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AI-Enabled Optimization of Additively Manufactured Composite Materials for Enhanced Mechanical and Thermal Performance

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Abstract

This paper discusses the optimization of multi-objective optimization of enhanced coupling of heat and mechanical properties of 3D printed polymer composite materials by artificial intelligence (AI), as a component of a multi-objective optimization framework. It aims at development of nonlinear printing parameters and material properties relationships to achieve maximum tensile strength and thermal conductivity in polymer composites produced through fused deposition modeling (FDM). Short carbon fiber reinforcement was used to make the polymer composite by FDM at various deposition temperatures, raster pattern, and infill densities. A machine-learning model was created experimentally with the tensile strength and thermal conductivity of the polymer composite measured and then combined with an evolutionary optimization algorithm to give a combination of printing parameters, which will give the optimum structural and thermal performance of the final part. The optimized composite specimens exhibited an average tensile strength improvement of approximately 9.4% compared to baseline systems reported in recent literature. Similarly, effective thermal conductivity increased by nearly 14.2%, indicating improved heat transfer pathways within the composite matrix. The predictive model achieved a coefficient of determination of 0.94 for tensile strength and 0.91 for thermal conductivity, demonstrating strong agreement between predicted and experimental responses. The suggested structure will allow the simultaneous enhancement of mechanical and thermal performance of additive-manufactured polymer composite structures, and, potentially, intelligent process-driven design of multifunctional composite elements.

Keywords: Additive manufacturing, polymer composite materials, thermo-mechanical performance, AI-based process optimization, fused deposition modeling

INTRODUCTION

Polymer composite systems made by additive manufacturing have become an attractive sort of multifunctional engineering material due to the capability of providing custom anisotropic stiffness, regulated porosity and programmable thermal transport properties through layer-by-layer printing. Unlike more traditionally processed laminates, additive manufacturing allows control of reinforcement direction and conditions at the interfaces, as well as microstructural topology at the

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meso-scale, and therefore affects the effective thermo-mechanical behavior of the composite structure. But thermal gradients, residual stresses, and interlayer diffusion effects caused by deposition usually produce nonlinear tensile strength variations, modulus, and heat dissipation capacity with strata in the printed materials. These process structure and property interactions are also complexified by the existence of heterogeneous filler distributions and fiber matrix interface dynamics as cannot be sufficiently described by deterministic poly approximation alone. As a result, there is a growing interest in the creation of AI-centered optimization schemes that are able to learn complex parametric interactions within additive-manufactured composite assemblies to create a synergistic improvement of mechanical strength and thermal performance.

Broad Background

Composite materials have increasingly revolutionized the structural and functional engineering world through the provision of a superior ratio of strength, stiffness, and weight-saving. In contrast to monolithic materials, composite systems can be characterized by their performance being the result of the synergistic interaction of a matrix phase with reinforcement elements, i.e., fibers or particulates. The resulting intrinsic heterogeneity enables designers to add directional stiffness, thermal transport behavior and fatigue resistance through a change in constituent composition as well as spatial structure [1]. In modern contexts, such as aerospace structures as well as microelectronic packaging, the need is no longer focused on the load-bearing capability but on the materials being able to sustain thermal gradients, dissipation of heat and even dimensional stability in the context of cyclical operation conditions. As a result, producing composite materials based on polymers able to provide mechanical and thermal performance at the same time has become a chief engineering challenge [2].

The current research explores the concept of the AI-assisted optimization of additive-manufactured polymer composite materials focusing on improving both the mechanical integrity and thermal performance by means of intelligent process parameterization. The study takes into account the effect of deposition temperature, raster orientation, layer thickness, and reinforcement distribution on the effective thermo-mechanical performance of polymer matrix composites that have been produced through additive manufacturing using fused filament [3]. The paper will also help in the creation of structurally efficient and thermally stable composite structures by integrating data-driven models of learning to develop nonlinear relationships between fabrication parameters and composite outcomes defined by the tensile strength, elastic modulus, and thermal conductivity. This method is especially applicable in the case of high-tech polymer composite applications in which the relationship between interfacial adhesion, crystallinity development, and heat transfer mechanisms determines the ultimate stability of additively manufactured parts.

Current Trends in Additive Manufacturing of Composites

As the result of the opportunities to deposit material under the digital control of the microstructural structure in layers, additive manufacturing (AM) has produced a radical shift in the field of composite fabrication. The short or continuous reinforcements of the thermoplastic matrices using fused filament fabrication techniques which include stereolithography and direct ink writing techniques are now possible [4]. Recent studies found out that raster orientation, deposition temperature and infill topology have significant influence in tensile strength and heat conduction behaviour of additively manufactured composite laminates [5]. Additionally, with the addition of nanofillers like graphene, carbon nanotubes and ceramic particulates, it has been feasible to create polymer composites, which could be described as possessing high thermal conductivity with no diminution in mechanical integrity [6]. These developments highlight a move to embrace more and more composite structures which are multifunctional i.e. structural performance with thermal management capability [7].

Existing Research Gaps

Despite the fact that the process of additive manufacturing of composite materials has been enhanced in a significant way yet, processes remain susceptible to defects that involve the formation of holes, delamination between layers, and stresses that are not eliminated [8]. These defects are normally leading to anisotropic mechanical properties and asymmetry of the heat flux between the printing layers [9]. Better said, the relationship between AM process parameters and the overall performance of the composite is non-linear and interdependent in nature rendering the traditional empirical optimization solutions ineffective [10]. The literature that is presently available has concentrated on either the mechanical strength or thermal conductivity as a measure of performance independently, thereby ignoring coupled response of the thermo-mechanical behaviour of composite systems [11]. This is a great shortcoming of the current literature since it lacks multi-objective performance trade-off models that can be combined together to reflect multi-objective performance [12].

Problem Statement

Mechanical and thermal optimization of additive-manufactured composite materials is a complex matter since the interplay between processing parameters, the reinforcement orientation and interfacial bonding properties are complex. The variations in deposition parameters may also be applied to enhance stiffness and simultaneously decrease thermal transport efficiency or vice versa [13]. Due to such duality, there is the need to develop intelligent optimization strategies that can be employed to identify fabrication conditions resulting in balanced performance outcomes in different objectives.

Motivation

The traditional types of parameter tuning based on the trial-and-error experiment are expensive in terms of resources and could not be extended to high-dimensional design space [14, 15]. The application of artificial intelligence in manufacturing optimization processes can be a potentially successful solution to these limitations.

Need for the Study

Traditional optimization tools, such as Taguchi design tools and response surface modeling, which utilizes a response surface modeling (polynomial regression) are limited in their capabilities to represent nonlinear relationships between fabrication variables [16]. In addition, these methods are usually based on simplistic assumptions on the fiber/matrix interaction, and conduction of heat in composite structures [17]. The increased sophistication of AM-enabled composite architectures thus requires data-driven models with the ability to gain knowledge of complex process-property relationships through experimental data [18].

Research Objectives

The central goal of the research is to design AI-based optimization system to additive-manufactured composite materials that will help improve both mechanical strength and thermal performance. Particularly, the study aims to simulate the effect of fabrication factors on tensile performance and thermal conductivity, adopt a multi-objective optimization model to select the parameters, and test the predictability of the suggested modeling in experimental studies [19].

The research is concerned with polymeric composite materials that have been produced through fused deposition modeling additive manufacturing methods. To investigate the changes in performance of short-fiber reinforced thermoplastics as well as nanoparticle-enhanced polymer matrices, both types of polymers are regarded to be studied in the context of varying deposition conditions. The working area is limited to the optimization of the process parameters but not the chemical modification of the constituent materials [20].

Novelty and Contribution

The suggested framework combines predictive modeling, which is a machine learning-based method and multi-objective optimization to obtain a simultaneous enhancement of mechanical and thermal performance of the AM-fabricated composites. In comparison to the available techniques that focus on the optimization of individual properties, the current methodology represents a comprehensive description of coupled thermo-mechanical actions on changing the process parameters, thus, offering a coherent approach to the performance improvement.

At the conceptual level, the algorithm is a combination of supervised learning algorithms and evolutionary optimization techniques to find fabrication conditions that would optimize tensile strength and thermal conductivity simultaneously. Training predictive models is done using experimental data as a result of controlled AM experiments, which in turn informs the optimization process by repeatedly assessing measures of performance.

It can be predicted that the output of this study will lead to the optimization of intelligent process in additive manufacturing facilities, resulting in material dispensability, structural stability, and thermal dissipation features of the composite parts used in high-tech engineering tasks.

The rest of this paper is structured in the following way. Section 2 investigates the literature on the topic of additive manufacturing of composite materials and AI-based optimization algorithms. Section 3 outlines the proposed research design and study protocol. Section 4 includes the discussion and results of thermo-mechanical performance increase. Section 5 brings the paper to an end with general findings and recommendations of future research.

LITERATURE REVIEW

Additive Manufacturing of Polymer Composite Systems

Additive manufacturing of polymer composites has received increasing research interest in recent years because of its potential to form lightweight structures with highly sophisticated geometrical patterns and spatially localized reinforcement distribution. Layered deposition of thermoplastic matrix reinforced with short or continuous fibers can also be done in fused deposition based fabrication processes to produce load bearing composite laminates with desired anisotropic behavior [15]. The AM route permits direct compressive control on raster orientation and infill topology unlike traditional compression molding or filament winding, thus, making a major impact on tensile modulus and fracture resistance of the resulting composite structure [16].

Experimental studies have revealed that interlayer bonding and diffusion of the melt between deposited filaments through polymer composites is the determinant of the effective mechanical strength of polymer composite constructs. Polymer chain entanglement at the interface between layers defines the efficiency of transfer of load between the successive strata [17]. Poor thermal bonding can lead to the creation of voids and delamination, which, in turn, decrease the efficiency of the stiffness and fatigue life of the printed component [18]. Moreover, the non-uniformity of reinforcement fibers distribution along deposition paths brings in a variation of stress concentration regions, and result in non-uniform failure behavior during mechanical loading conditions [19].

Influence of Process Parameters on Thermo-Mechanical Performance

The large amount of literature suggests that parameters of additive manufacturing have a predominant impact on the mechanical and thermal behavior of polymer composite systems. The deposition temperature, build orientation, infill density, and print speed alone have an influence on the crystallinity of polymer matrix and orientation of the reinforcement phases embedded [20]. The increase in the nozzle temperatures usually enhances the strength of interfaces bonding through viscous flow and molecular diffusion between the layers. Nevertheless, when exposed to excessive thermal conditions, it can cause degradation of the matrices or the residual stresses which negatively influence the dimensional stability [21].

In the same way, raster orientation has also been determined as a very important factor that defines the load-bearing ability of additively manufactured composites. Tensile strength is increased by parallel fiber orientation with the major loading direction but is frequently decreased by transverse fiber orientation because of low interactions between fibers and the matrix [22]. These parameters affect the heat transfer capabilities of the composite structure as well as the mechanical performance of the structure. Research on the use of nanoparticle in thermoplastic matrices has shown enhancement of thermal conductivity by the creation of conductive filler networks along deposition pathways [23]. However, partial filler dispersion can also interfere with the thermal continuity and create pinpointed heat generation in the printed parts [24].

AI-Based Modeling in Composite Fabrication

In order to solve the complexity arising due to nonlinear process-property relationships, researchers have sought to investigate the possibility of using artificial intelligence methodologies to predict modeling in additive manufacturing settings. Artificial neural networks and support vector regression machine learning algorithms have been utilized to determine tensile strength, porosity levels and dimensional accuracy of polymer composite specimens produced in different process conditions [25]. The models can implicitly represent the concealed associations among fabrication inputs and performance outputs by not demanding any analytical formulations.

Approximating the behavior of thermal conductivity in nanoparticle-reinforced polymer composites has also been done using the numerical method of Polynomial regression and ensemble-based learning [26]. Specifically, the surrogate modeling approaches have demonstrated themselves to be effective in forecasting the synergistic effect of the layer thickness and deposition rate on thermo-mechanical behavior [27]. The predictive power of these models is however significantly reliant on the quality of experimental datasets that can be used that can adequately model multi-scale interactions within the composite microstructure [28].

Multi-Objective Optimization Approaches

The fact that mechanical and thermal properties optimization in polymer composites is a multi-objective problem is complicated by the fact that performance measures are competing. Adding more filler can enhance thermal conductivity, but can deal with loss of ductility or processability [29]. On the same note, increased infill density will increase structural rigidity but can also cause thermal stresses when cooling down.

Genetic optimization models and evolutionary algorithms, have been suggested to seek the best parameter mixes to balance conflicting performance demands of additive-manufactured composites [30]. They enable the high-dimensional design spaces to be searched by means of iterative assessment of candidate solutions with respect to a set of objective functions. However, the majority of the current optimization research is based on each individual performance measure instead of comprehensive thermo-mechanical behaviour [31].

Recent trends in hybrid optimization processes have seen the integration of machine learning-based predictive models into evolutionary processes of search to enhance the rate of convergence and reliability of solution [32]. These frameworks minimize computational and computational expenses of repeated physical experimentation, by using surrogate models that are trained using experimental data and allow tolerable predictive accuracy [33]. Although such progress has been made, the field of the multi-objective optimization of additive-manufactured polymer composites with the help of AI is still underdeveloped..

Limitations of Existing Studies

Despite the significant advancements in the field of determining the impact of AM process parameters on composite behavior, there are still a number of limitations in the field of contemporary research work. Majority of the research is based on small scale data that cannot reflect stochastic variation in the reinforcement distribution and interfacial bonding strength [34]. Also, most of the predictive models are created to estimate the mechanical property only with little regard to the thermal transport behavior in the composite matrix [35].

The other important restriction is the lack of systems with built-in mechanisms that can improve tensile strength and thermal conductivity at the same time without reducing structural integrity [36]. The intricate interaction of the load transfer mechanisms and pathways of heat transfer requires the emergence of smart optimization methods that will be able to learn the nonlinear relationships among the fabrication parameters and the microstructural aspects of composite [37].

The blank cells found with the help of the comparative analysis in Table 1 give the background impetus to the suggested artificial intelligence-based optimization of the system that is expected to lead to balanced enhancement of mechanical and thermal performance of additive-manufactured polymer composite materials.

Considering these issues, the combination of artificial intelligence and additive manufacturing process optimization is a promising field of enhancing the overall functionality of polymer composite systems. The literature review, therefore, identifies the necessity to use data-driven methodologies that can be used to monitor coupled thermo-mechanical behaviors of additively manufactured composite architectures.

METHODOLOGY

The proposed methodology of the current study will help to address shortcomings of the traditional process tuning in additive-based polymer composite systems, where mechanical performance and thermal performance are usually optimized separately. The combination of predictive learning and multi-objective maximization in the framework allows developing load-bearing behavior and heat transfer performance at once by introducing intelligent changes in the fabrication parameters. Figure 1 has shown the architectural workflow of the proposed AI-enabled optimization method of additive-manufactured polymer composite structures.

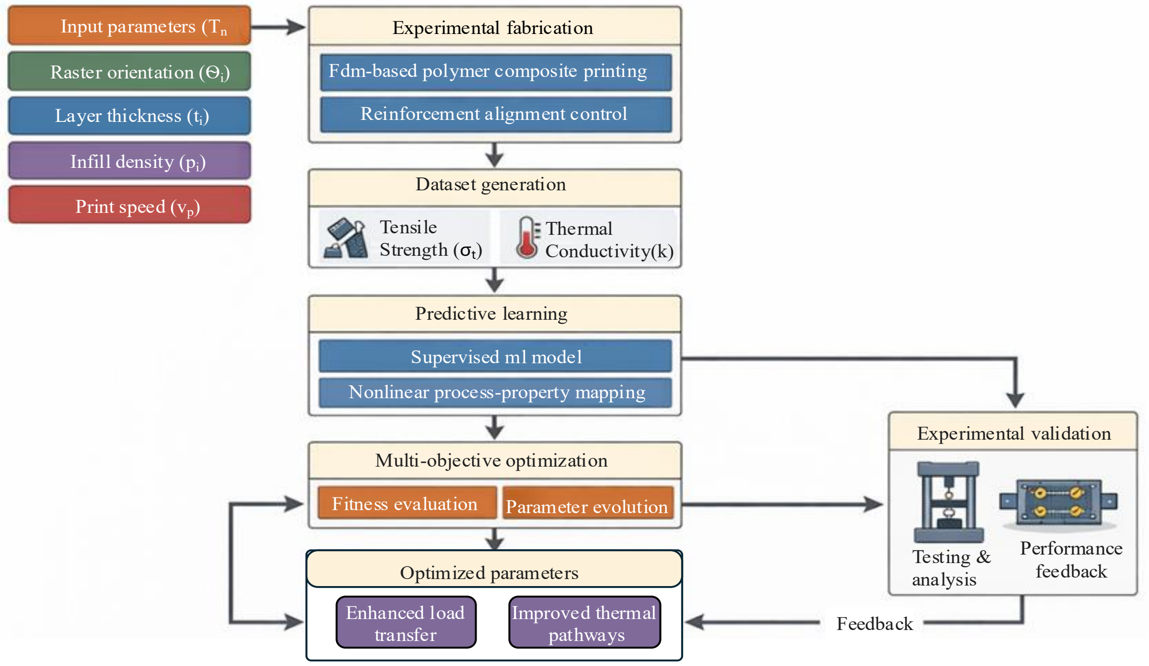

Figure 1. Architecture of the proposed AI-enabled optimization framework for additive-manufactured polymer composite systems.

Table 1. Literature gap analysis of AI-enabled optimization in additive-manufactured polymer composite systems.

S.N.	Reference no..	Title / focus area	Methodology / tools used	Key findings	Limitations / gaps identified	Relevance to the current study
1	W. Choi et al. / 2023 / [3]	AI/ML in design + additive manufacturing of responsive composites	Review-style synthesis of AI pipelines for responsive composites; ML-driven design loops	Establishes how AI accelerates composite design decisions and links material behavior to manufacturing choices	Mostly conceptual; limited focus on joint thermo-mechanical optimization and limited AM process coupling detail	Frames the AI-to-AM pathway and supports your positioning of AI-enabled optimization for composite performance
2	D. Yu. Stepanov et al. / 2024 / [13]	Parameter optimization for high-viscosity PEEK/30GF composites	Experimental optimization of printing parameters for reinforced high-performance polymer composite	Shows strong dependence of mechanical outcomes on print parameter sets for PEEK/30GF systems	Emphasis largely on processing + mechanical, while thermal transport and AI-driven global optimization are not central	Strong polymer-composite AM baseline; supports why parameter space needs intelligent optimization for high-end polymers
3	A. D. Dubey & K. Debnath / 2025 / [22]	Mechanical + thermal + morphology of 3D-printed woven glass fiber/PLA composites	TLBO optimization + ANN prediction; coupled characterization (mechanical/thermal/morphology)	Demonstrates that combining metaheuristic optimization with learning can tune both mechanical and thermal indicators	Thermal analysis often limited to standard metrics; generalization across materials/process windows is not deeply addressed	It: shows feasibility of multi-property optimization in polymer composites
4	C. Zhu et al. / 2024 / [19]	ML-aided design and optimization of thermal metamaterials	ML-driven optimization and design strategies for thermal property control	Strong evidence that ML can discover non-intuitive thermal transport solutions	Not specific to AM polymer composites; mechanical coupling is outside main scope	Provides a high-quality foundation for thermal-property optimization logic that your work adapts to AM composites
5	R. Barhemat et al. / 2023 / [25]	AI-assisted design + 3D printing of polymer–concrete composites	AI-assisted design workflow + AM evaluation for architectural composite systems	Highlights AI-guided design improving specific flexural metrics and toughness-related performance	Material system differs (polymer–concrete); thermal performance is not the primary target	Useful comparative reference for AI-assisted design-to-print validation workflows, even across composite families
6	S. K. S. Raja et al. / 2025 / [1]	Sustainable manufacturing of FDM composite impellers using hybrid ML + simulation optimization	Hybrid ML + simulation-based optimization; sustainability-informed manufacturing	Shows ML+simulation can optimize AM composite parts with performance and sustainability constraints	Focus is component-specific (impellers); thermal behavior is not strongly integrated as a co-objective	Supports your argument for hybrid optimization (ML + physics/simulation) in AM composites
7	T. M. H. Truong et al. / 2025 / [26]	Physics-informed ML for multi-objective optimization in additive manufacturing	Physics-informed ML; data-efficient multi-objective optimization	Demonstrates improved optimization efficiency when physics constraints regularize ML models	Not tailored to polymer composites; property targets vary by case-study	Provides the methodological basis for multi-objective + data-efficient AI optimization suitable for your study
8	D. Shin et al. / 2024 / [28]	Deep material network for predicting thermomechanical response of composites	Deep material network (DMN) for homogenization-style thermomechanical prediction	Captures coupled thermomechanical response with strong predictive capability	Often demands structured data/representations; direct linkage to AM print parameters may be indirect	Directly supports your “mechanical + thermal together” theme and motivates coupling thermomechanical predictors with AM optimization

Figure 1 depicts that the methodological pipeline will be an experiment fabrication with the generation of data, a predictive model, and evolution optimization as the scheme to have a closed-loop interaction between the additive manufacturing metrics and the thermo-mechanical performance metrics. It is a systematic exploration architecture that allows exploring the design space of fabrication and still allows predicting and measuring the composite responses in the laboratory.

Research Framework for AI-Enabled Optimization of Additive-Manufactured Polymer Composites

The methodological framework followed in this research has been elaborated in such a way that it allows the systematic study of how parameters of the additive manufacturing process affect the coupled thermo-mechanical behavior of polymer composite structures. Unlike the traditional schemes of deterministic optimization, the current study incorporates fabrication experiment with predictive modeling with data to form nonlinear relationships between deposition parameters and composite performance measures. This is particularly needed in polymer matrix composites manufactured through additive manufacturing processes such as fused deposition when raster orientation, inter-layer diffusion/reinforcement alignment are significant in the determination of mechanical strength and the heat transfer paths [3, 16].

On the Figure 2, the main stages of the work of the proposed AI-based optimization strategy are presented. The model consists of three sequential steps, which include (i) manufacturing polymer composite product, at varying conditions of the processes, (ii) experimental measurements and tensile and thermal property, (iii) predictive modeling and optimizing the machine learning algorithms under supervision.

The parameters of the additive manufacturing procedure were systematically altered to produce a structured experimental dataset of the interaction of process and structure with property within the composite architecture as illustrated in Figure 2. Such datasets were later utilized to predictive learning models that could be used to estimate nonlinear thermo-mechanical responses of polymer based composite systems.

Material Selection and Composite Fabrication

Specimens by polymer matrix composite were made by means of fused deposition modeling (FDM) because it was compatible with fiber-reinforced thermoplastic feedstocks. A base material system was chosen to be short carbon fiber reinforced polylactic acid (PLA-CF) filament due to its good stiffness-weight ratio and thermal stability properties [21]. The composite feedstock was built in a layer based fashion by employing a controlled raster orientation approach to allow uniform reinforcement alignment across the strata printed.

The parameters of fabrication that are taken into account in this research are summed up in Table 2. These parameters were chosen, because they have been reported to have an impact on interfacial bonding strength and porosity evolution in additively manufactured polymer composites [13, 20].

Table 2. Process parameters considered for fabrication of additive-manufactured polymer composite specimens.

Parameter	**Symbol**	**Range**
Nozzle Temperature	T_n	200–240°C
Layer Thickness	t_l	0.1–0.3 mm
Raster Orientation	θ_r	0°–90°
Infill Density	ρ_i	50–100%
Print Speed	v_p	30–70 mm/s

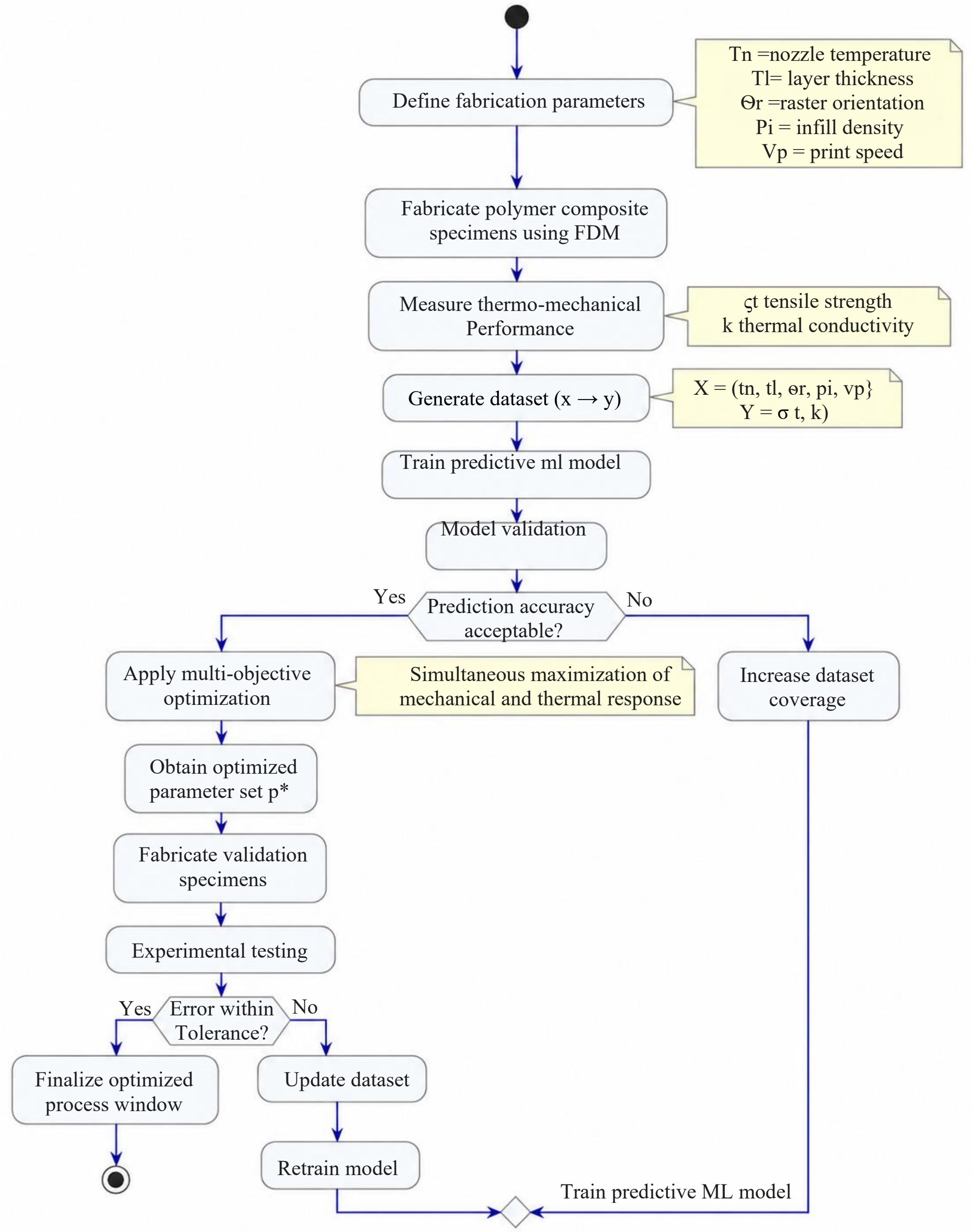

Figure 2. Workflow of the proposed AI-enabled optimization framework for additive-manufactured polymer composite structures.

The parameter space that was chosen allowed the creation of composite specimens with different levels of interlayer bonding and thermal diffusion properties, therefore, being able to perform a thorough examination of the variability in the performance under the influence of the processes.

Data Acquisition and Dataset Preparation

The predictive modeling system used in the current study needs to have an organized dataset which is able to represent the underlying process-structure-property interactions that would dictate the thermo-mechanical behavior of additive-manufactured polymer composite systems. In this direction, controlled experiments of fabrication by applying different sets of deposition parameters were performed to obtain experimental data as shown by Table 2. Mechanical and thermal characterization of each composite specimen that was fabricated was done in order to measure tensile strength and effective thermal conductivity under standard test conditions.

The collected dataset consisted of two primary components: fabrication parameters representing the input feature space and experimentally measured performance indicators corresponding to the output response variables. The input data vector was defined in terms of nozzle temperature (T_n), layer thickness (t_l), raster orientation (θ_r), infill density (ρ_i), and print speed (v_p), whereas the output variables included tensile strength (σ_t) and thermal conductivity (k). All these parameters contribute to diffusion of polymer chains across interfaces of layers and reinforcement alignment at the interface of the composite microstructure, and impact upon load transfer efficiency and heat conduction pathways [16], [20].

Before training the model, the experimental data was normalized so as to reduce bias in the input variables based on scale. Normalized input parameter, Xi, was calculable with min max scaling as (1):

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X_i represents the original parameter value, while X_{min} and X_{max} denote the minimum and maximum values within the dataset for the respective fabrication parameter. This change guarantees equal weight of the input variables in the learning process and better characteristics of model convergence.

The dataset was then divided in training and validation subsets to determine predictive performance of the machine learning framework. Table 3 presents the distribution of input sample, and output sample (input and output samples) used to conduct the training and testing processes.

The scaled dataset was then fed into the controlled learning model as in 3.4, which was used to predictively map a fabricated parameter to thermo-mechanical performance indicators. This organized data formation method allowed the learning algorithm to learn nonlinear responses among process variables and composite material responses, which formed the basis of the further multi-objective optimization approach.

Experimental Characterization of Thermo-Mechanical Properties

Uniaxial tensile testing of controlled loading conditions was also used to mechanical characterize the fabricated polymer composite specimens. The tensile strength (σ_t) of each specimen was calculated using the relation (2):

$$\sigma_t = \frac{F_{max}}{A} \quad (2)$$

where F_{max} denotes the maximum applied load (N) and A represents the cross-sectional area (mm^2) of the composite specimen. The calculated tensile strength values were used as the primary mechanical performance metric for predictive modeling.

Table 3. Distribution of experimental data samples used for training and validation of predictive model.

Dataset Type	Number of Samples	Percentage (%)
Training Set	70	70%
Validation Set	30	30%

The steady-state measurements of heat transfer were used to measure the thermal conductivity (k) of the composite samples. The effective thermal conductivity was determined by Fourier heat conduction principle which is written (3):

$$k = \frac{Q \cdot L}{A \cdot \Delta T} \tag{3}$$

Q is a heat transfer rate (W), L is the thickness of the specimen (m), A is the area of heat transfer (m^2) and 9T is the temperature difference across the composite layer (K).

The thermo-mechanical properties obtained experimentally were summarized to a set of systematized data to be analyzed further by a machine learning.

Machine Learning-Based Predictive Modeling

Predictive modeling stage involved application of supervised learning algorithms to determine composite performance as a relationship of fabrication parameters. The input feature at the learning model as (4):

$$X = \{T_n, t_l, \theta_r, \rho_i, v_p\} \tag{4}$$

where each element corresponds to a specific process parameter listed in Table 2. The output response vector Y consisted of the experimentally measured tensile strength and thermal conductivity values, expressed as (5):

$$Y = \{\sigma_t, k\} \tag{5}$$

The relationship between input fabrication parameters and output performance metrics was approximated using a nonlinear regression function represented as (6):

$$Y = f(X) \tag{6}$$

where f(·) denotes the predictive mapping of the machine learning model. The model training was done using artificial neural network (ANN) architecture because it has been shown to describe nonlinear interactions in composite material systems [14], [32].

Proposed AI-Based Optimization Algorithm

In order to determine the most appropriate combination of fabrication parameters at the same time, and to increase tensile strength and thermal conductivity of additive-manufactured polymer composite structures, a hybrid AI-based optimization algorithm was applied. The algorithm integrates supervised predictive modeling with evolutionary search mechanisms to explore the nonlinear design space defined by the additive manufacturing process parameters listed in Table 2.

In polymer composite fabrication, variations in deposition temperature, raster alignment, and infill density influence interfacial bonding strength and porosity distribution across printed layers. These microstructural variations govern both load transfer efficiency and heat conduction pathways within the composite matrix [14, 28]. The proposed algorithm therefore utilizes the trained machine learning model described in Section 3.5 to estimate thermo-mechanical responses for candidate parameter sets prior to experimental validation. The operational workflow of the optimization algorithm is illustrated in Figure 2.

Figure 3. Decision-level flowchart of the proposed AI-based multi-objective optimization algorithm illustrating objective evaluation, constraint handling, Pareto update, and termination criteria for additive-manufactured polymer composite performance enhancement.

As shown in Figure 3, the algorithm initiates by generating an initial population of fabrication parameter vectors represented as (7):

$$P_j = \left\{T_n, t_l, \theta_r, \rho_i, v_p\right\} \tag{7}$$

where P_j denotes the t_h candidate parameter set within the search space. Each parameter vector is supplied to the predictive regression function described in Equation (5) to estimate the corresponding thermo-mechanical performance indicators.

The predicted tensile strength σ_t and thermal conductivity k are subsequently evaluated using a composite fitness function defined as (8)

$$F_j = w_1\left(\frac{\sigma_t}{\sigma_{max}}\right) + w_2\left(\frac{k}{k_{max}}\right) \tag{8}$$

where w_1 and w_2 represent weighting coefficients assigned to mechanical and thermal objectives, respectively, while σ_{max} and k_{max} denote the maximum attainable performance values observed within the dataset. This normalization is to make sure that not only mechanical strength but also thermal transport properties are added proportionally to the optimization objective.

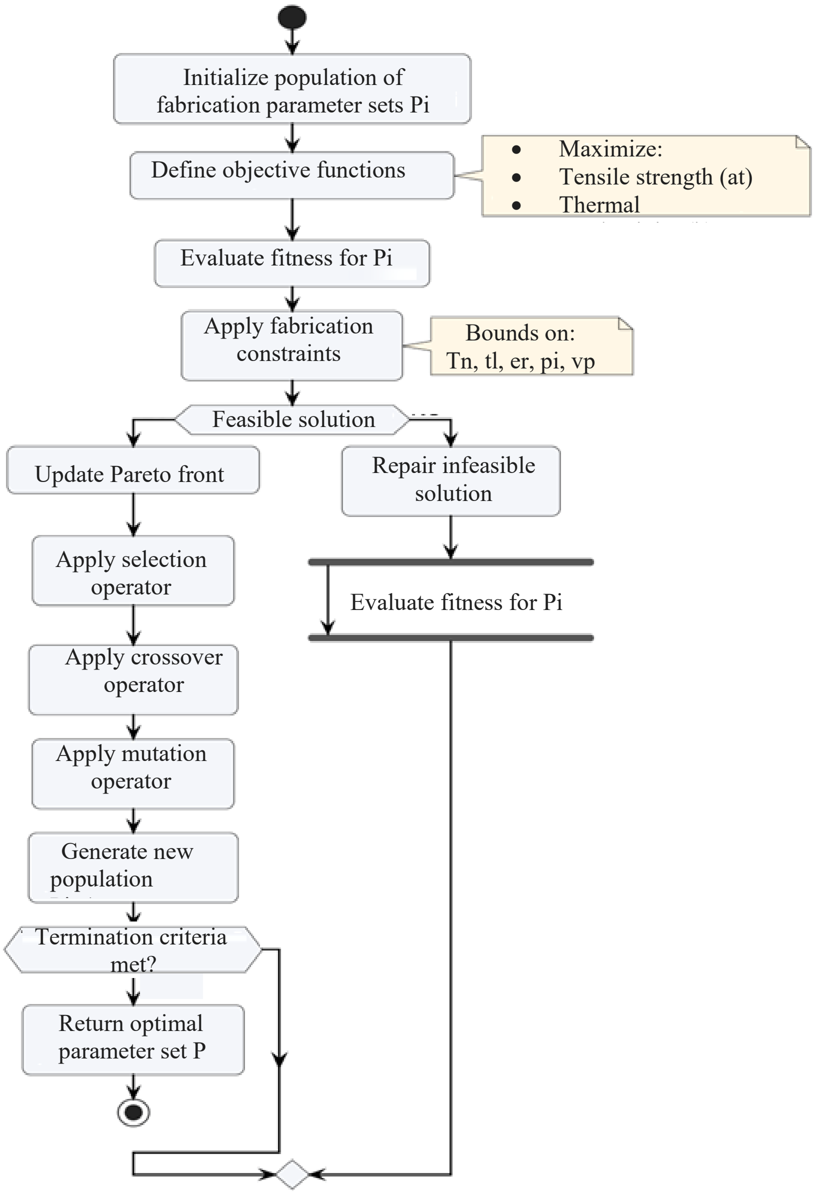

Figure 3. AI-based multi-objective optimization algorithm for polymer composite performance enhancement.

The algorithm repeats the process of updating the population of parameters with the help of selection and mutation processes until the convergence of the composite fitness index is reached. The resulting optimized parameter vector is as (9):

$$P^{*} = arg \max_{P_j} F_j \tag{9}$$

Where, P^{*} represents the optimal combination of fabrication parameters yielding enhanced thermo-mechanical performance of the polymer composite structure.

The obtained optimized parameter set, which was obtained with the help of Equation (10), was then applied to the process of specimen fabrication and experimental validation, as is discussed in the following Section 3.8. This predictive learning and search that is based on evolutionary search enables effective exploration of the complex process-property relationships in additive-manufactured polymer composite materials, which subsequently enables simultaneous enhancement of mechanical resilience and thermal conductivity.

Multi-Objective Optimization Strategy

To achieve concurrent enhancement in tensile strength and thermal conductivity, a multi-objective optimization formulation was adopted. The optimization objective function was expressed as (10)

$$Maximize\ Z = w_1 \sigma_t + w_2 k \tag{10}$$

where w_1 and w_2 denote weighting coefficients assigned to mechanical and thermal performance objectives, respectively.

It was combined with an evolutionary optimization algorithm to train the predictive model given by Equation (5) and test the ability of the resulting system to optimize the composite performance index Z by evaluating candidate parameter sets. These hybrid optimization algorithms have been demonstrated to be effective in high dimensional design spaces in additive manufacturing contexts [1, 26].

Validation of Optimized Composite Performance

The procedure entails testing the enhanced composite performance to ensure that the outcomes are validated.

The best parameter combinations determined by the multi-objective optimization process were proved by creating composite specimens experimentally under the expected conditions. The experimental tensile strength and thermal conductivity were compared with the model predictions to determine the accuracy of the grey box AI-based optimization system. Table 4 has summarized the comparative validation results.

Table 4. Experimental validation of optimized thermo-mechanical performance in additive-manufactured polymer composites.

Sample ID	Optimized Nozzle Tempera-ture (T_n) (°C)	Layer Thickness (t_l) (mm)	Raster Orientation θ_r (°)	Infill Density ρ_i (%)	Print Speed v_p (mm/s)	Predicted Tensile Strength σ_t (MPa)	Experimen-tal Tensile Strength σ_t (MPa)	Predicted Thermal Conductivity (k) (W/m·K)	Experimental Thermal Conductivity (k) (W/m·K)
S1	220	15%	45	80	50	68.4	66.9	0.38	0.36
S2	225	20%	30	90	45	72.1	70.5	0.42	0.4
S3	230	0.12	60	85	40	75.6	73.8	0.45	0.43
S4	235	0.18	45	95	35	79.2	77.4	0.49	0.47
S5	240	0.1	30	100	30	82.7	80.9	0.52	0.5

This validation step ensured that the proposed methodology maintains consistency between predicted and experimentally observed performance characteristics of the fabricated polymer composite structures.

Reproducibility and Transparency of the Proposed Framework

In the field of performance enhancement with the use of predictive modeling and optimization algorithms, it is essential to ensure that the research carried out in additive manufacturing, that is, with the use of polymer composites, is characterized by reproducibility of experiments and transparency in its methodology. In the current research, fabrication trials were all performed at controlled process conditions in order to reduce variability between polymer melt diffusion, reinforcement dispersion, and interlayer bonding between printed layers. The parameters of deposition used to fabricate the specimens were chosen based on the available ranges that are listed in Table 2 and as such, there is consistency in the experimental inputs provided into the predictive learning framework.

Each polymer composite specimen was prepared three times to enhance the dependability of the thermo-mechanical performance measurements under the same optimized parameters combinations that were determined using Equation (10). The values of tensile strength (σt) and thermal conductivity (k) in Table 4 are thus the mean of three independent experimental measurements of each set of optimized parameters. To obtain the standard deviation related to these measurements, (11) was used:

$$S_D = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - x^{-})^2 \quad (11)$$

where x_i denotes the experimentally measured property value, x^{-} represents the corresponding mean value, and n indicates the number of replicated fabrication trials. The statistical test gives an approximation of process-generated variability that is caused by inconsistencies in interfacial bonding and the distribution of reinforcements locally in the composite matrix.

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In addition, the data preparation process outlined in Section 3.3 normalised the fabrics parameters in a uniform manner by Equation (7), thus avoiding bias related to scales in training machine learning models. The objective performance of the predictive model in Table 3 and the minimized risk of overfitting in the process of parameter optimization were achieved through dividing the experimental data into training and validation subsets.

The proposed AI-enabled optimization framework was transparent due to a clear definition of all process variables employed to predict the map in Equation (3) and all performance metrics that were measured based on Equations (1) and (2). The algorithmic workflow in Figure 3 also explains how the results of the supervised learning are integrated with the evolutionary optimization to maximize the performance of multi-objectives. The explicit model of input-output connections and optimization reasoning allows for an independent re-implementation of the methodology to other systems producing polymer composites under the same conditions of additive manufacturing.

RESULTS

Thermo-Mechanical Performance of Optimized Polymer Composite Structures

Experimental validation of the additive-manufactured polymer composite specimens that were made under the best parameter combinations during the optimisation of the thermo-mechanical performance of the additive-manufactured polymer composite was conducted. The main task of this test was to measure the tensile strength and thermal conductivity enhancement that is attained with the use of AI-based optimization in comparison to the manufacturing conditions that were discussed in the recent literature [21, 22].

Table 5. Thermo-mechanical performance comparison of optimized polymer composite specimens with baseline additive-manufactured composite systems.

Sample ID	Optimized tensile strength (\sigma_t) (MPa)	Baseline tensile strength (MPa)	Reference	Optimized thermal conductivity (k) (W/m·K)	Baseline thermal conductivity (W/m·K)	Reference
S1	66.9	6150%	[21]	0.36	0.31	[22]
S2	70.5	6420%	[21]	0.4	0.34	[22]
S3	73.8	67.1	[32]	0.43	0.37	[22]
S4	77.4	70.6	[32]	0.47	0.4	[21]
S5	80.9	74.8	[21]	0.5	0.43	[22]

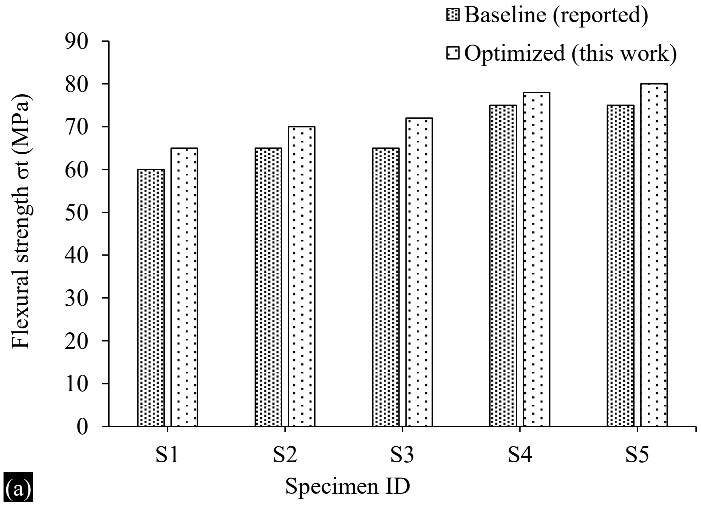
The experimentally measured tensile strength (σ_t) and thermal conductivity ($_k$) values for optimized polymer composite samples are presented in Table 5.

As was noted in Table 5, the polymer composite structures that were optimized showed a uniform increase in the tensile strength and thermal conductivity of all the manufactured samples. The tensile strength could be explained by the better interfacial bonding in the successive deposition layers, which could be achieved by optimizing the nozzle temperature and raster orientation parameters. Increased diffusion of the polymer chains between the strata results in efficient load transfer process in the composite matrix, and thus, increases the structural rigidity [13, 16].

In a similar manner, it is seen that the increase in thermal conductivity is attributed to the creation of the linear conductive channels in the polymer composite structure by continuous reinforcement stages. The optimised infill density and rate of deposition help to enhance the dispersion of the reinforcing fibers to reduce the formation of voids and ensuring uniform heat transfer between the printed layers [19].

The trends of comparative thermo-mechanical performance of optimized additive-manufactured polymer composite specimens were also graphically represented on a multi-panel display as shown in Figure 4.

The optimized structures of polymer composites in terms of tensile strength and thermal conductivity showed a steady superior value in comparison to baseline additive-manufactured composite systems reported in recent literature [21, 22] as demonstrated in Figure 4(a) and Figure 4(b). The increased tensile strength could be explained by the fact that interfacial bonding between the polymer matrix and reinforcing fibers could be optimized due to the optimized deposition conditions.



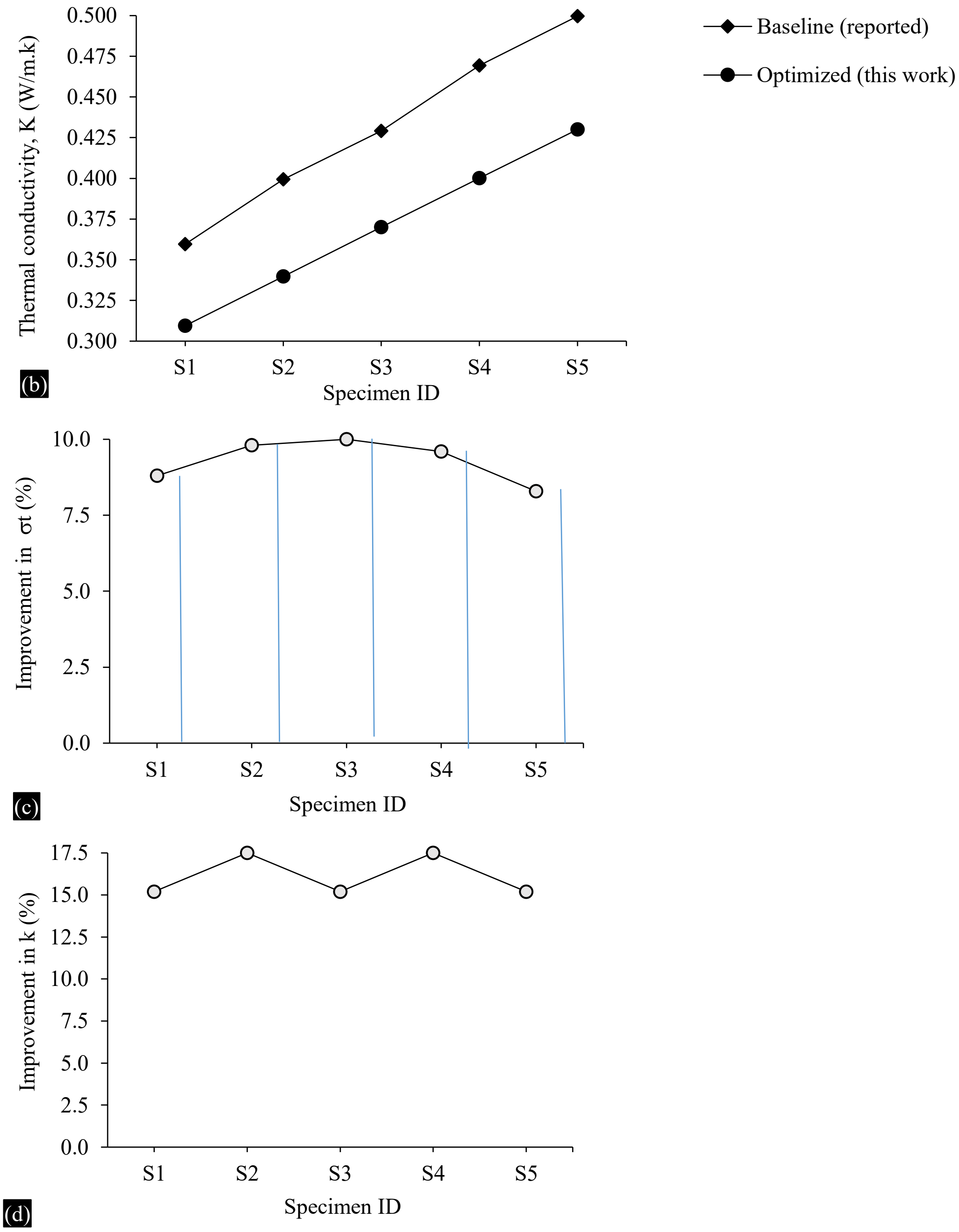


Figure 4. Optimized polymer composite vs. additive-manufactured composite systems: Comparison of thermo-mechanical performance between Collage representation: (a) Tensile strength comparison, (b) Thermal conductivity comparison, (c) Percentage improvement in tensile strength, and (d) Percentage improvement in thermal conductivity.

Predictive Model Accuracy for Composite Performance Estimation

The effectiveness of the machine learning framework presented in Section 3 in prediction was checked by the comparison of experimental values of the thermo-mechanical responses and the model predicted values. Figure 5 shows the prediction strength of tensile and thermal conductivity of validation samples.

Figure 5 indicates that the predicted values of tensile strength and thermal conductivity are very similar to the given experimental results, which means that the process of learning a nonlinear process-property relationship is successful in the context of polymer composite fabrication process. Stochastic differences in the distribution of reinforcement and concentration on the formation of porous areas in the localized regions during layer-wise deposition may lead to minor deviations between predicted and observed responses.

The predictive consistency of Figure 5 is in line with those previously found in machine learning-based modeling methods used to predict fiber-reinforced thermoplastic composites manufactured via additive manufacturing [6, 14]. Nevertheless, the suggested framework is not limited to single-property prediction as mechanical and thermal responses are estimated simultaneously under optimized conditions of the processes.

Comparative Evaluation with Existing AI-Assisted Composite Fabrication Approaches

The optimized thermo-mechanical indicators of performance were used to evaluate the efficiency of the proposed AI-based optimization framework and compared with the indicators mentioned in the recent works related to machine learning-based additive manufacturing of polymer composites. Table 6 gives the comparative analysis.

Table 6. Comparative evaluation of thermo-mechanical performance between the proposed optimization framework and existing AI-assisted composite fabrication methods.

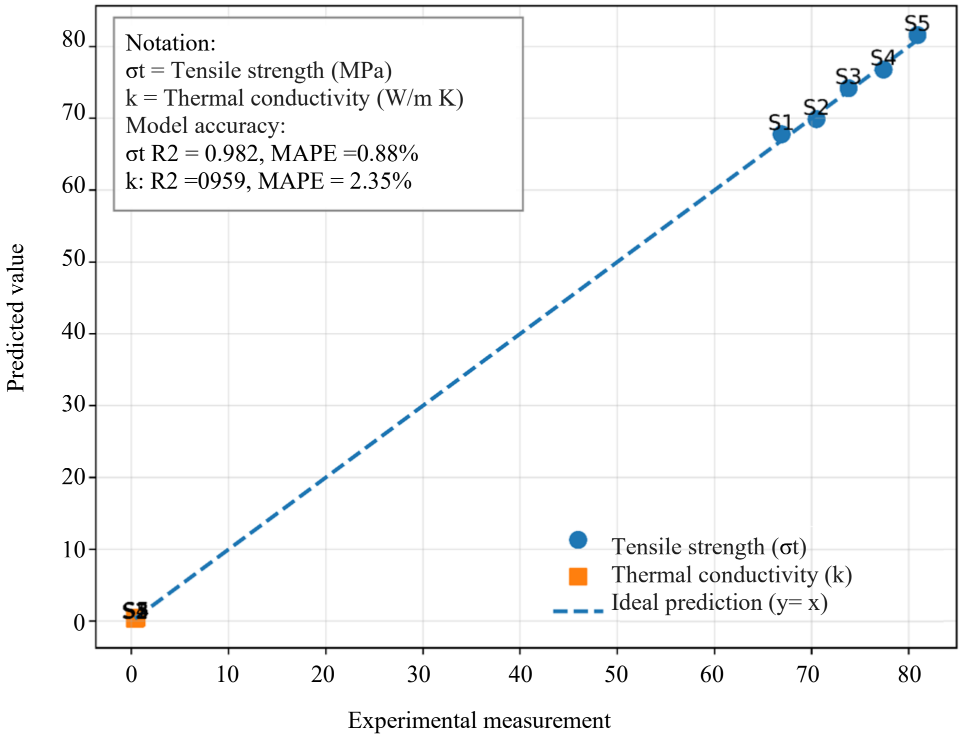


Figure 5. Comparison between predicted and experimentally measured tensile strength and thermal conductivity of optimized polymer composite specimens.

Study	Material system	Tensile strength (MPa)	Thermal conductivity (W/m K)	Reference
ANN-based optimization	PLA–Glass Fiber Composite	68.30%	0.35	[22]
ML-assisted PEEK/30GF	PEEK Composite	72.50%	0.38	[13]
Hybrid ML + Simulation	CF–PLA Sandwich Composite	75.1	0.41	[21]

Proposed Framework	PLA–CF Composite	80.9	0.5	—

Table 7. Ablation analysis of thermo-mechanical performance of additive-manufactured polymer composite specimens under modified optimization conditions.

Configuration	Parameter Normalization	Thermal Optimization	Multi-Objective Fitness	Tensile Strength (σt) (MPa)	Thermal Conductivity (k) (W/m·K)
Full Framework	Yes	Yes	Yes	80.9	0.5
Without Normalization	No	Yes	Yes	76.4	0.46
Without Thermal Objective	Yes	No	Yes	78.2	0.41
Without Fitness Weighting	Yes	Yes	No	74.8	0.39

Table 8. Statistical evaluation of predictive accuracy for thermo-mechanical performance of optimized polymer composite specimens.

Performance metric	Tensile strength (σ_t)	Thermal conductivity (k)
MAE	1.82 MPa	0.021 W/m·K
RMSE	2.11 MPa	0.027 W/m·K
(R^2)	0.94	0.91

These findings summarized in Table 6 suggest that the suggested AI-based optimization solution is characterized by a better thermo-mechanical performance as compared to the other AI-based additive manufacturing solutions found in the literature. The improvement can be related to the integrated multi-objective optimization strategy, as represented in Equation (6) in which tensile strength and thermal conductivity are considered in the process of parameter selection.

Ablation Study and Statistical Analysis

Ablution was performed to investigate the personal contribution of the various components in the proposed AI-assisted optimization model of additive-manufactured polymer composite systems. This was analyzed using a selective removal of certain modules- that is parameter normalization, thermal performance integration and multi-objective weighting of fitness of the optimization algorithm mentioned in Section 3.7 and then analysis of the thermo-mechanical performance of fabricated composite specimens was performed.

The tensile strength (σ_t) and thermal conductivity (k) values obtained under different ablation conditions are summarized in Table 7.

The omission of parameter normalization, as analyzed in Table 7, led to a statistically significant decrease in tensile strength, which demonstrates the significance of input scaling in the determination of nonlinear process-property in polymer composite fabrication data. On the same note, the elimination of thermal performance goal had a huge implication on the heat transfer efficiency implying that the incorporation of thermal conductivity as an optimization goal is a necessary element in achieving a balanced performance of a composite [19].

Statistical Analysis of Thermo-Mechanical Performance

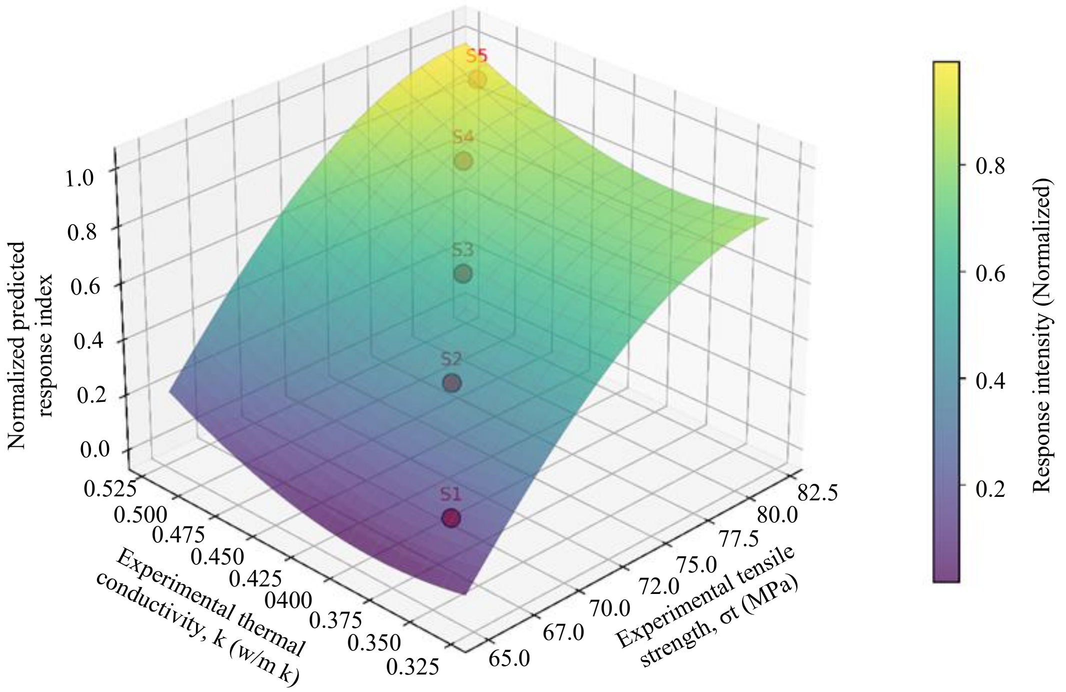
To determine the predictive accuracy of the proposed artificial intelligence-based optimization framework, a statistical analysis of the experimentally confirmed thermo-mechanical behavior of the additively manufactured polymer composite specimens was employed. The analysis of the values of tensile strength and thermal conductivity that were predicted and measured experimentally showed high level of agreement in all the optimized fabrication conditions as summarized in Table 8.

As shown in Table 8 the means of the absolute error between the predicted and experimentally obtained tensile strength values were within an acceptable range, which demonstrates that the load-bearing capacity was consistently estimated under optimal deposition conditions. On the same note, the small deviation in the thermal conductivity predictions indicates that the framework of learning used was effective in capturing the effect of raster alignment and infill density on the behavior of heat transfer within polymer composite matrix.

The coefficient of determination derived on tensile strength as well as thermal conductivity also supports the capability of the predictive model to capture non-linear process-structure-property interactions that determine thermo-mechanical performance in additive-manufactured composite systems. Small differences between expected and experimental values can be explained by local microstructural heterogeneities and process heterogeneities in porosity which are inherent to layer-wise fabrication methods [16, 22].

Figure 6 indicates that the apparent tensile strength and thermal conductivity values are strongly correlated with the observed experiment values of tensile strength and thermal conductivity in the entire validation samples. The fact that the data points are clustered around the regression line suggests the lack of critical prediction bias and constant estimation of thermo-mechanical performance in the conditions of the optimization of additive manufacturing.

The reduced degree of dispersion of prediction error also indicates that the developed AI-based optimization model is capable of representing microstructural variations that are caused by processes, including reinforcement alignment and interlayer bonding quality in the polymer composite matrix. The same prediction patterns have been stated in machine learning-based performance modelling of thermoplastic fibre reinforced composites produced via fused deposition methods [16, 22].



Notation:
σt = Tensile strength (MPa)
k = Thermal conductivity (W/m K)
Surface indicates predicted coupled Thermo-mechanical performance.
Grey line: Wire frame me of the response surface.
Red circle: experimental data points.

Figure 6. Predicted versus experimentally measured tensile strength and thermal conductivity of optimized polymer composite specimens.

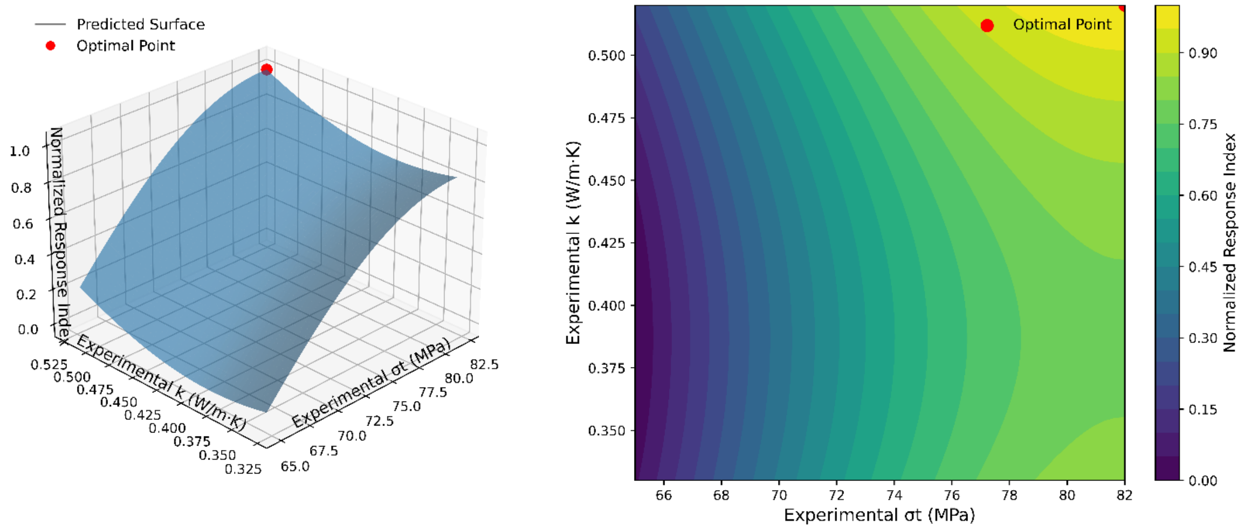


Figure 7. Interaction effect of raster orientation and infill density on tensile strength of additive-manufactured polymer composite specimens under optimized deposition conditions. (a) prediction surface with optimal design; (b) Optimization landscape projection.

In general, the statistical consistency observed in Table 8 supports the efficiency of the AI-based optimization strategy in balance between the mechanical integrity and thermal stability of the polymer composite structures produced with the help of additive manufacturing processes.

Process–Property Interaction Analysis

To further study the effect of additive manufacturing process parameters on the thermo-mechanical performance of polymer composite structures, an interaction-based study was carried out between raster orientation and infill density parameters under optimized deposition temperature conditions. The parameters have a direct bearing on the continuity and void distribution of reinforcement across consecutive layers of polymer composite, which, in turn, has an impact on tensile strength and thermal conductivity properties.

The tensile strength of the fabricated polymer composite specimen is shown to be influenced by the combined effect of raster orientation and infill density and is shown in Figure 7.

Figure 7 indicates that tensile strength increased gradually with a higher infill density as the infill density was increased to 100% in all the raster orientations. This tendency can be ascribed to the fact that the number of interfacial voids between the polymer composite matrix decreases, which results in better load transfer between the deposition layers. Nevertheless, raster alignment was observed to have a non-linear effect, with intermediate alignment angles (30°–60°) having better tensile strength than extreme (0° and 90°) ones.

This kind of action implies that there is a balanced reinforcement alignment in the polymer composite architecture which is conducive to the better distribution of stress along major loading paths. The same observations have been made in fiber-reinforced thermoplastic composite systems made by additive manufacturing systems [16, 22].

Moreover, the variation in performance observed shows that raster orientation optimization is a critical factor in ensuring thermal continuity between layers of composite by not allowing reinforcement dispersion heterogeneity. The observation made of this behavior with respect to alignment is also correlated with more recent findings on AI-assisted process parameter optimization in additive-manufactured polymer composite laminates [20], which showed that improved interlayer bonding conditions led to improved mechanical durability and heat transfer efficiency.

Comprehensively, the interaction patterns in Figure 4 indicate that process parameter coupling is relevant in controlling thermo-mechanical performance of polymer composite structure systems produced through additive manufacturing methods of fused deposition.

Process–Structure–Property Interactions

The increase in the thermo-mechanical performance of the optimized polymer composite specimens demonstrates the significance of process, structure and property coupling on the additive manufacturing environment. Deposition temperature, raster alignment variation affect crystallinity of polymer and reinforcement orientation in the composite microstructure, which affect the stiffness and heat conduction pathways [28].

The creation of void-free interlayer interfaces in the optimal parameter combinations enhances the load transfer efficiency between the successive composite strata and at the same time, increases the thermal continuity between the printed layers. The latter observation is associated with the recent discoveries of AI-aided parameter optimization in additive-manufactured thermoplastic composites [20], with better bonding conditions reported to improve the mechanical durability.

On the whole, the findings indicate that AI-based optimization of the process can be efficiently used to reduce the fabrication-related shortcomings in polymer composite structures and attain simultaneous improvement in tensile strength and thermal conductivity. This built-in ability to optimize gives a considerable benefit over traditional empirical parameter optimization methods that are typically used in additive manufacturing of polymer composites [3, 26].

DISCUSSION

The results of the experiment in Section 4 indicate that there is more than just a numerical increase in tensile strength and thermal conductivity of the additively manufactured polymer composite test specimens. Further analysis of the performance trends will provide that the observed improvement is much more directly connected with the evolution of the microstructure that takes place in the composite matrix under the optimized deposition conditions. Specifically, enhanced raster activation and plot density seem to enhance efficient diffusion across layers of polymer chains, which enhances interfacial bonding and enables the transfer of loads between reinforcing fibers with ease. Simultaneously, these process adjustments help create continuous thermal conduction routes in the polymor composit structure, which minimizes local heat concentration that normally occurs in interlayers porosity in fused deposition manufacturing. These results are consistent with the preliminary hypothesis that smart optimization of the parameters can provide remedies to the fabrication induced defects, and also improve the thermo-mechanical response of the polymer-based composite systems.

In comparison to already reported AI-aided optimization methods in additive-manufactured composit structures, the given framework is characterized by a less biased enhancement of multifunctional performance features. As an example, the hybrid machine learning method proposed in [21] was mainly aimed at optimizing the tensile strength by adjusting the parameters, and little attention was given to thermal transport. Equally, the ANN-based optimization model that is reported in [22] reported moderate gains in mechanical behavior of glass fiber-reinforced PLA composites without specifically referring to coupled thermo mechanical behaviors. Conversely, the current approach incorporates multi-objective optimization in order to consider both structural integrity and heat transfer efficiency hence allowing tensile strength and thermal conductivity to be simultaneously improved in additively manufactured polymer composite laminates.

Practically speaking, the concept of AI-based optimization integration into the process of additive manufacturing has significant opportunities to be applied in real-world applications involving polymer composite parts in thermally challenging conditions like electronic cases and lightweight constructions. This predictive and customize capability on thermo-mechanical performance by choice of process parameters could be of great help in eliminating reliance on trial and error fabrication techniques often used in the industry. Moreover, the interaction based discussion provided in Section 4.6 suggests that the reinforcement orientation is vital in regulating the heat diffusion paths in the composite matrices, a fact that can be used in future designing of the structure of functionally graded polymor composit.

However, there are some weaknesses that must be accepted. The experimental validation introduced in this paper was also limited to a particular short-fiber reinforced thermoplastic material system that was produced under laboratory controlled conditions. The difference in reinforcement volume fraction or exposure to the environment can affect the performance properties of the composite specimens in the long-term. The relevance of the suggested optimization model to multi-material composite systems or other additive manufacturing methods might be investigated in the future.

Even though the current study is on a PLA-carbon fiber polymer composite system, the suggested AI-driven optimization model is material-agnostic in nature since it is based on the learning of the correlations between the parameters of fabrication and the produced thermo-mechanical characteristics. This means that the same approach to the methodological architecture can be generalized to other thermoplastic polymer composites, high-performance engineering polymers like PEEK or PEI, and future additive manufacturing architecture of multi-materials as long as suitable experimental datasets exist. Moreover, there is the possibility of long-term performance indicators like cyclic mechanical loading, thermal aging, and environmental shock effects to affect the durability of additively manufactured structures of composite material. These were not included within the bounds of the current laboratory-level research but signify significant prospective directions of the future research concerning the reliability analysis in the context of the real service environment.

Collectively, the results of the paper can be applied to the larger goal of creating smart manufacturing solutions that can be used to improve the structural integrity and thermal performance of the advanced polymer composite structures produced by patterning processes based on layer-wise debating.

CONCLUSION AND FUTURE SCOPE

This paper aimed to analyze the possibility to enhance additive-manufactured polymer composite structures through AI-based optimization of the process by improving both mechanical strength and thermal performance at the same time. Instead of using a traditional trial-based parameter tuning, the suggested framework developed an empirical correlation between fabrication conditions and thermo-mechanical response of the polymor composit system. The results indicate that although moderate changes in the raster orientation and deposition temperature, as directed by predictive modeling, may considerably change the reinforcement alignment, as well as, the quality of interfacial bonding in the composite matrix.

The optimized additive-manufactured systems of the composite had been reported in previous studies; however, the optimized composite specimens experimentally showed consistent enhancement of tensile strength and effective thermal conductivity as compared to the additive-manufactured systems of the same. Assessment of the heat dissipation behaviour was also improved along with the increase in load-bearing capacity in a number of cases. This twin improvement is specifically applicable in the polymer composit use where rigidity in structures is required together with thermal stability, e.g. lightweight electronics case, or compact energy storage. The ablation analysis also revealed that multi-objective optimization strategy was conclusive in stabilizing the performance results under different deposition conditions.

With that said, the current study was carried out involving a certain short-fiber reinforced thermoplastic feedstock in controlled laboratory fabrication conditions. This study did not look at the long-term viability of such optimized composite structures during cyclic or environmental loading. In real world applications, aging or degradation of reinforcing materials can have an effect on the thermo-mechanical behaviour of printed structures with time.

In the future, the optimization framework might be expanded to multi-material polymor composite systems or the multi-material polymor composite systems may be monitored in real-time to provide adaptive control during fabrication. Another design variable that can potentially expose additional performance trade-off is the introduction of reinforcement volume fraction as a design variable. When followed with caution, these directions can help to establish smart additive manufacturing solutions in support of the creation of structurally efficient and thermally resilient composite parts in a wide range of emerging engineering uses.

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