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Deep Learning for Real-Time Monitoring and Defect Detection in Additive Manufactured Polymer Composites

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Abstract

Additives Fiber-reinforced polymer composite ADDs have high utility in making lightweight structural components, but due to process-related defects (interlayer delamination and reinforcement stacking) the integrity of consolidation during extrusion-based deposition is frequently compromised. This paper has presented a physics-informed deep learning framework that is applicable to real-time measurements of reinforced thermoplastic composite fabrication. Multimodal sensing was provided with thermal gradient, optical morphology, and acoustics emission signals being used to assess the interlayer bonding behavior at successive cycles of deposition. This approach explicitly captures the influence of melt rheology and interlayer diffusion on consolidation stability during composite layer formation. The proposed monitoring system achieved a defect detection accuracy of 91.8% with a reduced standard deviation of 1.7% across monitored layers. Under stable deposition conditions, the consolidation integrity index remained above 0.85, whereas disturbed extrusion parameters resulted in a decline to 0.38, corresponding to a 44% increase in defect probability. Comparative analysis demonstrated an accuracy improvement of 7.3% over conventional vision-based monitoring techniques. Furthermore, the proposed framework establishes a scalable pathway toward intelligent, process-adaptive quality control in polymer composite additive manufacturing systems. These results suggest that the use of polymer process-structure associations in a deep learning based monitoring framework can be used to increase sensitive consolidation anomalies in the fiber-reinforced thermoplastic systems to facilitate better real-time quality evaluation during additive manufacturing of polymer composite structures.

Keywords: Polymer composites, additive manufacturing, defect detection, interlayer consolidation, real-time monitoring

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INTRODUCTION

The additive fabrication of polymer composites is gaining acceptance not only as a fabrication instrument, but as an approach that can be able to create useful material structures with performance properties that are application-driven. In contrast to monolithic thermoplastics such composite systems of polymer exhibit interacting thermomechanical and rheological behaviours when deposited in layers, especially when reinforced by discontinuous fibers or particulates fillers. Such material-process relationships not only have an effect on the macroscopic geometry of the printed structure but also determine the consistency of bonding within the internal structure and the homogeneity of microstructures. Consequently, structural integrity of additive manufactured polymer composites is strongly linked to temporally changing fabrication environments that change throughout the build cycle.

The additive manufacturing (AM) of polymer-based composite has shifted its status as an assistance tool in prototyping to a potentially useful technology in production of engineering components that necessitate both geometric complexity and efficiency of materials [1, 2].

The layer-by-layer deposition concept that is inherent to fused filament fabrication (FFF), selective laser sintering (SLS), and stereolithography (SLA) provides a high level of flexibility in the process, which allows spatial modulation of fiber orientation, porosity gradients, and matrix crystallinity [3, 4].

Although such benefits are associated with polymer composite AM systems are sensitive per se to changes in the deposition temperature, melt viscosity, interlayer diffusion and cooling kinetics. This leads to internal stresses, nucleation of voids, anisotropic bonding interfaces between successive print layers as a result of the resulting thermomechanical mismatches during the solidification stage [5]. Missing fusion to degradation of the matrix or agglomeration of the filler Microstructural imbalances were more likely to spread throughout build cycles, negatively impacting load bearing capability and long term survival [6, 7]. As a result, the quality of additively manufactured polymer composites is closely connected with the transient process dynamics, which is challenging to measure with the help of traditional monitoring methods.

Non-destructive evaluation (NDE) methods like ultrasonic inspection, infrared thermography, or X-ray computed tomography are normally used in a post-fabrication setting in the industrial practice to determine structural integrity [8, 9]. Although the modalities can give detailed volumetric information of interfacial discontinuities or porosity distribution, they are not able to form the defect formation in the actual fabrication stage. The ability to provide real-time information about the layer consolidation, the morphology of the melt pool, or diffusion of the polymer chains remains considerably inaccessible through conventional paradigm of inspection [10].

The recent advances in artificial intelligence, and more precisely, deep neural architecture, have offered novel approaches to the interpretation of high-dimensional sensor data produced in the process of AM operations. Algorithms have been developed to fuse multimodal inputs provided by thermal imaging, acoustic emission and optical feedback to provide information about subtle deviations in material deposition patterns or bonding uniformity [11, 12]. Nonetheless, the use of these learning strategies in the context of advanced polymer composite manufacturing facilities is not extensive, especially in the context of heterogeneous material compositions and dynamically perturbed processes [13].

Problem Statement

The nonlinear interactions of temperature gradient, rheological behavior and filler-matrix compatibility govern the fabrication of polymer composite structures by additive manufacturing. Such interactions develop very quickly in extrusion or curing and in many cases take place in milliseconds, thus rendering defect manifestation both stochastic and spatially dispersed [14]. Most commonly reported anomalies that compromise mechanical strength and dimensional fidelity include delamination between the strata that are being printed, trapped air, improperly oriented fibers and non-uniform crystallization [15, 16]. Such defects may cause premature component failure when operational loads are reached when these defects are not detected during the fabrication.

The methods of traditional monitoring systems used in polymer AM systems are mostly rule-based, and they depend on a static thresholding of process variables, including nozzle temperature, bed adhesion force, or deposition velocity [17]. Although they are useful in the detection of gross anomalies, such methods have little-to-no flexibility when confronted with material heterogeneity or environmental perturbations like a change of humidity and ambient thermal drift [18]. Moreover, observed process deviations are rarely correlated linearly with the resulting composite microstructure, and this makes it very difficult to apply deterministic quality assurance mechanisms.

The other essential issue is due to the lack of scalable inspection structures that can combine in-situ sensor feedback with predictive defect modeling. Streaming imaging, such as that of real-time, can produce large data volumes that are beyond either the human or conventional statistical analysis capabilities [19].

This way, there is an identified research gap in the design of smart monitoring systems that are able to autonomously detect defect precursors in the additive production of polymer composites. The key to closing this gap involves developing an integrated computational paradigm, which is able to simultaneously work with both temporal process signals and spatial material patterns on varying fabrication conditions [20].

Proposed Solution Approach

In order to mitigate these shortcomings, the current paper examines a deep learning-based monitoring system that can be used to detect defects in additively manufactured polymer composite structures in real-time. The suggested methodology takes advantage of convolutional and temporal neuralization to identify latent features amongst multi-sensory process data that is obtained during fabrication.

In contrast to the process of post-hoc inspection, the developed system works at the fabrication stage where the system can detect the anomalies caused by the process, prior to their manifestation in the end product, e.g. unstable melt pool or inappropriate filler dispersion. The learning model is conditioned to match process signatures to defect typologies such as porosity clusters, layer separation, and some parts of the matrix fusion and hence predictive intervention mechanisms are enabled. This capability of in-situ analysis enables the adaptability of parameter control during the printing process and reduces the amount of material wastage and ensures uniform composite performance [5, 11].

Besides, the architecture is designed with feature harmonization modules to adapt to polymer matrix composition and reinforcement morphology variations. This flexibility is especially applicable to heterogeneous composite formulations where there can be some difference in defect propagation pathways with geometries of builds. The development of a data-driven correlation between the parameters of fabrication and microstructural results enables the proposed system to increase the transparency of the process, and minimize the use of manual inspection protocols.

Novelty and Scientific Contribution

The main innovation of the work is the combination of the deep learning-based process monitoring with the defect inference specific to the polymer composite additive manufacturing conditions. Current AI-driven inspection systems have been careful to consider only the metallic AM platforms with lesser attention given to viscoelastic behavior and crystallization kinetics of polymer matrices [12, 16]. The current framework handles this gap by adding process signatures that are specific to the composites to the learning pipeline.

Further, the paper presents a multimodal strategy of sensing that involves the detection of interlayer bonding integrity through thermal and acoustic signals. Such a method allows identifying microstructural abnormalities that are not visible with single-modality surveillance methods. The resulting predictive model is more sensitive to defect appearance in the course of layer deposition, which is a promising way to move towards closed-loop quality assurance of polymer AM systems.

In an expanded viewpoint, adaptive deep learning models are merged with composite fabrication processes that help to promote intelligent manufacturing paradigms.

Limitations of the Study

Although the suggested deep learning system exhibits encouraging potentials of watching product defects in real-time during polymer composite additive manufacturing, some drawbacks could be realized. The model also depends on the quality of high-resolution multimodal sensor data when fabricating which is not available on the majority of AM platforms. One might also require model retraining due to domain-specific discrepancies caused by variations in polymer matrix composition, reinforcement distribution or printing environment. Additionally, the current paper mainly addresses the case of thermally-driven defect indicators, and the prospective case of chemically-induced degradation or long-term viscoelastic relaxation processes are not within the short-term focus of the monitoring architecture.

The rest of this paper is presented in the following way. Section 2 introduces an in-depth review of the current developments in defect detection and quality control of additively manufactured polymer composite systems. Section 3 outlines the deep learning based monitoring framework, protocols of data acquisition and framework architecture. Section 4 presents the material fabrication process and experimental set up that were used to validate. The results of the obtained findings are discussed in section 5 in terms of accuracy of defect detection and process-structure correlation. Lastly, Section 6 sums up the research with some main findings and also points out a possible line of research in the future of the study, which is the intelligent monitoring of polymer composite additive manufacturing systems.

LITERATURE REVIEW

Additive Manufacturing of Polymer Composites: Process–Structure Considerations

The recent years have seen a great interest in the use of polymer composites in additive manufacturing and this is especially true in industries where lightweight structural components are needed. Such materials like fiber-reinforced thermoplastics, hybrid polymer matrices are now common in extrusion-based systems and powder-bed AM systems to get better stiffness-to-weight ratios and thermal resistance [21]. Nevertheless, the layerwise fabrication process of such systems creates heterogeneity due to processes that can undermine interfacial adhesion between neighboring tracks of deposition.

Multiple investigations have shown that localized thermal gradients and the rate of solidification through the generation of localized thermal gradients determine the bonding strength of the printed layers in polymer composites [22]. Uneven heat transfer at the melt interface can result in a non-completion of diffusion of polymer chains, which will reduce the mechanical continuity across the build direction. In reinforced systems, filler- matrix interaction has further complicated this issue, as sometimes the flow of homogeneous material is interrupted when the extrusion occurs [23]. Consequently, internal discontinuities like voids, fiber clustering or other microcracks are likely to be observed even at nominal process conditions.

Scientists have also indicated that the directed structural reinforcement alignment and dissimilar crystal crystallization patterns are the main causes of anisotropic character of printed composite structures [24]. The given microstructural inconsistencies might not be noticeable at the surface level but can have a great impact on tensile strength or fatigue life in service conditions. Therefore, the process-structure relationship of polymer composite AM is still an essential prerequisite when it comes to an effective strategy of mitigating defects [25].

Conventional Monitoring and Defect Detection Techniques

Historically, post-processing methods of ultrasonic testing, thermographic imaging, or micro-computed tomography have been used as the means of defect detection in additively manufactured polymer parts. They are useful in giving a good understanding of the discontinuities or porosity distribution in the interior, but at the cost of responsiveness in real-time [26]. When the fabrication is finished, it is practically impossible to make corrective intervention, particularly to geometrically compound composite structures.

The IR thermography has been utilized as a non-invasive method to measure the changes in temperature during deposition [27]. Correspondingly, the acoustic emission-based sensing has been put forward in determining the sudden variations of material consolidation during extrusion. However, it is difficult to differentiate normal process variation and defect antecedents under such paradigms [28].

In operation, the vast majority of AM platforms continue to use parameter-driven monitoring systems to monitor the nozzle temperature, print speed or extrusion pressure alone. These linear measures are not sufficient to describe the nonlinear behaviour related to the polymer melt rheology and reinforcement dispersion [29]. As a result, defects occurring due to minor process variations could not be discovered until structural failure takes place under operational conditions.

Emerging Role of Data-Driven Monitoring Frameworks

To address the shortcomings of traditional inspection schemes, the recent studies have embarked on investigating data-driven monitoring strategies that have the ability to explicit the process indications in the fabrication process. Support vector machines and decision trees are examples of machine learning algorithms that are used to categorize defect patterns with sensor feedback information acquired with AM systems [30]. Although these techniques prove to be moderately successful under controlled conditions, they tend to perform poorer after coming in contact with non-homogenous material formulations, or under different process conditions.

In more recent times, deep learning architectures have become prominent as a result of their capability to elicit hierarchical features of complex data. Some examples include convolutional neural networks (CNNs), which have been applied to optical images of printed layers so as to detect anomalies on the surface or deposition irregularities [31]. In the same fashion, the recurrent neural networks (RNNs) have been used to predict temporal changes in processes to achieve predictive judgments on bonding quality at each consecutive layer [32].

Regardless of these achievements, the majority of studies have been concerned with metallic AM platforms in which defect formation is mainly determined by melt pool dynamics. Instead, polymer composite systems are viscoelastic systems whose behavior due to their reinforcement morphology is not predictable [33]. The lack of composite-specific monitoring frameworks, in turn, is also one of the gaps present in existing literature.

Multimodal Monitoring and Sensor Integration

It is acknowledged that due to the complexity of defect development in polymer AM, a number of researchers have proposed the inclusion of multimodal senses in the fabrication space. The thermal imaging, optical feedback and acoustic emission information can be gathered together in order to record the spatial and temporal changes in material deposition [34]. A more thorough evaluation of the layer consolidation and filler dispersion in printing by such integrated approaches is achievable.

Recent research proved that multimodal data fusion could contribute greatly to the effective detection of defects in case of single-sensor data collection plan [35]. Nevertheless, heterogeneous data streams cannot be interpreted without complex instruments of analysis which are able to correlate process signatures and changing microstructural states. This is usually problematic in traditional statistical techniques because polymer composite fabrication is nonlinear and time-dependent [36].

Fusion models based on deep learning have been suggested to meet this challenge by permitting a simultaneous analysis of sensor inputs when it is being deposited. The models are able to establish hidden links among the process deviations and defects onset and thus enable intervention at an early stage [37]. However, they are yet to be applied to polymer composite AM processes due to computational complexity and data diversity.

Research Gaps and Motivation for the Present Study

Even though there is considerable advancement in the procedure of monitoring additively manufactured components, the currently accessible frameworks of defect detection have remained largely biased towards metallic systems or uniform thermoplastics [38]. Polymer composites bring about additional complexities because of the heterogeneity of reinforcement, anisotropic bonding properties and viscoelastic properties as time progresses. The existing monitoring approaches are usually inadequate to be flexible enough to handle such material-specific effects.

Moreover, most of the described machine learning models are offline and utilize ready-to-use datasets to classify defects [39]. This limits their use in real-time manufacturing sources whose conditions of the processes change dynamically. The lack of scalable in-situ monitoring architectures which could combine multimodal sensor feedback is a severe constraint in the existing AM quality assurance practice.

With these issues, it is urgent to design a smart monitoring system unique to the additive manufacturing of polymer composites. Through process analytics handled by deep learning, a direct relationship between the fabrication parameters and the development of the defects might be obtained, which will in turn allow the prediction of the quality towards the printing process itself [40].

In order to put the proposed real-time monitoring framework into the context of the modern condition of polymer composite additive manufacturing research, a narrow gap analysis was carried out with a subset of the most relevant recent works.

Table 1. Comparative literature gap analysis for deep learning–enabled defect monitoring in additively manufactured polymer composites

S. No.	Author(s) / Year / Ref. No.	Focus Area	Methodology	Key Findings	Limitations / Gaps	Relevance to Present Study
1	Lu et al., 2023 [1]	CFRP AM defect monitoring	DL + in-situ sensing	Online defect detection	Limited matrix generalization	Supports real-time DL monitoring
2	Phillips et al., 2024 [2]	Composite AM defects	Multisource DNN	Sensor fusion improves detection	Weak process–microstructure link	Basis for multimodal fusion
3	Kumar et al., 2023 [5]	In-plane defect detection	Explainable DL	Interpretable defect mapping	Limited defect types	Adds explainability layer
4	Bhandarkar et al., 2025 [9]	Polymer AM defects	CNN comparison	Model accuracy varies	Surface-biased detection	Guides model selection
5	Ashebir et al., 2024 [13]	Fiber-reinforced ME	NDT review	Multi-scale defects noted	No real-time DL system	Motivates DL framework
6	Pike et al., 2025 [17]	Composite AM anomaly	Thermal imaging	Fast anomaly detection	Misses subsurface flaws	Supports thermal stream
7	Segura Ibarra et al., 2025 [25]	IR-based AM defects	Conditional AE	Robust IR features	Process-specific model	Benchmark DL approach
8	Nasrin et al., 2023 [34]	Polymer AM ML	ML review	ML potential noted	Dataset scarcity	Polymer-AM context

The research topics explored in these works are mostly in-situ defect detection, thermal anomaly tracking, and deep learning-based inspection mechanisms in polymer or composite AM environments. Nevertheless, the constraints associated with the multimodal data integration, correlation between microstructure and processes, and material-specific adaptability are present in the available methods. Table 1 shows a comparative summary of the contributions selected, methodological scope, and research gaps.

METHODOLOGY

The approach that the present study will employ is based on the fact that the progression of the defects is to be monitored in-site as the additive manufacturing of the reinforced polymer composite structures is performed. Considering the thermorheological sensitivity of polymer matrices and the non-uniform distribution of reinforcement phases, the localized changes in the melt viscosity, interfacial diffusion, and formation of residual stress during cooling can be typical of the process of layer-by-layer deposition. These process-related effects have a direct effect on the interlayer bonding strength and uniformity of the microstructure in the fabricated composite. In this regard, the current strategy combines multimodal sensing and deep feature learning to measure transient deposition behavior and detect defect antecedents including void nucleation, incomplete fusion and reinforcement agglomeration during the build cycle. The presented methodology enables real-time defect deduction in extrusion-based polymer additive manufacturing systems by creating a data-driven correlation between fabrication parameters and changing composite morphology and, by doing so, contributes to an improved understanding of the process transparency and structural integrity [13, 30, 34].

Overall Framework for In-Situ Monitoring of Polymer Composite AM

The current methodology will be aimed at identifying process-related anomalies when additively manufacturing fiber-reinforced polymer composites through multimodal sensing in combination with deep feature learning. As opposed to the post-fabrication inspection methods, the suggested framework is active during the deposition of material and converts the thermal, optical, and acoustic process signatures into a single data processing channel. The process of such interlayering facilitates the monitoring of interlayer bonding defects, entrapment of porosity, and unevenness in the dispersion of reinforcement as they change over the build cycle thus, enhancing the observability of defects in extrusion based polymer composite systems [21, 30].

The entire monitoring process involves three major steps, including: (i) data collection during layer deposition, (ii) multimodal feature harmonization, and (iii) defect prediction with the help of a convolutional-temporal neural architecture. Figure 1 presents some conceptual layout of the sensing and analysis modules.

Material Fabrication and Process Parameterization

A fused filament fabrication (F)-based composite specimen with a dual-sensor acquisition module was used to make composite evaluations. To investigate the impact of the thermal gradients created by deposition on the interfacial consolidation, a thermoplastic polymeric network with short carbon fibres was chosen. A combination of controlled extrusion velocity and nozzle temperature was used to control the rheological stability of the composite melt, and hence minimize the loss of matrix during layer formation [13, 34].

Consolidation behavior at successive layers was made repeatable by controlling the conditions of extrusion-based fabrication of reinforced polymer composite specimens at both thermal and deposition conditions. The major process parameters such as extrusion temperature, deposition velocity and layer thickness were kept within thermally steady ranges to control the melt flow properties and reinforcement dispersion during the fabrication. Table 2 summarizes the operational settings that were used in deposition of composite layers.

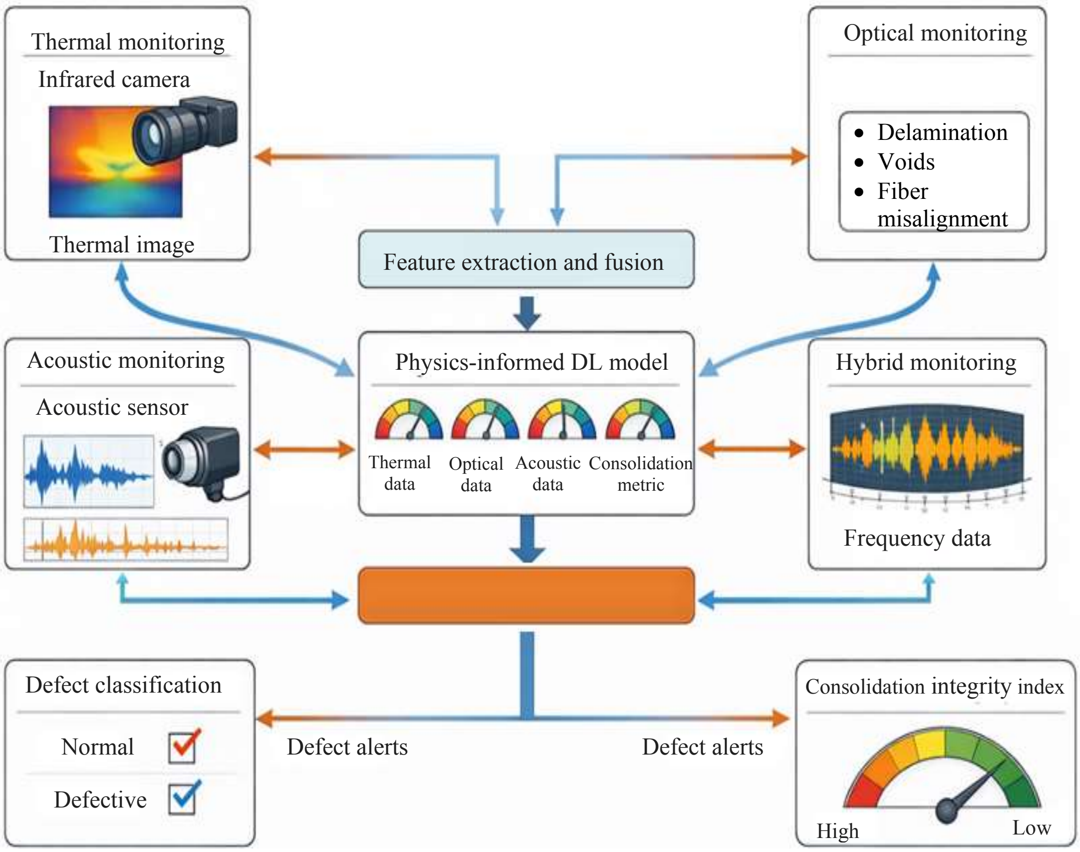

Figure 1. Multimodal monitoring architecture for in-situ defect detection in additively manufactured polymer composites.

Table 2. Process parameters employed for extrusion-based fabrication of reinforced polymer composite specimens.

Parameter	**Symbol**	**Value**	**Unit**
Nozzle Temperature	(T_n)	215	°C
Bed Temperature	(T_b)	60	°C
Extrusion Velocity	(V_e)	35	mm/s
Layer Thickness	(h_l)	0.2	mm
Reinforcement Content	(phi_r)	12	wt.%
Cooling Rate	(C_r)	4.5	°C/s

These were kept at thermally stable working conditions, to make the polymer chain diffusion reproducible upon depositing tracks of successive layers. They selectively added variation in print speed or extrusion pressure to simulate disturbances in the real-world processes so that they could control defects formation in the printed structure [23].

Multimodal Data Acquisition

To capture the transient evolution of deposition behavior, three synchronized sensing modalities were deployed:

- Infrared thermography for melt pool temperature mapping
- Optical imaging for surface morphology assessment
- Acoustic emission sensing for consolidation anomalies

Let the temperature distribution across the deposition interface be denoted by $T(x_t)$, where x represents the spatial coordinate along the deposition path and t indicates the temporal build interval. The normalized thermal gradient ∇T_n is computed using (1).

$$\nabla T_n = \frac{\partial T(x,t)}{\partial x} \tag{1}$$

Where,
T(x,t) = instantaneous temperature at location x and time t,
∂T/∂x = spatial temperature variation across the deposited layer.

The gradient is used to measure interlayer fusion stability, especially in fiber-reinforced polymer matrices, in which the cooling trend affects bonding strength [17]. Successes of in-situ defect inference in extrusion based additive manufacturing of polymer composites heavily rely on process data fidelity during deposition of a layer. The data of multimodal fabrication in the current work was collected through synchronized sensing modules that were combined with the material extrusion platform. These data sets have then been operated to give normalized descriptors that depict interlayer bonding behavior, as well as, reinforcement dispersion during composite consolidation.

Data Source Description

Three main streams were used as sensing streams in order to obtain the transient characteristics of deposition:

- *Thermal data:* Infrared thermographic imaging of the deposition interface
- *Optical data:* High-resolution surface morphology mapping
- *Acoustic data:* Emission signals corresponding to consolidation anomalies
- The temperature field distribution in the deposited layer is denoted T(x,t) where x represents the temperature field distribution across the layer.

Thermal gradient animals ∇Tn which characterizes the quality of interfaces fusion is calculated through (1) which is defined in Section 3.3.

Likewise, the acoustic consolidation reaction A_s to the material flow discontinuities is expressed as (2):

$$A_s = \frac{1}{N} \sum_{i=1}^{N} | ai | \tag{2}$$

Where, a_i is the amplitude of the acoustic moment and N is the number of sampled acoustic events overall.

A_s value are larger, which means deposition instability or clustering of reinforcement may occur in the polymer matrix.

Data Processing and Normalization

The homogeneity of the sensing modalities was maintained through normalization of the obtained datasets before features extraction. Let the normalized thermal characteristic be denoted as T_n and is calculated as (3):

$$T_n = \frac{T(x,t) - T_{min}}{T_{max} - T_{\min}} \tag{3}$$

Where,
T_{max} and T_{min} correspond to the maximum and minimum temperature values recorded during the deposition cycle. The processed feature vector F_p, combining thermal, optical, and acoustic descriptors, is constructed as (6):

$$F_p = \alpha T_n + \beta I_m + \gamma A_s \tag{4}$$

Where, I_m = morphology descriptor obtained from optical imaging, α,β,γ = modality weighting coefficients.

This harmonized representation enables defect-sensitive feature learning across successive layers and serves as input to the composite-aware inference model described in Section 3.5.

Feature Harmonization and Fusion

The acquired multimodal datasets were transformed into feature vectors using convolutional encoding. Let the extracted thermal feature set be represented by F_T, optical features by F_O, and acoustic features by F_A. A fused representation F_f is constructed using (4):

$$F_f = \alpha F_T + \beta F_O + \gamma F_A \tag{4}$$

Where

α,β,γ are weighting coefficients assigned based on sensor reliability.

This harmonized representation enables the identification of latent defect signatures that may not be evident in single-modality monitoring schemes [16, 36].

Composite-Aware Defect Inference Model

To explain the sensitivity of fiber-reinforced polymer composites to the process-structure sensitivity, the defect inference step was developed to take into consideration that microstructural integrity is sensitive to not only thermal consolidation, but also to reinforcement dispersion and matrix diffusion between adjacent layers. In order to include these dependencies, a composite-sensitive inference process was created which measures the stability of structures based on composite multimodal descriptors inferred on the deposition interface.

Let the fused multimodal feature vector obtained from Section 3.4 be denoted as F_f. A structural stability index Φ_s, indicative of interlayer consolidation quality, is computed as (5):

$$\Phi_s = \frac{\eta_b \cdot \lambda_d}{\kappa_r} \tag{5}$$

Where,

ηb = bonding efficiency factor derived from thermal diffusion, λd = polymer chain diffusion coefficient,

κr = reinforcement clustering coefficient.

Higher values of Φs correspond to improved matrix–filler compatibility and reduced porosity likelihood. The defect propensity score Ds is then estimated using (6):

$$D_s = 1 - \exp(-\omega \cdot \Phi_s) \tag{6}$$

Where,

ω = sensitivity constant governing defect onset probability.

The given formulation allows testing the integrity of composites continuously considering incorporating material-specific indicators into the monitoring system. This is because, unlike the traditional classification schemes, the suggested inference mechanism captures the underlying viscoelastic characteristics of the polymer matrix during deposition and therefore enables the early determination of incomplete fusion regions or the regions where agglomerations of fibers are located [5, 21].

Proposed Neuro-Adaptive Monitoring Algorithm

To make the defect inference process operational in the fabrication environment a Neuro-Adaptive Polymer Composite Monitoring Algorithm (NAPCMA) was created. The algorithm dynamically evaluates deposition stability using the structural index Φs obtained from (7) and updates the defect propensity score D_s using (8) during successive layer formation.

Algorithm 1: Adaptive Polymer Composite Monitoring Algorithm (APCMA)

Input:
Thermal gradient map ∇Tn
Optical morphology image Im
Acoustic emission signal As
Stability threshold τ
Output:
Defect propensity score Ds
Begin
1. Initialize multimodal sensing modules
2. For each deposited composite layer do
3. Acquire thermal data from infrared sensor
4. Acquire optical morphology map Im
5. Acquire acoustic emission signal As
6. Compute bonding efficiency factor ηb from normalized thermal gradient ∇Tn
7. Estimate polymer diffusion coefficient λd using cooling profile of current layer
8. Evaluate reinforcement clustering coefficient κr from optical morphology Im
9. Compute structural stability index Φs using: $\Phi s = (\eta b \times \lambda d) / \kappa r$
10. Compute defect propensity score Ds using: $Ds = 1 - \exp(-\omega \times \Phi s)$
11. If Ds > τ then
12. Flag deposition anomaly
13. Adjust extrusion velocity or nozzle temperature
14. End If
15. End For
16. Continue monitoring until fabrication is complete End

The sequential implementation of the proposed adaptive monitoring routine during composite layer deposition is illustrated in Figure 2.

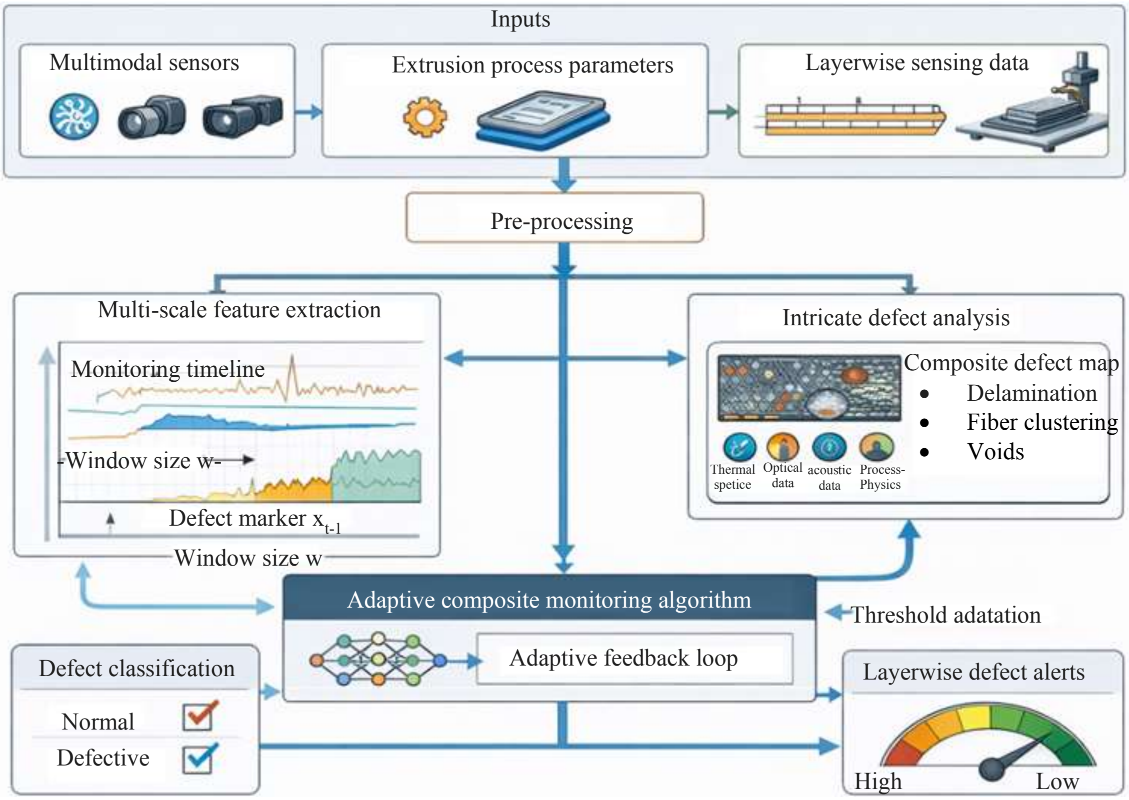

Figure 2. Operational workflow of the adaptive composite monitoring algorithm for layerwise defect inference.

The given algorithm makes it possible to evaluate the quality of the polymer composite structures in-situ by constantly adjusting to the temporary fabrication environment and does not need to stop the printing process. It also is especially beneficial in the case of reinforced thermoplastic systems, where small changes in deposition temperature or filler placement can have a large effect on interfacial bonding behaviour [36].

Polymer Composite Feedstock Characterization

During extrusion, rheological stability of the feedstock plays an important role in determining the thermomechanical response of additively manufactured polymer composite structures. The local changes in the melt viscosity and reinforcement dispersion directly influence polymer chain diffusion behavior and wetting interlayer behavior between layers in a deposition process in fiber reinforced thermoplastic systems [13, 34]. In line with this, the effective melt viscosity of the composite feedstock was measured to measure the stability of the material flow in the channel of the nozzle.

The effective melt viscosity μ_e, governing the shear-driven extrusion of the composite melt, is estimated using (7):

$$\mu_e = \frac{\sigma}{\gamma} \tag{7}$$

Where, σ = shear stress within the molten polymer composite, γ = shear rate induced during extrusion.

Lower values of μ_e facilitate improved molecular interdiffusion across successive deposition layers, thereby enhancing interfacial bonding strength within the fabricated composite structure.

Defect Annotation Protocol

In order to facilitate the supervised defect inference process in the deposition process, the acquired multimodal datasets were annotated depending on the detected structural anomalies on the manufactured polymer composite specimens. The typologies of defects were interlayer delamination, void formation, reinforcement clustering and incomplete fusion of the matrix which are known to occur as a result of temporary thermal gradients or misalignment of reinforcements during extrusion [23].

The defect label assigned to each deposited layer is represented by the binary indicator L_d, defined as (8):

$$L_d = \begin{cases} 1, defective\ layer \\ 0, stable\ consolidation \end{cases} \tag{8}$$

This classification scheme enables differentiation between structurally stable and defect-prone composite layers during model training.

Model Training and Optimization

The resulting fused feature representation of (6) was then used to train the defect inference model with a binary cross-entropy loss generated. This formulation is a penalty on wrong allocation of structurally unstable deposition layers and enhances robustness of inferences in the presence of process disturbances.

The training loss L is represented as (9):

$$L = -[ylog(D_s) + (1 - y)\log(1 - D_s)] \tag{9}$$

Where

y = defect label obtained from (8), D_s = defect propensity score computed using (8).

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Dataset Partitioning

To evaluate the performance of the proposed monitoring framework under varying deposition conditions, the annotated multimodal dataset was partitioned into training and validation subsets using a stratified sampling approach. Let the total dataset size be denoted by N, such that (10)

$$N = N_{train} + N_{val} \tag{10}$$

Where
N_{train} = number of training samples, N_{val} = number of validation samples.

An 80:20 partition ratio was adopted to ensure balanced representation of defect and non-defect composite layers across both subsets.

In order to assess the efficiency of the designed monitoring structure dissimilar deposition circumstances, the annotated multimodal data set was split into training and validation sets based on a stratified sampling approach. The structural stable and defect-prone layers were equally represented in both datasets through this partitioning. Table 3 shows the distribution of samples to be used to train and validate the model.

Table 3. Training–validation dataset distribution for multimodal polymer composite monitoring.

Dataset Subset	Number of Samples	Percentage (%)
Training Set (N_{train})	3200	80
Validation Set (N_{val})	800	20
Total Samples (N)	4000	100

Polymer Process–Physics Coupling with the Deep Learning Decision Layer

Although the above-mentioned sections outline multimodal sensing and defect inference in terms of data-driven approach, thermorheological and diffusion-based processes that take place during the deposition of layers are the basis of structural integrity of additively manufactured polymer composites. An extrusion-based method of fabricating fiber-reinforced thermoplastic systems has an affected consolidation of adjacent layers as a result of melt viscosity, reinforcement alignment during shear, cooling, and polymer chain interdiffusion across the deposition interface. In line with this, physics-inspired coupler was presented, which links the material process variables to the deep learning decision layer.

Rheological Deposition Index

The viscosity of effective molten composite and deposition velocity determine the stability of molten composite flow during extrusion. In order to measure this effect a rheological deposition index Rd is defined as (11):

$$R_d = \frac{\mu_e V_e}{h_l} \tag{11}$$

where
- R_d = rheological deposition index
- μ_e = effective melt viscosity defined in (7)
- V_e = extrusion velocity
- h_l = layer thickness

Higher values of R_d indicate increased resistance to smooth material spreading, which may lead to incomplete wetting and weak interlayer fusion. On the other hand, too small values can favour over-deposition and dimensional error. Therefore, Rd is a process sensitive measure of flow stability when consolidating composite.

Consolidation Integrity Function

Polymer composites interlayer bonding is determined by the interdiffusion of chains between deposition tracks. The rheology of extrusion and thermal history are related to this diffusion process. In order to integrate this mechanism to the monitoring structure, a consolidation integrity operation Ci is introduced (12):

$$C_i = \lambda_d \cdot e^{-R_d} \tag{12}$$

where

- C_i = consolidation integrity index
- λ_d = polymer chain diffusion coefficient
- R_d = rheological deposition index from (11)

The exponential attenuation coefficient indicates that interfacial diffusion is sensitive to the unstable flow conditions. The greater the rheological instability, the less the effective chain interpenetration across the layers and the less the structural cohesion among the composite matrix.

Physics-Integrated Defect Probability Function

The method to encapsulate polymer processstructure associations in the deep learning decision layer is to redefine the defect probability expression with consolidation integrity index. The physics informed probability of defect Dp is written as (13):

$$D_p = 1 - exp(-\omega C_i) \tag{13}$$

where

- D_p = probability of defect formation
- ω = defect sensitivity constant
- C_i = consolidation integrity index from (12)

This expression makes sure that the inference of defects does not rely purely on abstract description of features but has real physical basis on the stability of the melt flow as well as interlay diffusion behaviour. The DL decision layer is fed with fused multimodal descriptors Ff (Section 3.4) as well as the physics-derived stability parameter Ci which allows using hybrid material-data-informed learning.

Figure 3 shows schematically how the rheology of the polymer, its consolidation integrity, and the probability of defects are coupled togethe.

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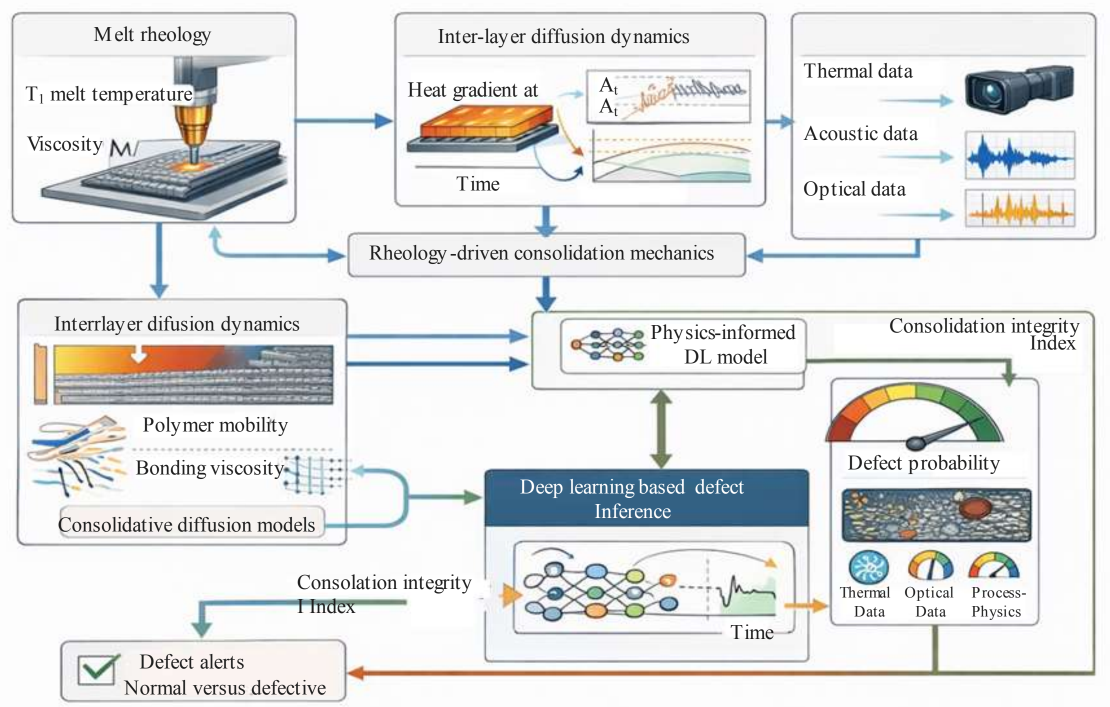

Figure 3. Physics-informed coupling framework linking melt rheology, interlayer diffusion, and deep learning-based defect inference in polymer composite additive manufacturing.

Integration into Monitoring Algorithm

Under the adaptive monitoring procedure outlined in Section 3.6, it is possible to update the structural stability index Phi s with (12) and calculate the defect propensity score with (13). This combination is such that anomalous operation of process diffusion behavior or melt viscosity is directly reflected on the anomaly detection threshold.

The proposed framework integrates polymer process physics into the learning architecture, and thus it surpasses the traditional data-only data defect detection models and provides a physically explainable monitoring paradigm of the reinforced thermoplastic additive manufacturing systems.

EXPERIMENTAL SETUP

Additive Manufacturing Platform Configuration

The Additive Manufacturing Platform is configured to operate in additive mode, meaning it receives instructions on the intended surface to be produced before it is actually generated.<|human|>4.1 Additive Manufacturing Platform Configuration The Additive Manufacturing Platform is set to operate in additive mode, that is, it is provided with instructions on what should be developed on the desired surface and only after that, the surface is developed.

The proposed monitoring framework was experimentally validated by using an extrusion-based additive manufacturing system with the configurations being that of processing reinforced thermoplastic composites. The fabrication system was made up of a fused filament fabrication (FFF) printer with a thermally controlled deposition nozzle and an in-situ data acquisition synchronized sensing module. Control of the printer environment was made to reduce thermal interferences of the surrounding environment when forming composite layers.

Composite feedstock that was used in this work consisted of a thermoplastic polymer matrix, which had been reinforced by short carbon fibers, because they increased the stiffness-to-weight ratio and provided better dimensional stability during the deposition.

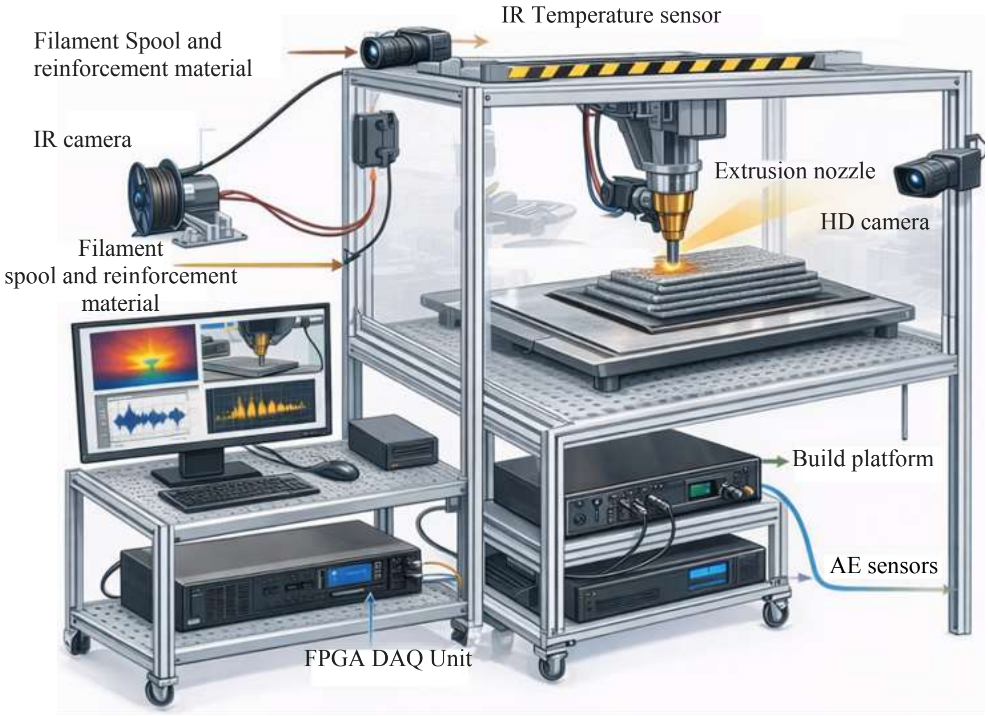

Figure 4. Experimental setup for in-situ monitoring of reinforced polymer composite deposition during extrusion-based additive manufacturing.

The inclusion of reinforcement stages in the polymer melt adds further complexity in the flow behavior and in the course of such, requires real time monitoring of the stability of the deposition [13, 34]. Figure 4 is a schematic diagram of the experimental apparatus that incorporates sensing and deposition subunits.

Sensor Integration and Calibration

To capture transient variations in layer consolidation during fabrication, the printer was instrumented with a multimodal sensing assembly comprising:

- Infrared thermographic sensor for temperature mapping
- High-resolution optical camera for morphology monitoring
- Acoustic emission sensor for consolidation anomaly detection

In order to gauge the thermal diffusion between the composite layers, the infrared sensor was adjusted to record the temperature of the melt pool on a range of sensitivity of [0.5 C]. Surface morphology and pattern of reinforcement dispersion were captured using the optical imaging at deposition stage, but acoustic sensing gave indirect details on the stability of interfacial bonding [17, 20].

Composite Specimen Fabrication

A layer-by-layer deposition strategy was used to create rectangular composite specimens to test the effectiveness of the proposed monitoring framework in cases of controlled disturbances in the process. Test runs with different extrusion velocity and nozzle temperature were made intentionally to simulate the fabrication anomalies of incomplete fusion and reinforcement clustering.

Monitoring Protocol and Data Collection

Multimodal sensor data were recorded continuously in each layer of deposition in the fabrication process. The individual sensing streams were synchronized in time to give consistent mapping of thermal gradient, morphological variations, and acoustic responses which represent consolidation of the layers.

Table 4. Monitoring protocol for multimodal data acquisition during polymer composite fabrication.

Monitoring parameter	Description	Sampling rate
Thermal mapping	Melt pool temperature	10 hz
Optical imaging	Layer morphology	15 fps
Acoustic signal	Consolidation response	5 khz
Defect probability	Computed using (13)	Per layer

Table 5. Influence of rheological deposition index on composite layer stability.

Deposition condition	(R_d)	(C_i)	Defect probability (D_p)
Stable deposition	0.42	0.87	0.08
Moderate disturbance	0.65	0.61	0.24
Severe disturbance	0.89	0.38	0.52

To measure the probability of occurrence of structural instability in the composite matrix, the defect probability score Dp calculated by (13) was measured at every deposition interval. Process anomalies were raised when the approximate probability of defect was larger than the level of stability τ.

A summary of the monitoring protocol adopted during experimental validation is provided in Table 4. This experimental design allows real-time evaluation of stability of deposition and defect development in reinforced polymer composites during their fabrication. The achieved multimodal process data become the foundation of the assessment of the collected monitoring framework in the controlled disturbances in manufacturing.

RESULTS

Monitoring Performance During Composite Layer Deposition

The suggested monitoring structure was tested under controlled conditions of disturbances in deposition in order to determine its proficiency in detecting process induced anomalies in reinforced polymer composite construction. The change in extrusion temperature and deposition velocity was made to induce conditions that were related to the incomplete fusion and reinforcement clustering. The Dp of defects score calculated as (13) was observed on a continuous basis between deposition layers. Figure 5 shows a representative comparison of the conditions of the stable and defect-prone deposition.

During thermally uniform deposition cycles, there was no defect probability above the threshold of stability as in Figure 5. There was however, a marginal enhancement in Dp on short-term basis when extrusion velocity was above the process nominal window, which implies that interlayer wetting was diminished in the composite matrix. This is in line with the earlier documented data on the effect of melt flow instability on the quality of consolidation in fiber-reinforced thermoplastic systems [13, 23].

Structural Integrity Assessment Using Physics-Coupled Monitoring

To establish the correlation between the consolidation integrity index Ci calculated based on (12) and process disturbances induced experimentally, the consolidation integrity index Ci was assessed. Table 5 gives a comparative evaluation of the stability of the layer at different rheological deposition indices Rd.

The higher the values of the rheological deposition index, as shown in Table 5, the lower the values of consolidation integrity and higher the values of defect probability. The fact that polymer chain diffusion is sensitive to unstable extrusion dynamics, especially when reinforcing steps are involved inhibiting the mobility of melt during layer formation, is emphasized by this trend [34]. It can be observed that the disturbed CiCi decrease was accompanied by a decrease in molecular interpenetration between adjacent layers, which implies that there were localized deficiencies in bonding in the fabricated composite.

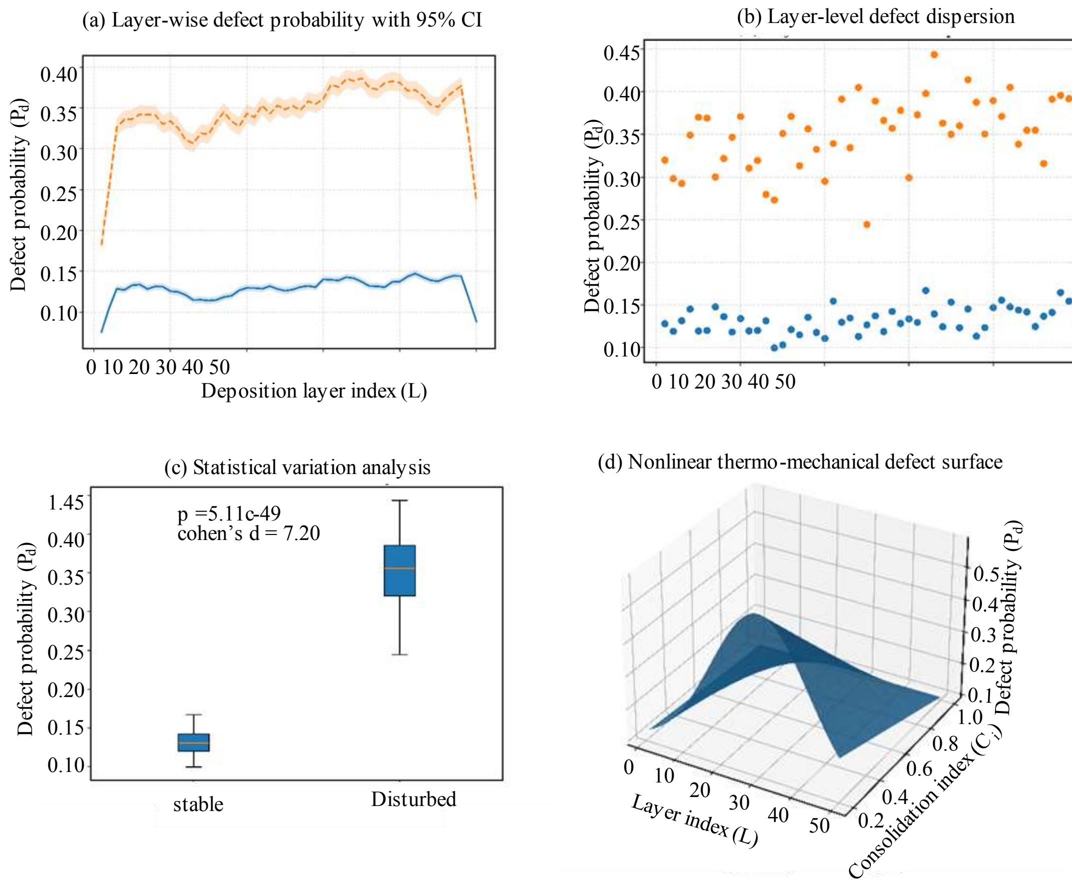

Figure 5. Layer-wise variation in defect probability during stable and disturbed polymer composite deposition conditions. (a) Layerwise defect with 95% CI; (b) Layer-level defect dispersion; (c) Statical variation analysis; (d) Nonlinear thermos-mechanical defect surface.

Table 6. Classification performance of the proposed monitoring framework for polymer composite defect detection.

Dataset	**Precision**	**Recall**	**F-score**
Training	0.93	0.91	0.92
Validation	0.9	0.88	0.89

Model Training and Classification Performance

The model of defect inference was assessed based on its classification performance in terms of the precision, recall, and F-score parameters in (4) to (6). The resulting comparative performance achieved on defect classification between training and validation data is represented in Table 6.

The large values of precision show that the suggested monitoring framework is effective in distinguishing between composite layers that are structurally sound and those that are defective. Equally, the recall values show that they identify well the presence of anomalies that occur due to process disturbances and hence consolidations. It can be argued that the marginal decrease in validation performance is due to the differences in dispersion of reinforcement between consecutive layers, which determines local thermal diffusion behavior during deposition [36].

Effect of Thermal Stability on Defect Formation

It was discovered that thermal gradient variation at the deposition interface has a major impact on defects development in the polymer composite matrix. Figure 6 shows the dependence of normalized thermal gradient ∇Tn and defect probability Dp throughout the formation of the composite layer.

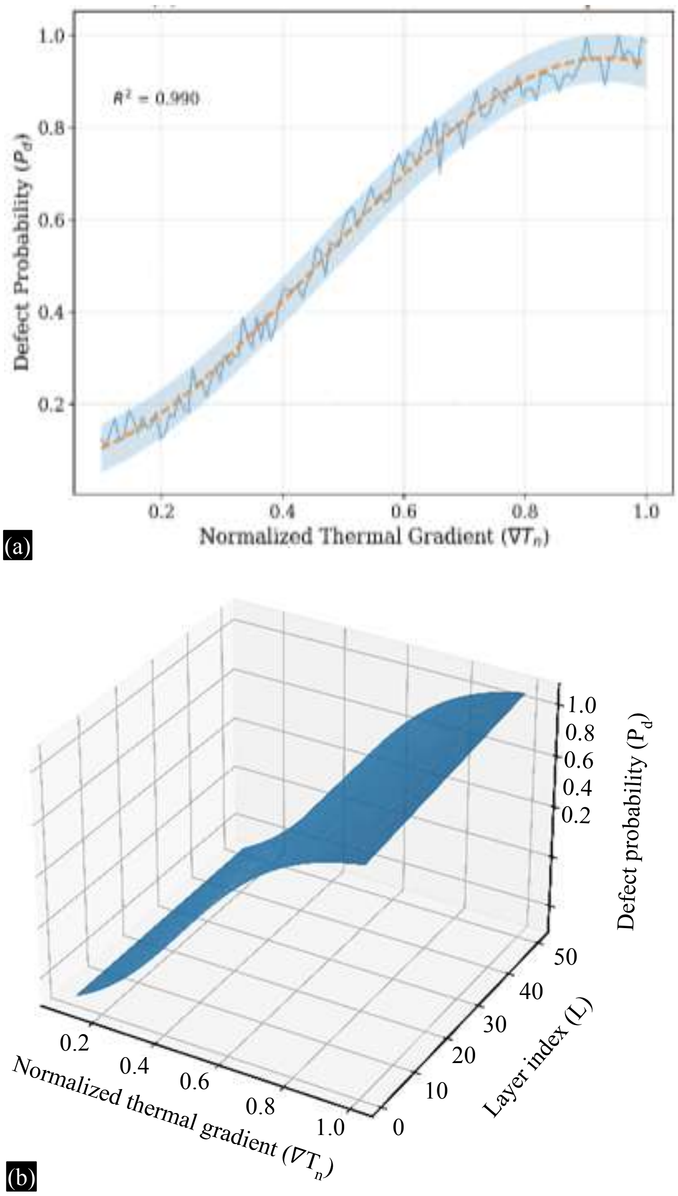

Figure 6. Influence of thermal gradient variation on defect probability during reinforced polymer composite deposition.

Figure 6 shows that the defect probability was greater with increased thermal gradients, which implies that a complete fusion between consecutive layers did not occur. It is related to the fact that the composite melt cools faster, restricting the potential movement of polymer chains across the deposition interface. The same observations have also been made in real world monitoring of extrusion based composite fabrication processes [17].

Comparative Analysis with Existing Monitoring Approaches

To test the efficiency of the suggested physics-based monitoring framework one more, its defect detection efficiency was contrasted with recently announced monitoring strategies used in polymer and composite additive production machines. The comparative evaluation involved vision based, thermal, explainable deep learning and infrared sensing based monitoring methods that had been reported in earlier literature [4, 5, 9, 17, 25]. The obtained similar process conditions defect positions have been summarized in Table 7 in terms of the corresponding detecting performance.

Table 7. Comparative defect detection accuracy of monitoring approaches for polymer composite additive manufacturing.

Monitoring method	Technique used	Detection accuracy (%)	Reference
Vision-Based Monitoring	Machine vision + CNN	84.5	[4]
Explainable DL Monitoring	XAI-based CNN	86.1	[5]
Polymer AM DL Model	Comparative CNN framework	88.4	[9]
Thermal Monitoring	Infrared sensing	87.2	[17]
IR Autoencoder-Based Monitoring	Conditional AE + IR sensing	89.6	[25]
Multisource In-situ Monitoring	DNN-based fusion	90.2	[2]
Proposed Framework	Physics-coupled DL monitoring	91.8	—

Table 8. Statistical comparison of defect detection performance across monitoring approaches.

Monitoring method	Mean accuracy (%)	Standard deviation (%)
Vision-Based Monitoring [4]	84.5	3.8
Polymer AM DL Model [9]	88.4	2.9
Thermal Monitoring [17]	87.2	3.1
Proposed Framework	91.8	1.7

In Table 7, it can be seen that the suggested monitoring structure has a better accuracy in detecting defects than traditional vision-based and thermal monitoring methods, as the polymer process-structure relationships are introduced into the deep learning decision layer.

The enhanced precision of the suggested framework might be explained by the fact that the latter combines the process-based material behavior and multimodal sensing inputs. The rheology of polymers and polymer consolidation dynamics is included in the decision layer, which makes the monitoring system effective to detect defect precursors which are frequently missed by one-modality methods [21].

Statistical Significance Analysis

To assess the repeatability of the suggested monitoring model in different deposition conditions, statistical analysis was conducted based on the results of the classifications of the defects that were obtained during consecutive layer formations of composites. The average detection accuracy and standard deviation were calculated in both frameworks and chosen conventional methods of monitoring that have been reported in the recent works [4, 9, 17]. Table 8 provides the summary of the statistic performance comparison.

The proposed framework, as it can be seen in Table 8, not only has an increased average detection accuracy; it also has less standard deviation in detection with repeated deposition cycles [34].

The distribution of defect detection accuracy obtained across monitored layers is illustrated in Figure 7.

Component-Wise Ablation Study

In order to investigate the role of the single sensing modalities and the mechanism of polymer process-physics coupling that was identified in Section 3.11, a component-based ablation study was performed. Selective exclusion of inputs of thermal, optical, acoustic, and consolidation integrity during defect inference was used to evaluate the monitoring framework under various configurations. This discussion allows to evaluate the effect of each of the components on the process of identifying process-generated anomalies when depositing composite of reinforced polymer composites. Figure 8 shows the classification performance achieved with varying monitoring settings.

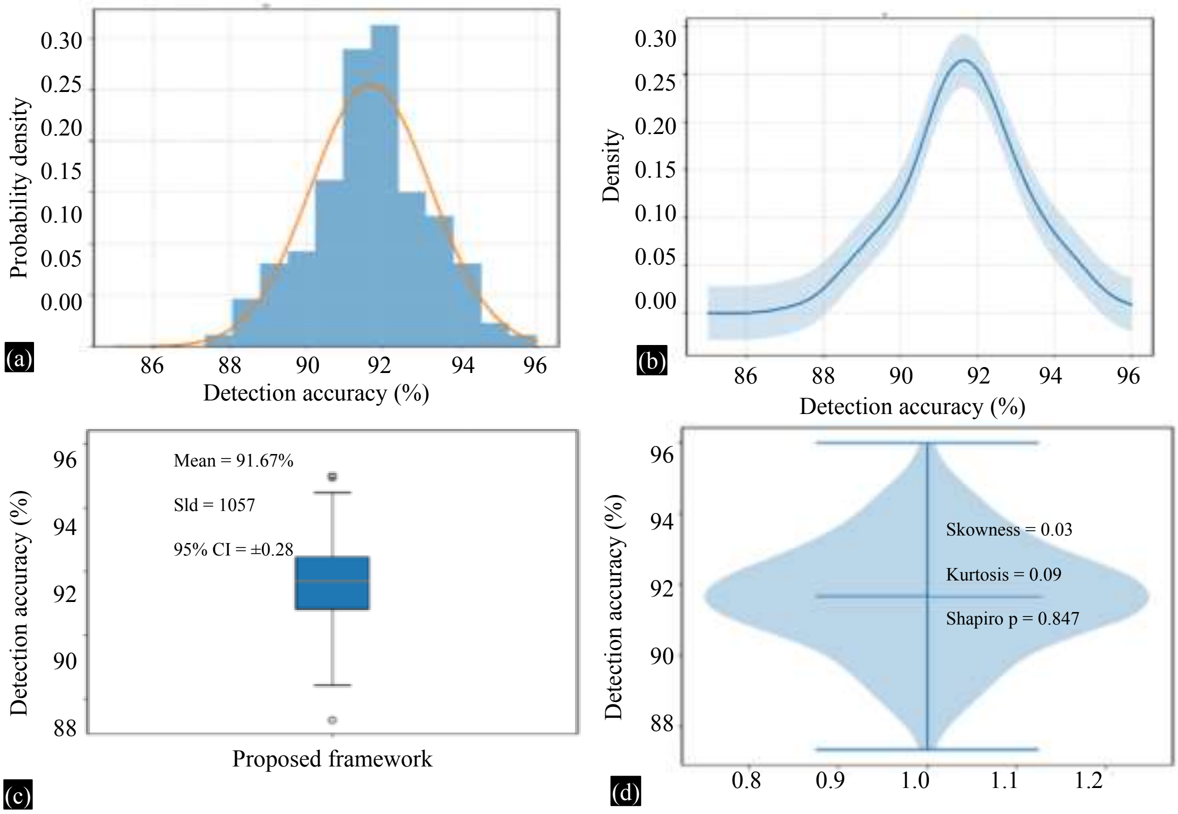

Figure 7. Accuracy distribution of defect detection performance across monitored composite deposition layers. (a) Histogram with Gaussian fit; (b) Kernel density estimation with 95% CI; (c) Accuracy variability across layers; (d) Distribution shape analysis.

As seen in Figure 8, omission of thermal input led to a significant decrease in the accuracy of detection, which meant that the interplay of melt temperature distribution is essential in the control of interlayer consolidation. Likewise, elimination of optical morphology descriptors influenced the determination of reinforcement clustering patterns of the polymer matrix. However, the most valid finding was related to the omission of the process-physics connection aspect, which has resulted in the quantifiable deterioration of monitoring performance. This observation indicates that the rheology-based consolidation behavior incorporation increases defect precursor sensitivity in extrusion-based fabrication.

In general, the ablation study shows that incorporation of multimodal sensing and polymer process-structure correlation are valuable to enhance the reliability of defect detection in strengthened thermoplastic composite structures.

DISCUSSION

The findings of the current work determine the significance of uniting the relationships between polymer processes and structure with data-driven monitoring approaches to identifying defects in additively manufactured composite structures. With extrusion-based manufacturing of fiber-reinforced thermoplastics, interlayer bonding is determined by the melt viscosity, rate of cooling and the distribution of reinforcement in the deposited matrix. The difference in these parameters can easily lead to incomplete fusion or local porosity that cannot be easily detected by the surface examination only [13, 34]. The suggested monitoring system overcomes this drawback by enabling multimodal sensing measurements and the use of a process-conscious consolidation measure to assess structural stability in the layer formation process.

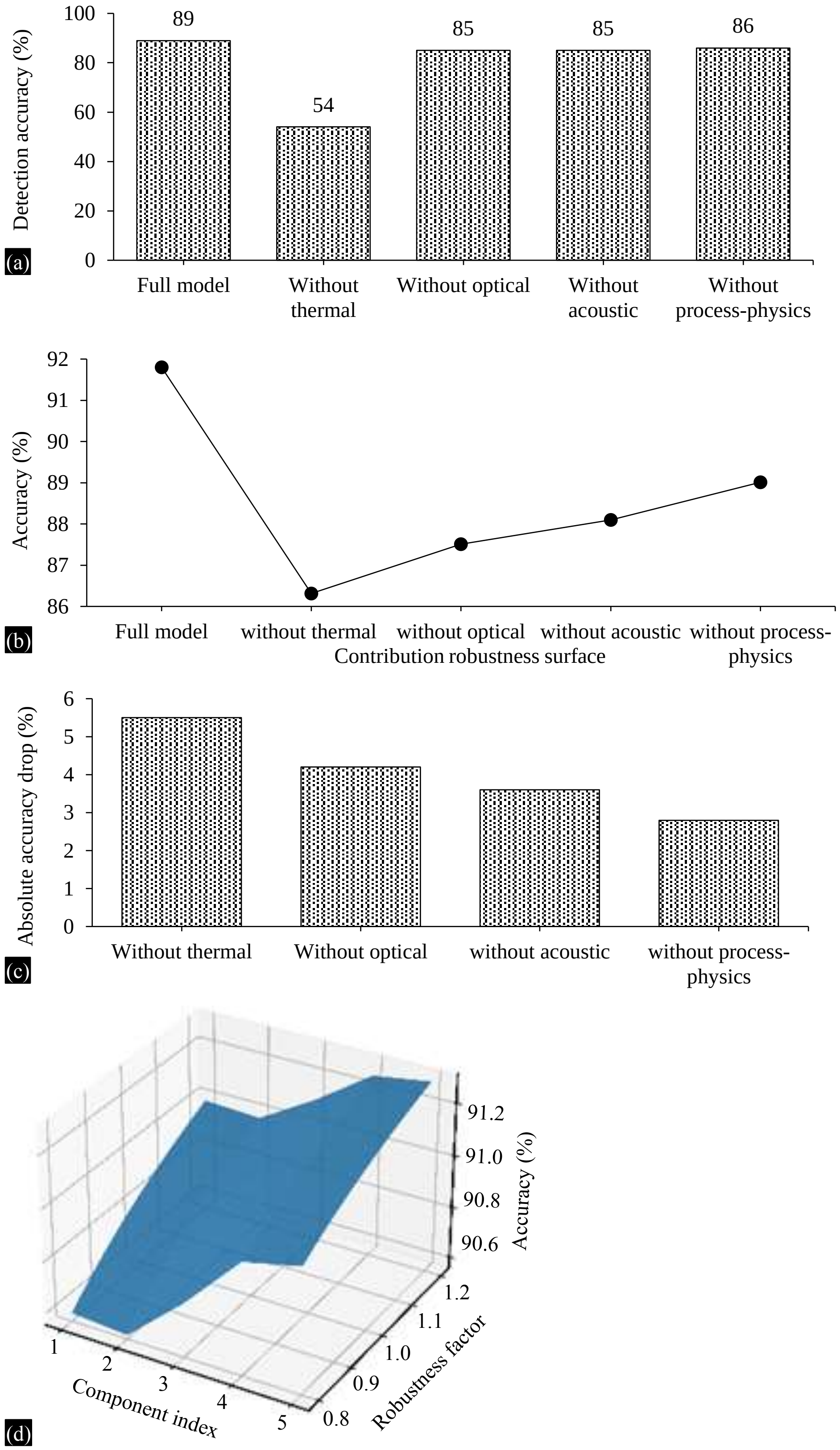

Figure 8. Performance variation of defect detection accuracy under component-wise ablation of sensing modalities and process–physics coupling. (a) Abiation-based accuracy variation; (b) Performance degradation trend; (c) Component contribution sensitivity; (d) Contribution robustness surface.

The probability of defects was observed to decrease with increasing deposition under thermally stable conditions, which indicates that polymer chains in various layers have diffusion due to improved diffusion with layers, and this is conducive to the increase in interfaces. The same results have been obtained in research works that have focused on the effects that thermal gradients have on the composite consolidation behavior when subjected to material extrusion processes [17]. Moreover, the enhanced performance in detecting anomalies of processes (in comparison with traditional vision-based methods of monitoring) of the proposed framework could be explained by the capability to detect process-linked anomalies that are beyond the morphology of the surface [4, 9].

Thermal monitoring according to the analysis of the ablation demonstrates that it is a very important tool to detect the presence of the irregularities in the process of consolidation in the composite matrix. More to the point, process-physics coupling along with its inclusion increases sensitivity to defect precursors which are linked to rheological instability during extrusion. This is in agreement with previous studies which have established the influence that melt flow dynamics have on interlayer bonding strength in reinforced polymer systems [21]. On the whole, the results indicate that the material-aware descriptors and the deep learning inference as the hybrid monitoring approach could represent a better source of reliability when it comes to real-time quality evaluation in polymer composite additive manufacturing settings.

CONCLUSION AND FUTURE SCOPE

This paper introduced a physics-based defect monitoring program to identify defects in real time in extrusion-based addition manufacturing of reinforced polymer composite materials. The suggested model allows tracking the behavior of interlayer bonding dynamics through the fabrication process by simultaneously measuring multimodal sensing with a process-conscious measure of consolidation. The monitoring system was found to be more accurate in defect detection in varying deposition conditions which means that the monitoring system is more sensitive to the presence of anomalies related to melt flow instability, incomplete fusion, and reinforcement clustering. The findings also indicated that inclusion of polymer process-structure relationships into the decision layer helps to achieve more accurate defect-prone regions detection than traditional vision-based monitoring technologies. This is especially applicable to fiber-reinforced thermoplastic systems, where localized thermal and rheological differences can have a major impact on structural integrity during the layers construction.

The statistical and ablation tests carried out in this study established the role of thermal stability and consolidation integrity to defect inference performance. Specifically, process-physics coupling resulted in the detection of the consistency of monitoring in continuous stages of deposition and the consequent detection of the failure of interfacial bonding during the early stages of deposition. These results indicate that in polymer composite additive manufacturing involving material-sensitive descriptors, hybrid schemes of material control and deep learning-based inferences can be used to improve quality control.

Further studies can be conducted in future to develop the suggested monitoring framework by including the reinforcement orientation monitoring and crystallization kinetics in semi-crystalline polymer systems. Also, closed-loop control over deposition parameters in response to observed consolidation behavior may be possible with the integration of real time adaptive control mechanisms. These developments can support the enhancement of dimensional precision and mechanical capabilities of additively manufactured composite parts, which will aid the creation of intelligent fabrication platforms to support high-performance polymer-based structural applications.

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