP-TOPSIS approach. *Results Eng*. 2024;24:103018.

    doi: 10.1016/j.rineng.2024.103018

32. Mushtaq RT, Wang Y, Rehman M, *et al*. Investigation of the mechanical properties, surface quality, and energy efficiency of a fused filament fabrication for PA6. *Rev Adv Mater Sci*. 2023;62(1):20220332.

    doi: 10.1515/rams-2022-0332

33. Raja S, Jayalakshmi M, Rusho MA, *et al*. Fused deposition modeling process parameter optimization on the development of graphene enhanced polyethylene terephthalate glycol. *Sci Rep*. 2024;14(1):30744.

    doi: 10.1038/s41598-024-80376-4

34. Borah J, Chandrasekaran M. Development of ANN model for predicting mechanical properties of 3D printed PEEK polymer using FDM and optimization of process parameters for better mechanical properties. *Phys Scripta*. 2024;99(11):116005.

    doi: 10.1088/1402-4896/ad7f0f

35. Villegas AI, Garcia JP, Carillo J, Espalin D. *Bead-Weaved Layered Prints for Improved Interlayer Adhesion in Additive Manufacturing*. United States: University of Texas at Austin; 2024.

    doi: 10.26153/tsw/58049

36. Alharbi A, Alosaimi W, Alyami H, *et al*. Selection of data analytic techniques by using fuzzy AHP TOPSIS from a healthcare perspective. *BMC Med Inform Decis Mak*. 2024;24(1):240.

    doi: 10.1186/s12911-024-02651-8

37. Lambiase F, Liparoti S, Pace F, Scipioni SI, Paoletti A. A multidisciplinary approach to investigate the influence of process parameters on interlayer adhesion in material extrusion additive manufacturing. *Int J Adv Manuf Technol*. 2024;133(11):5553-5570.

    doi: 10.1007/s00170-024-14079-5

38. Kumar MS, Farooq MU, Ross NS, Yang CH, Kavimani V, Adediran AA. Achieving effective interlayer bonding of PLA parts during the material extrusion process with enhanced mechanical properties. *Sci Rep*. 2023;13(1):6800.

    doi: 10.1038/s41598-023-33510-7

39. Altıparmak SC, Yardley VA, Shi Z, Lin J. Extrusion-based additive manufacturing technologies: State of the art and future perspectives. *J Manuf Process*. 2022;83:607-636.

    doi: 10.1016/j.jmapro.2022.09.032

40. Polo-Triana S, Gutierrez JC, Leon-Becerra J. Integration of machine learning in the supply chain for decision making: A systematic literature review. *J Ind Eng Manag*. 2024;17(2):344-372.

    doi: 10.3926/jiem.6403

41. Mishra A, Linh NTD, Bhardwaj M, Pinto CM, editors. *Multi-criteria Decision Models in Software Reliability: Methods and Applications*. CRC Press; 2022. Available from: https://books.google.co.in/books?hl=en&lr=&id=lqcveaaaqbaj&oi=fnd&pg=pp1&dq=%5b41%5d.%09mishra,+a.,+linh,+n.+t.+d.,+bhardwaj,+m.,+%26+pinto,+c.+m.+(eds.).+(2022).+multi/criteria+decision+models+in+software+reliability:+methods+and+applications.+crc+press.&ots=hrepmhkbj6&sig=wlxd5kraczllcgqu3vvkrdhr0vw&redir_esc=y#v=on epage&q&f=false [Last accessed on 2025 Jul 22].

42. Sæterbø M. *A Decision Support Framework for Metal Additive Manufacturing Adoption in Small and Medium-Sized Enterprises*; 2024. Available from: https://www.hdl.handle.net/10037/35740 [Last accessed on 2025 Jul 22].

43. Getachew MT, Shiferaw MZ, Ayele BS. Recent advances of additive manufacturing for aerospace industries: Methods, materials, challenges, and future outlooks. In: *Solomon*

Workneh Fanta Mesfin Wogayehu Tenagashaw Muluken Temsgen Tigabu. 2025. p47.

doi: 10.1007/978-3-031-77339-6_4

44. Li Z, Chang L. Development of wear-resistant polymeric materials using fused deposition modelling (FDM) technologies: A review. *Lubricants*. 2025;13(3):98.

doi: 10.3390/lubricants13030098

45. Klenam D, Asumadu T, Bodunrin M, *et al*. Toward sustainable industrialization in Africa: The potential of additive manufacturing-an overview. *Front Manuf Technol*. 2025;4:1410653.

doi: 10.3389/fmtec.2024.1410653

46. Al-Sammak KA, Al-Gburi SH, Marghescu I, *et al*. Optimizing IoT energy efficiency: Real-time adaptive algorithms for smart meters with LoRaWAN and NB-IoT. *Energies*. 2025;18(4):987.

doi: 10.3390/en18040987

47. Glogar M, Petrak S, Mahnić Naglić M. Digital technologies in the sustainable design and development of textiles and clothing-a literature review. *Sustainability*. 2025;17(4):1371.

doi: 10.3390/su17041371

48. Yan Z, Guo X, Hui J, Lv J, Xu Z. Optimization of energy consumption and dimensional accuracy for fused deposition modeling processes through a hybrid method. *Int J Adv Manuf Technol*. 2025;137:2335-2354.

doi: 10.1007/s00170-025-15294-4

49. Ghaith K. Integrating eco-innovation with AI: Reimagining non-heritage cultural product design through sustainable technological interventions. *J Next Gener Rese*. 2025;1:1-12.

doi: 10.70792/jngr5.0.v1i2.58

50. Natarajan M, Pasupuleti T, Kumar V, Kiruthika J, Katta LN, Silambarasan R. *Development of AI Prediction Tool for Fused Deposition Modeling of ABS Material for Automobile Applications* (No. 2025-28-0127). SAE Technical Paper; 2025.

doi: 10.4271/2025-28-0127

51. Łach Ł, Svyetlichnyy D. Advances in numerical modeling for heat transfer and thermal management: A review of computational approaches and environmental impacts. *Energies*. 2025;18(5):1302.

doi: 10.3390/en18051302

52. Fan H, Liu C, Bian S, *et al*. New era towards autonomous additive manufacturing: A review of recent trends and future perspectives. *Int J Extrem Manuf*. 2025;7:032006.

doi: 10.1088/2631-7990/ada8e4

53. Jalasri M, Panchal SM, Mahalingam K, Venkatasubramanian R, Hemalatha R, Boopathi S. Ai-powered smart energy management for optimizing energy efficiency in high-performance computing systems. In: *Future of Digital Technology and AI in Social Sectors*. United States: IGI Global; 2025. p. 329-366.

doi: 10.4018/979-8-3693-5533-6.ch012