




Additive Manufacturing of Composites: A Framework for Digital Twin-driven Lifecycle Management

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Abstract. Traditional composite additive manufacturing (CAM) systems are challenging to manage because of the intricacy and variety of manufacturing processes, undermining product quality reliability. This research presents a life cycle management (LCM) framework for CAM to improve product quality. The framework being examined is a manufacturing system founded on a cloud-edge collaborative architecture comprising four modules: product design, product manufacturing, data traceability, and cloud management. Finite element analysis (FEA) is a computer analysis technique utilized in the product design phase to forecast the tensile characteristics of the product. A digital twin (DT) platform is employed during the product manufacturing phase to simulate manufacturing processes and validate the software process parameters. Using a physical platform for manufacturing is crucial for validating the hardware execution outcome. The Bayesian optimization long short-term memory (LSTM) algorithm is utilized in the product data tracing phase to monitor the production data of both the DT platform and the physical platform and detect potential software and hardware faults. A cloud-based management platform supervises the production process, enabling the traceability of product manufacturing data. For clarification, consider the example of continuous carbon fiber-reinforced nylon composite additive manufacturing. Experimental results indicate that the DT-driven LCM framework can improve product quality. Concerning data traceability, the F1 score for software data identification is 92, while the F1 for hardware data identification is 98.

Keywords: Composite additive manufacturing, Digital twin, Life cycle management, Bayesian optimization, LSTM

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1 INTRODUCTION

Composite material products produced through additive manufacturing (AM) have gained extensive utilization in the aerospace, defense, and automotive industries. Composite additive manufacturing (CAM) involves the molding of two different materials. The manufacturing process is complex and

variable, requiring the guarantee of uniform product quality from the design stage to production. Researchers have utilized digital twin (DT) technology for AM's life cycle management (LCM) to resolve the challenges above. DT technology monitors AM processes, predicts performance, detects anomalies, optimizes process parameters, and forecasts production costs, thereby improving the overall AM process and aiding LCM [1]. Data-driven approaches are being incorporated into the AM life cycle, including machine learning, product-process co-design, and life cycle evaluation to facilitate AM LCM [2]. To improve the current LCM framework for AM, researchers have successfully incorporated machine learning and the principles of collaborative product and process design [3].

Although numerous DT-driven AM LCM systems have been proposed, they exhibit significant interconnectivity and complexity regarding extensibility. Concerning material handling, there is a scarcity of performance analysis of materials. DT technology is frequently employed within established frameworks to facilitate viewing physical manufacturing processes and offer feedback on the state of actual AM. Applying machine learning techniques to detect anomalous data presents considerable difficulties in swiftly determining the source of defective products. Moreover, testing frameworks make it difficult to distinguish between software flaws, such as process parameters and control logic, and hardware errors, such as physical actuators.

The above framework divides the CAM life cycle into four distinct modules. Each module works autonomously, exchanges data, and supports future scalability. The design phase involves conducting finite element analysis (FEA) on materials. Simultaneously, the DT is detached from the actual production process. After loading verification, the DT is employed to simulate manufacturing, and the software process is transferred to the physical device for actual production. Using the edge layer for device status monitoring and anomaly detection can reduce raw data transmission, ensuring that only data rich in important information is transmitted. Data from two manufacturing processes is extracted, and the Bayesian optimization long short-term memory (LSTM) algorithm is employed to identify them individually. This procedure aims to identify potential sources of flaws in the production process and swiftly detect software and hardware malfunctions. The cloud-based management platform receives and stores product information and data, which will be uniformly stored in the cloud. Data will support external access. A distinctive identity is created throughout manufacturing, facilitating thorough production process tracking.

This paper is structured as follows: Section 2 discusses related works. Section 3 constructs a framework for the life cycle of CAM. Section 4 uses continuous carbon fiber-reinforced nylon composite additive manufacturing as an example to verify the framework's validity. Section 5 presents conclusions.

2 RELATED WORKS

2.1 Digital Twin for Composite Additive Manufacturing

DTs are a technology that replicates physical environments in a virtual format. Creating a highly virtual and realistic twin model facilitates the representation of the actual system in the physical realm. Michael Grieves first presented the concept of DTs in 2003 during a discussion on product lifecycle management [4]. Digital Twins (DTs) are a digital information system that processes physical entities digitally and fully replicates all their physical attributes. Researchers at NASA define DTs as: "An integrated, multi-physics, multi-scale, probabilistic simulation of a complex product, utilizing the most accurate physical models, sensor updates, and other relevant data." [5]. The primary characteristics of DTs are their strong connectivity, bidirectional interaction, and data-driven essence between physical and virtual entities. Compared to conventional simulation, the twin model significantly enhances the reliability of virtual simulation.

CAM is a technology that converts digital models into material accumulative structures. It is a byproduct of Industry 4.0, combined with DT technology. AM offers significant benefits compared to traditional subtractive methods, including the capacity for customized small-scale production, economical material usage, and expedited prototyping. Manufacturing hollow, intricate components

initially yields substantial cost reductions while improving strength. Secondly, AM is primarily a digital fabrication method. This approach drastically reduces the design-to-production cycle while preserving the current manufacturing workflow. Nonetheless, it is essential to acknowledge that AM currently possesses certain limits. Initially, traditional manufacturing settings were manually optimized and regularly changed, a labor-intensive procedure prone to inaccuracies. Secondly, the manufacturing process is not easily visualized, impeding users' capacity to intuitively comprehend the complexities of the process, especially with the production of equipment for composite materials. Thirdly, the collective efficacy of the equipment employed in AM is inadequate, primarily due to human and mechanical faults.

DT technology is being incorporated into the process to tackle the prevailing challenges in AM. Due to its digital and information-centric attributes, it can resolve the previously described issues. AM goods are linked to transdisciplinary, highly integrated, and digital manufacturing domains. Amalgamating many technological methods is essential for efficiently implementing product design and production processes. An analysis of DT technology vs conventional AM highlights significant benefits. DT technology can optimize process parameters and improve industrial visualization. This improvement is accomplished by obtaining and validating process parameters, diminishing the frequency of physical equipment malfunctions.

2.2 Life Cycle Management of Composite Additive Manufacturing

The product life cycle begins at the design phase and continues through production, usage, and the conclusion of its lifecycle. LCM has proven highly beneficial across multiple disciplines, with extensive application in biomedicine, railways, aircraft, and automobile production. Garrido et al. [6] suggested a framework for the automated creation of industrial DTs, incorporating automatically generated simulation models, machine tool control projects, and management tools to facilitate the whole life cycle of industrial DTs. Kong et al. [7] conducted a thorough life cycle assessment of ammonia co-firing systems in their foundational study. This groundbreaking study was the inaugural examination of the life cycle of ammonia co-firing systems from the viewpoint of the complete industrial chain. The authors' methodology was thorough, encompassing all stages from fuel production and transportation to co-firing.

AM is a digital technology that facilitates the customization of product fabrication. AM products consist of procedures, including material handling, fabrication, and elongation processes. The procedures above are intricate and variable, complicating the adoption of standardized management protocols. The product design, manufacturing, and testing environments operate with considerable independence, hindering rapid data interaction among them. This complicates the attainment of the requisite product quality. As a result, numerous experts have recently focused on the AM life cycle. Manco et al. [8] employed a process-based cost modeling methodology to assess capital and variable expenses, aiming to minimize the costs of additively made items while preserving quality. Cardeal et al. [9] created a process-based cost model to analyze the life cycle cost and viability of additively made spare components. Ma et al. [10] established a comprehensive full-dimensional sustainability life cycle evaluation framework to gain fundamental insights into the sustainability performance of additively manufactured items throughout their life cycle.

The thorough LCM of composite additive-made items is outlined based on the ideas and methodology defined for LCM in AM. The LCM of composite additive-produced items includes three separate phases: design, manufacturing, and traceability. The stages are interrelated, with data from each stage influencing the others. Figure 1 illustrates the conceptual basis for this LCM strategy. A consolidated platform is created to oversee the specified processes, allowing for the traceability of product manufacturing data post-test completion. The amalgamation of cloud manufacturing technology and DT technology enables the cloud to surmount data obstacles. DTs can validate manufacturing parameters, forecast manufacturing processes, and establish a closed-loop lifecycle management system. Simultaneously, they substantially reduce the quality risks associated with human variables.

Lifecycle management in CAM is structured around three primary stages: design, manufacturing, and traceability. In the design stage, all composite AM processes require product modeling and slicing. FEA, while optional, can efficiently predict final product strength. In the manufacturing stage, DT models enable virtual verification via G-code and control programs and are applicable across various CAM processes. Physical manufacturing remains a required step for all CAM processes. During traceability, different CAM processes may encounter software anomalies or hardware malfunctions, potentially affecting final product quality. Therefore, anomaly data traceability is essential.

Although the proposed lifecycle management framework for CAM is applicable to various CAM systems, challenges remain when scaling up to large-scale production. This is primarily because large-scale manufacturing typically relies on mature commercial control systems, most of which do not support direct data interaction with external platforms. This limitation significantly hinders the implementation of DT-based verification. As a result, DT verification is currently more feasible for small-scale, independently developed AM systems rather than for commercialized, closed-source platforms. Furthermore, during the traceability phase, the diversity of CAM equipment and processes must be taken into account. Effective traceability requires training specialized datasets tailored to the specific characteristics of composite materials and their manufacturing processes to meet the demands of anomaly tracking during production.

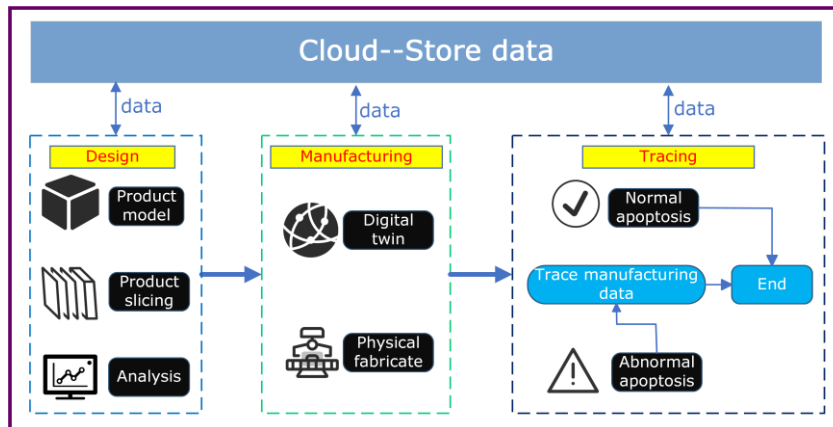


Figure 1: Concept of life cycle design for additive manufacturing products.

3 LIFE CYCLE FRAMEWORK FOR COMPOSITE ADDITIVE MANUFACTURING

The production of composite material items requires the sequential layering of two materials in the AM process. The design and manufacturing procedures of these goods are complex and variable. Compared to traditional single-material AM techniques, composite material products are prevalent in high-end applications. These applications require high-quality requirements and the capability to trace the provenance of the created products and the associated manufacturing data. Figure 2 illustrates the life cycle framework for AM of composite materials. This system integrates multiple technologies, including FEA, DTs, cloud data management, and identification. The framework comprises four distinct modules: product design, product manufacturing, data traceability, and cloud administration. The main functions of the product design module are the creation of the initial product model, the production of G-code via slicing, and the implementation of FEA. The product production module comprises DT manufacturing and physical manufacturing. DT manufacturing involves the integration of software process parameters and control logic. In contrast, physical

production requires incorporating validated process parameters and control logic and exporting manufacturing data. The data tracing process employs a Bayesian optimization LSTM algorithm, an advanced machine learning model, to systematically trace production data and detect probable software and hardware faults in manufacturing. The execution of cloud data management entails the amalgamation of edge computing and IoT technologies. A personal computer operates as an edge device, acquiring and storing industrial data before relaying it to the cloud for centralized administration. In the traditional AM life cycle frameworks, the FEA of materials is inadequate during the initial design phases. DTs are employed exclusively to enhance the visualization of physical production processes, consequently hindering the thorough simulation of the manufacturing process. The discovery of problems during data analysis presents a considerable barrier, as it is frequently impossible to determine whether these defects stem from software or hardware components.

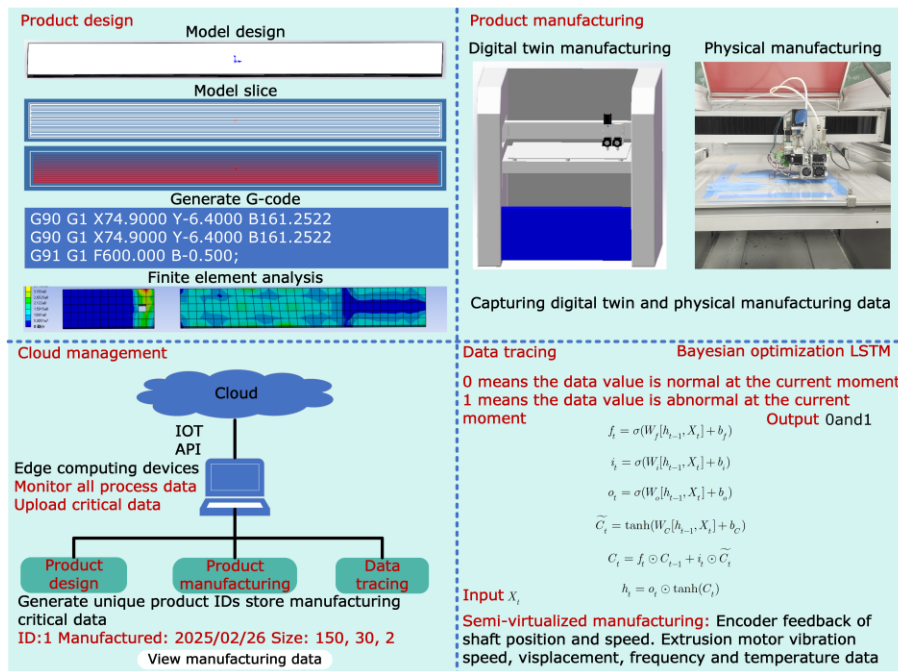


Figure 2: Lifecycle framework for composite additive manufacturing.

3.1 Product Design

The product design process parallels the traditional AM method, primarily involving model design, model slicing, G-code generation, and FEA. The model design employs SOLIDWORKS for modeling, aiming to create a model of the printed product based on the dimensional specifications. The model slicing procedure employs proprietary composite material slicing software that accounts for the unique characteristics of two different materials, devises the laying path, and produces the requisite G-code file. The G code includes positional and velocity data for the XYZBC axes, absolute and relative movement parameters, and print head temperature details. This extensive array of parameters comprises the essential software process parameters. FEA utilizes Ansys simulation to forecast the tensile strength of the spline. The model integrates nylon and continuous carbon fiber configurations, with tensile strength metrics derived from simulations based on G-code data.

3. To simulate the material extrusion by the BC axis in the physical manufacturing process, it is essential to establish a trajectory interface that replicates the extrusion process. The trajectory visualization interface utilizes C# WPF 3D visualization technology. The current extrusion amount, position, and speed data of the BC axis are used to visualize the trajectory of dual-head AM, thereby achieving the objective of simulation manufacturing.

4. The Siemens S7 protocol enables the integration of the specified components, facilitating effective data exchange. The virtual controller, human-machine interface, trajectory visualization interface, and virtual actuator are integrated to create a comprehensive DT model.

The mechanical actuator is designed using CAD modeling software and subsequently integrated into the DT model and visualization interface. Various actuator structures are established to attain the intended movement of the virtual actuator. The operational procedure involves the interactive interface parsing the G-code and transmitting the data to the virtual controller, which concurrently generates manufacturing instructions and simulates temperature variations of the dual-nozzle head. The virtual controller executes the manufacturing process, while the trajectory visualization interface manages the mechanical actuator's movement and displays the movement trajectory of the dual-nozzle head.

The manufacturing data of the DT is categorized into two segments: the first comprises data from the virtual controller about axis location, speed, and extrusion nozzle temperature, while the second pertains to the substrate and fiber distribution of the track, as illustrated in Table 1. The data extraction and recognition procedure employs C# WPF to create an interactive and visual trajectory interface. The Siemens S7 protocol acquires both data streams at 1-second intervals, logging results directly into preconfigured Excel templates. The virtual controller extracts data categories such as XYZBC axis position, velocity, and printhead temperature to verify control logic and process parameters.

Data categories	Nylon extrusion shaft		Fiber extrusion shafts	
X-axis position mm	-84.5	74.265	-155.72	-58.495
X-axis speed mm/s	0.000178814	0.3492236	0	3.6076903
Y-axis position mm	-11.559	1.6	0.778	2.179
Y-axis speed mm/s	71.501854	0	0	0
Z-axis position mm	0	0	0.15	0.15
Z-axis speed mm/s	0	0	0	0
Extrusion-axis position mm	12.271	109.172	544.493	665.499
Extrusion-axis speed mm/s	0.000178814	2.964437	0.10704994	0
Extrusion temperature °C	239.79	240.64	260.12	259.19

Table 1: Data extracted during digital twin manufacturing.

3.2.2 Physical manufacturing

The physical manufacturing process is carried out by inputting process parameters and control logic that align with the DTs. The manufacturing process aligns with that of the DT. The manufacturing process involves loading the G-code file into the interactive interface and parsing and transmitting the data to the physical controller. After receipt of process parameters and control logic, the print head is subjected to a preheating procedure. The temperature is regulated using verified PID parameters, ensuring adherence to specified temperature requirements during printing. The physical actuator commences the manufacturing process upon sending manufacturing instructions at the interface.

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The CAM system comprises a 5-axis motion platform, as shown in Figure 4. The X, Y, and Z axes govern the nozzle's positioning, while the B and C axes facilitate the extrusion of nylon and continuous carbon fiber materials. The heating rod regulates the nozzle temperature, while the thermocouple provides real-time feedback. The stepper motor operates based on pulses received from the physical controller. In contrast, the stepper drive configuration is modified using the DIP switch, motor current, and load-displacement per revolution to ensure compatibility with the lead screw. The manufacturing process aligns with the DT model, utilizing a spaced filling method alternating between continuous fibers and nylon.

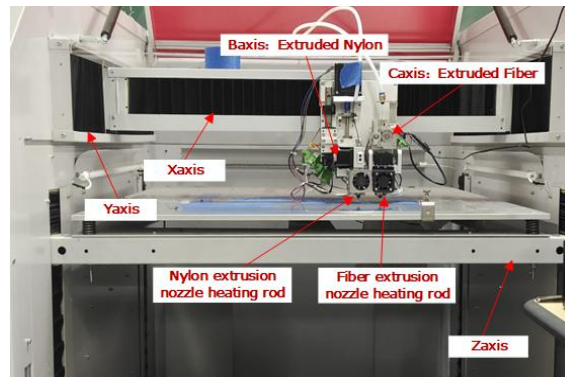


Figure 4: Physical composite additive manufacturing equipment.

Physical manufacturing data is collected using temperature and vibration sensors. The temperature sensor utilizes a thermocouple, with analog-to-digital conversion conducted by a temperature transmitter. The vibration sensor collects data on the motor's vibrations using the Bluetooth transmission protocol. Most failures occur within the BC axis during manufacturing, as shown in Table 2. Data is extracted utilizing the interval extraction method, with a specified extraction interval of 1 second. The extracted physical manufacturing data is used to detect hardware defects in the manufacturing process.

Data categories	Nylon extrusion shaft		Fiber extrusion shafts	
X-axis vibration speed mm/s	1	1	1	0
Y-axis vibration speed mm/s	2	0	1	1
Z-axis vibration speed mm/s	1	0	0	0
X-axis vibration displacement mm	11	1	2	0
Y-axis vibration displacement mm	16	1	3	3
Z-axis vibration displacement mm	1	2	2	2
X-axis vibration frequency Hz	32	42	37	8
Y-axis vibration frequency Hz	32	37	67	36
Z-axis vibration frequency Hz	49	69	65	42
Extrusion motor temperature °C	25.63	25.69	24.62	24.81
Extrusion nozzle temperature °C	239.94	240.18	258.32	261.05

Table 2: Data extracted during physical manufacturing.

3.3 Data Traceability

The mathematical principle of LSTM, as shown in Equation (3.1), addresses the gradient vanishing and explosion problems of traditional recurrent neural networks (RNN) by introducing a gating mechanism and a cell state. This structure enables LSTM to effectively capture long-term dependencies by regulating information flow, retaining relevant patterns in long sequences, and discarding irrelevant data. We define the time step as t , the input as $X_t \in R^m$, and the cell state as $C_{t-1} \in R^n$, with $W_f, W_i, W_o, W_C \in R^{n \times (m+n)}$ representing the parameter matrix and $b_f, b_i, b_o, b_C \in R^n$ the bias term. The forget gate determines which information to discard from the cell state C_{t-1} , and calculates the forgetting factor $f_t \in [0,1]^n$, where σ denotes a sigmoid function that maps values to the range $[0,1]$. The input gate determines which new information is added to the cell state. It generates candidate information C_t using function \tanh , which maps values to the range $[-1,1]$, and simultaneously computes the input factor $i_t \in [0,1]^n$. The cell state C_t is then updated by combining the previous memory C_{t-1} with the new candidate information C_t . Old memories are partially retained through the forget gate f_t , while new information is selectively added via the input gate i_t . The output gate determines the current hidden state h_t , which is influenced by both the updated cell state and the current input. It computes the output factor $o_t \in [0,1]^n$ and subsequently calculates the hidden state.

$$\begin{aligned}
 f_t &= \sigma(W_f[h_{t-1}, X_t] + b_f) \\
 i_t &= \sigma(W_i[h_{t-1}, X_t] + b_i) \\
 o_t &= \sigma(W_o[h_{t-1}, X_t] + b_o) \\
 C_t &= \tanh(W_C[h_{t-1}, X_t] + b_C) \\
 C_t &= f_t \odot C_{t-1} + i_t \odot C_t \\
 h_t &= o_t \odot \tanh(C_t)
 \end{aligned} \tag{3.1}$$

LSTM's gating mechanism and cell state resolve traditional RNNs' gradient vanishing/explosion issues while enabling robust modeling of long-range dependencies [13]. This model can effectively regulate the flow of information, remember patterns in long sequences, and discard irrelevant data. The collection of hyperparameters of the LSTM is represented by $x \in X \subset R^d$, the dimension of the hidden layer is defined by h , the learning rate is represented by ∂ , the number of LSTM layers is represented by L , and the dropout ratio is represented by P . The objective function is the loss function $f(x)$ on the validation set, and the optimal parameters x^* are sought. Bayesian optimization models the process using Gaussian processes (GP) and selects the next evaluation point using an acquisition function $f(x)$. It is divided into the derivation of the a priori and a posteriori distributions of Gaussian processes, assuming that $f(x)$ they obey a Gaussian process in Equation (3.2), where is the mean function $\mu(x)$ and covariance function $K(x, x')$ in Equation (3.3). The posterior distribution is derived for a given set of observations $D_{1:t} = \{x_i, y_i\}_{i=1}^t$. Among them $y_i = f(x_i) + \epsilon_i$ is noise $\epsilon_i \sim N(0, \sigma_n^2)$. The joint distribution is in Equation (3.4), and the posterior distribution is (3.5). The acquisition function is expected to improve, and the improvement function is defined as $I(x) = \max(f_{\min} - f(x), 0)$ where the current optimal observation value f_{\min} and the

expected improvement are in Equation (3.6). Under the Gaussian process, the closed-form solution is in Equation (3.7). ϕ and φ represent the cumulative distribution function and probability density function of the standard normal distribution, respectively, and ξ denote the exploration parameter.

$$f(x) \sim GP(\mu(x), K(x, x')) \quad (3.2)$$

$$K(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2} \sum_{i=1}^d \frac{(x_i - x'_i)^2}{l_i^2}\right) \quad (3.3)$$

$$\begin{bmatrix} f \\ f(x_{t+1}) \end{bmatrix} \sim N\left(0, \begin{bmatrix} k + \sigma_n^2 l & K \\ K^T & k(x_{t+1}, x_{t+1}) \end{bmatrix}\right) \quad (3.4)$$

$$k_{ij} = k(x_i, x_j), K = [k(x_{t+1}, x_1), \dots, k(x_{t+1}, x_t)]^T$$

$$f(x_{t+1}) | D_{1:t} \sim N(\mu_t(x_{t+1}), \sigma_t^2(x_{t+1})) \quad (3.5)$$

$$\mu_t(x) = K^T(k + \sigma_n^2 l)^{-1} y$$

$$\sigma_t^2(x) = k(x, x) - K^T(k + \sigma_n^2 I)^{-1} K$$

$$EI(x) = E[I(x)] = \int_{-\infty}^{f_{\min}} (f_{\min} - f) p(f | D) df \quad (3.6)$$

$$EI(x) = (f_{\min} - \mu_t(x) - \xi) \phi(Z) + \sigma_t(x) \varphi(Z) \quad (3.7)$$

$$Z = \frac{f_{\min} - \mu_t(x) - \xi}{\sigma_t(x)}$$

When new data is entered into the trained LSTM model, the predicted probability p is the model's positive class probability. Anomaly scores are calculated using a confidence level $confidence = \max(p, 1 - p)$, and thresholds are updated based on recent data distribution using a sliding window method. Maintain a fixed-size window, for example, with a confidence level of 5 samples $n = 5$. After entering new data, the current sample's score is added to the window, and the oldest data is removed. The position index $k = (n - 1)p_w$ must be calculated using the threshold calculation, which is the median of the window p_w . This is often taken as 0.95 in industrial anomaly detection. The final threshold value is calculated using linear interpolation. Here's the interpolation formula $Q_p = X_i + f \bullet (X_{i+1} - X_i)$: the integer part of linear interpolation $i = \lfloor k \rfloor$, the decimal part is $f = k - i$ the window data i after the update X_i and the final anomaly threshold Q_{p_w} . If the score exceeds the threshold, there is a defect in the product's manufacturing.

A Bayesian optimization LSTM technique is utilized to independently train and test the obtained dataset to detect probable software and hardware problems in the manufacturing process. The training and testing datasets comprise production data under both normal and abnormal settings. The data preparation phase employs normalization and outlier elimination to maintain training integrity. Due to the challenges associated with producing abnormal state data during production, the method of manually inducing faults is utilized to create such data. The input data comprises normal and abnormal production data gathered during the DT and physical manufacturing processes. In contrast, the output data is represented as 0 and 1, indicating the identification result as normal or abnormal. The data in the training set must be subjected to some processes, including mixing, shuffling, and partitioning. 80% of the data is designated for training, while the remaining 20% is allotted for evaluating the training outcomes. The amalgamation of production data with a DT enhances trajectory visualization, allowing software-induced faults to be detected in manufacturing. Defects encompass nylon and fiber fractures, absent components, and geometric irregularities. Identifying data, including motor vibration and temperature obtained during the production process, enables the diagnosis of hardware-related faults such as motor lockup, overheating, and overspeed

anomalies. The amalgamation of DTs, physical manufacturing, and a Bayesian optimization LSTM algorithm allows for separating software and hardware defect diagnosis, expediting the localization of defect sources.

3.4 Cloud Management

Cloud management encompasses storing and administering essential data generated during the three stages of AM of composite materials. Cloud management enables the thorough execution of the product's life cycle. Figure 5 depicts the hardware of the edge computing device. It consists of a switching power supply, an edge computing gateway, and a network switch. The edge computing gateway is connected to the network switch. The switch connects the personal computer and physical manufacturing apparatus to the edge above the computing gateway. The 4G technology employed by the edge computing gateway facilitates access to and configuration of the cloud platform. The PC functions as a data transmission system, overseeing all facets of production and employing the API to transmit critical industrial data. The cloud concurrently uses the MQTT protocol to manage the DT and actual manufacturing processes. The MQTT agent functions as a data conduit, aggregating information from multiple sources and storing it until retrieved by the subscriber [14-16]. Dimensions and finite element simulation data are produced during the product design phase. Both DT and physical manufacturing data are collected during the product manufacturing phase. The data tracing phase generates the outcomes of manufacturing data identification. The cloud can access edge computing devices to monitor the real-time DT and physical manufacturing processes. The PC obtains product-dimensional data using the SOLIDWORKS API and FEA data via the Ansys API and thereafter saves it in the specified file directory. The Siemens S7 protocol enables the acquisition and storage of data from DTs and physical industrial processes. The saved data is analyzed utilizing a Bayesian optimization LSTM algorithm, and the identification outcome is used to ascertain the qualification of the currently made product. The data management process retains the identification result data. Upon completion of the design, manufacturing, and identification stages, a distinctive identification number will be assigned to the product in production. This number will be used in the data tracing process. Simultaneously, technicians test the product's tensile strength to determine its precise value and then upload the result to the cloud management system.

Our cloud-based system transmits data from edge devices and PCs to the cloud using 4G networks and the MQTT protocol. However, this architecture may be vulnerable to security threats such as man-in-the-middle attacks, eavesdropping, and data forgery. The MQTT protocol, while lightweight and efficient, lacks built-in encryption and robust authentication mechanisms, making it a potential target for attackers. To mitigate these risks and prevent data leakage during transmission, we have integrated a TLS/SSL encryption layer over the MQTT protocol to ensure data confidentiality and integrity. Additionally, we implement certificate-based mutual authentication between publishers and subscribers to block unauthorized device access and enhance system security.

To further strengthen our communication framework, we enforce strict session timeout policies, regularly rotate security credentials, and monitor traffic patterns for anomalies using intrusion detection systems. These combined measures help protect against advanced persistent threats and ensure that only verified and authorized devices participate in the data transmission process, significantly reducing the risk of compromise across our networked manufacturing environment.

As a centralized data repository, the cloud platform presents significant risks of unauthorized access, duplication, or data theft if adequate access control and encryption measures are not enforced. The stored data includes highly sensitive information such as dimensional design files, finite element simulation results, manufacturing process parameters, and product strength data. To mitigate these risks, we have implemented a role-based access control mechanism to precisely manage user permissions and ensure that each role can access only the data necessary for its function. Additionally, sensitive data, such as FEA results and process parameters, is protected using tiered encryption and dynamic key management via a Key Management Service, which is regularly updated to defend against emerging threats.

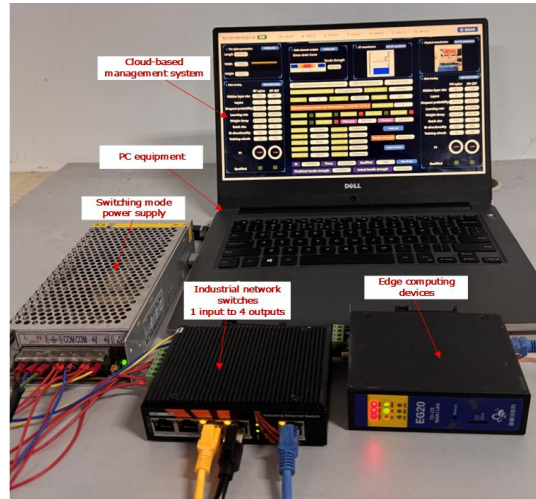


Figure 5: Hardware composition of edge computing devices.

To ensure data integrity and traceability, we employ blockchain technology to hash and store manufacturing data, thereby preventing tampering during transmission and storage and improving the reliability of traceability. Each product ID is linked to a corresponding data package stored in the cloud as an immutable record, enabling precise accountability and rapid auditing when quality issues arise. Furthermore, we have adopted real-time monitoring and anomaly detection tools to identify unusual access patterns or unauthorized activities. Although cloud-based management throughout the additive manufacturing lifecycle provides substantial benefits in convenience and intelligent functionality, it also introduces significant data security risks. These risks can be effectively mitigated through the implementation of comprehensive safeguards, including encrypted data transmission, device authentication, and access control, ensuring the confidentiality, integrity, and availability of manufacturing data.

4 ADDITIVE MANUFACTURING EXPERIMENTS ON CONTINUOUS CARBON FIBER-REINFORCED NYLON COMPOSITES

The proposed LCM framework for AM of composite materials employs DTs, deep learning, and LCM throughout product manufacturing [17]. This technology addresses several primary challenges: It utilizes DT technology to simulate composite materials' complete AM process, validate the process flow and parameters, and decrease the expenses of testing physical equipment. Secondly, it examines the challenges related to pinpointing the origin of defects in the manufacturing process. Abnormalities in manufactured products complicate the rapid identification of whether defects stem from software or hardware. Product design, manufacturing, and data identification processes operate independently, and there is an absence of a cohesive data management platform to track data throughout the manufacturing process. A specimen produced through AM techniques was employed for verification to address these challenges. The specimen consisted of a continuous carbon fiber-reinforced nylon composite material.

4.1 Product Design

Experimental validation in carbon fiber-reinforced nylon CAM confirmed the framework's operational efficacy. In the product design process, SOLIDWORKS was employed to develop the preliminary model of the product, a standard cuboid spline measuring 150 millimeters in length, 13 millimeters in width, and 2 millimeters in height. The CAD software exports STL and G-code files to automate

toolpath generation and streamline layer-by-layer fabrication planning. A distribution model of continuous carbon fiber and nylon materials is constructed in Ansys based on the data in the G-code file to conduct an FEA experiment. Material properties require precise definitions for all constituent materials according to their standardized classifications. The material properties encompass the elastic constant, Poisson's ratio, density, and strength [18]. The continuous carbon fiber material possesses a density of 1.8 g/cm^3 , a Young's modulus of 100 GPa , a yield strength of 480 MPa , and a Poisson's ratio of 0.38 . The density of nylon material is 1.14 g/cm^3 , its Young's modulus is 2.8 GPa , the yield strength is 70 MPa , and the Poisson's ratio is 0.39 . The following phases involve meshing and the incorporation of boundary conditions. Subsequently, the LS-DYNA (85) model performs an axial equivalent displacement stretch. The solution is then executed to obtain the anticipated tensile strength result. The FEA experiment data indicates that the model's tensile strength varies. The instant tensile fracture coincides with the model's maximum tensile strength of 566 MPa . Figure 6 illustrates the FEA experiment. Figure 6 (a) delineates the procedure of the FEA experiment for tensile strength, whereas Figure 6 (b) compares the maximum tensile strength and the average tensile strength over time.

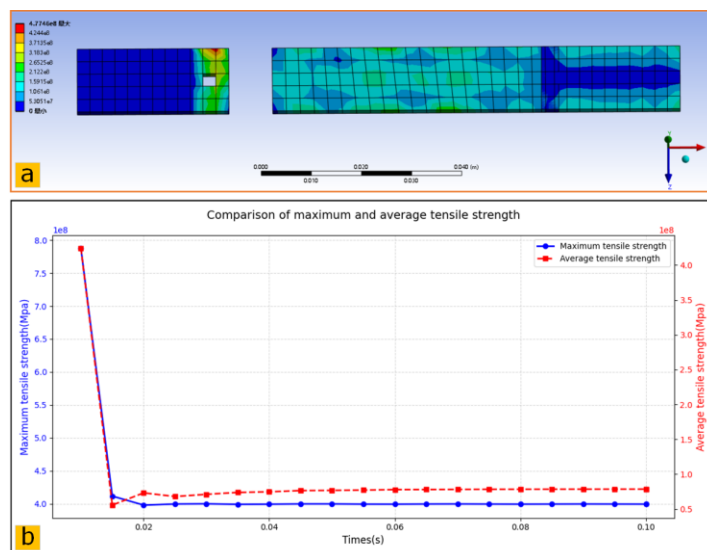


Figure 6: Finite element analysis experiment: (a) Experiment, and (b) Maximum and average tensile strength.

4.2 Product Manufacturing

4.2.1 Digital twin manufacturing

The experimental framework for DT manufacturing involves creating a DT model and transferring the control software from this model to the virtual controller. The Nettoplcsim software will map the virtual IP address to the physical IP address for the S7 protocol connection. The G-code file, produced during the product design process, is then uploaded into the interactive interface of the DT. The interactive interface interprets the G-code and transmits and receives data. Simultaneously, the visual trajectory interface is activated, and the DT production process is commenced by the manufacturing command situated at the interactive interface.

The interactive interface facilitates the transmission and reception of data from the ongoing manufacturing process during the experiment. It offers instantaneous feedback on pertinent metrics,

including the ongoing manufacturing process status, motor position, motor speed, current G-code parameters, layer count, and manufacturing duration. Simultaneously, the relevant parameters of the motor and nozzle are conveyed to ensure software data traceability. The control program employs interpolation to govern the motor shaft and PID control to regulate the nozzle temperature. G-code instructions direct the manufacturing process. The visual trajectory interface calculates the extrusion volume of continuous carbon fiber and nylon, which is subsequently utilized to ascertain the corresponding trajectory length. In this interface, blue denotes the nylon trajectory, whereas red indicates the continuous carbon fiber trajectory. The visual interface subsequently exports the trajectory data for juxtaposition with the G-code data.

Figure 7 illustrates the impact of DT production, while the visual trajectory interface elucidates its manufacturing process. Figure 7 (a) illustrates the infill trajectory and density of the first two layers of nylon AM, filled at an angle of 0 degrees. Figure 7 (b) depicts the application of continuous carbon fibers onto a nylon layer, including 14 fibers. Figure 7 (c) illustrates the fiber installation procedure from a lateral viewpoint, indicating a specified thickness along the Z-axis of geometric space. Figure 7 (d) represents the finished result, with the fibers encased in nylon.

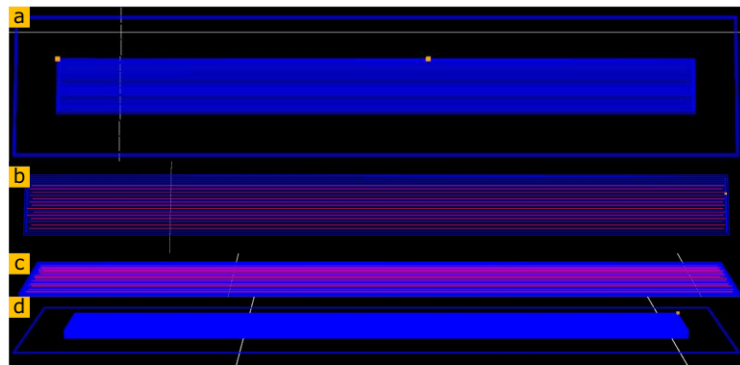


Figure 7: Digital twin manufacturing effect: (a) Nylon, (b) Continuous carbon fibers, (c) Lateral viewpoint, and (d) Final result.

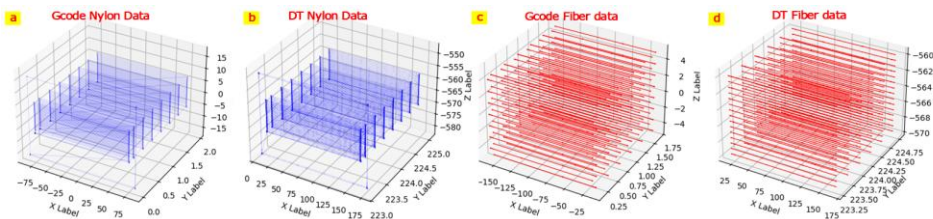


Figure 8: Comparison of G-code and digital twin product data: (a) G-code nylon data, (b) Digital twin nylon data, (c) G-code fiber data, and (d) Digital twin fiber data.

Figure 8 illustrates the comparison between the end product data and the G-code data, thereby validating the execution efficacy of the G-code data within the DT paradigm. Figure 8 (a) has the G-code nylon data. The X-coordinate is 149.8 mm, the Y-coordinate is 1.95 mm, and the Z-coordinate is 12.8 mm. Figure 8 (b) presents the nylon data for DT production, with an X-axis coordinate of 149.801 millimeters, a Y-axis coordinate of 1.949 millimeters, and a Z-axis coordinate of 12.801 millimeters. Figure 8 (c) presents the G-code continuous carbon fiber data, indicating an absolute X-axis coordinate of 147.44 mm, a Y-axis coordinate of 1.5 mm, and a Z-axis coordinate of 9.8 mm. Figure 8 (d) presents the DT continuous carbon fiber data, indicating an X-axis coordinate of 147.439

mm, a Y-axis coordinate of 1.499 mm, and a Z-axis coordinate of 9.8 mm. The DT demonstrates significant accuracy with the G-code data, enabling the verification of software process parameters and control logic in a completely virtual setting.

4.2.2 Physical manufacturing

The physical manufacturing process relies on the established manufacturing platform, into which the validated control program is uploaded into the physical controller. The validated G-code file is subsequently uploaded into the human-machine interface, which interprets the G-code and manages data transmission and reception. Simultaneously, production directives are transmitted to the physical controller.

The human-machine interface collaborates with the production process using the DT concept in the experiment. The XYZ three-axis mechanism in the physical device regulates the nozzle's spatial positioning, while the BC two-axis governs the volume of material extruded from the two nozzles. The B axis regulates the extrusion volume of the nylon material, while the C axis governs the extrusion volume of the continuous carbon fiber material. The imperative of severing continuous carbon fiber materials post-extrusion is critical, and a cylinder is utilized to control the cutting head. The nozzle temperature is controlled by a temperature regulator that employs a thermocouple for temperature measurement and a heating element to provide heat to the nozzle. Figure 9 illustrates the manufacturing process. Figure 9 (a) demonstrates the production process. Figure 9 (b) illustrates the continuous fiber that has been laid. Figure 9 (c) displays the placed nylon. Figure 9 (d) illustrates the completed manufactured product.

Bluetooth sensors and temperature transmitters enable data acquisition. Bluetooth sensors are applied to collect vibration data from the XYZBC three-axis, while thermocouples and temperature transmitters are utilized to acquire temperature data from the motor and nozzle. The gathered data is subsequently recorded in a specified file using the time interval extraction method for hardware data traceability.

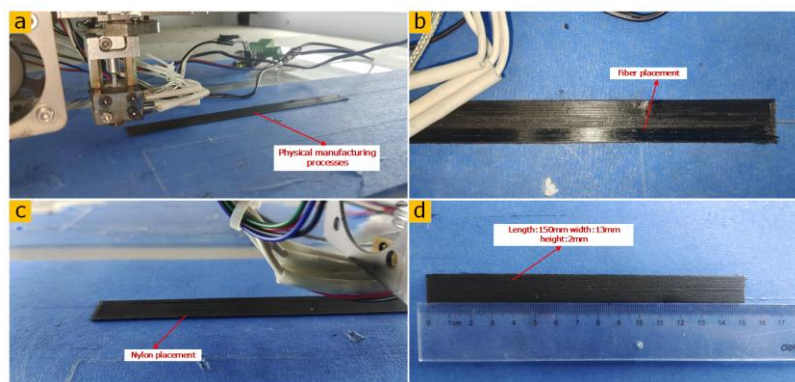


Figure 9: Physical manufacturing experiment: (a) Physical process, (b) Continuous fiber placement, (c) Nylon placement, and (d) Complete manufactured product.

4.3 Data Traceability

The execution of data tracing is guided by a Bayesian optimization LSTM deep learning system, utilizing a dataset that includes standard and anomalous manufacturing data. The acquisition of exception data from non-conforming products supplements the gathering of manufacturing data from conforming items. The two data sets are subsequently combined and distinguished utilizing label values. Before the training phase, processing the gathered DT and physical production data to

remove outliers is essential. The data must first be standardized and then scrambled. Conventional machine learning methodology divides datasets into an 80% training subset and a 20% holdout testing subset for performance evaluation. It is essential to modify the dropout layer of the model to reduce the likelihood of overfitting [19]. In industrial production data recognition, the accuracy index is prone to distortion because of the small percentage of anomalous data. Thus, the F1 score is utilized to precisely represent the model's identification proficiency for the minority class. The ideal hyperparameter selection, aligned with the maximum F1 score, is attained by Bayesian optimization of LSTM to guarantee the effectiveness of the training procedure.

4.3.1 Digital twin for manufacturing data traceability

DT manufacturing data traceability consists of two components: the traceability of nylon sample data within the DT model and continuous carbon fiber sample data traceability. The challenges in generating abnormalities during manufacturing indicate that manual configuration of software process parameters leads to the production of abnormal data. The Z-axis position of the DT remains in the same plane throughout the nylon track laying process. The Z-axis speed remains constant at zero. The Z-axis speed will be omitted from the data processing. Table 3 demonstrates that the DT for manufacturing nylon and continuous carbon fiber data models utilizes different hyperparameters, leading to diverse test results. The data is trained and tested according to the specified hyperparameters, with the resulting model's accuracy, precision, recall, and F1 score reported.

Figure 10 presents the confusion matrix alongside the correlation analysis heatmap for the LSTM classification model applied to DT nylon and fiber data. The confusion matrix serves as a statistical instrument for presenting the outcomes of a model evaluation. In contrast, the correlation analysis heat map depicts the associations between input features and output values [20]. The input is defined by the collected characteristic data, while the output consists of a label value of 0 or 1, representing the two states of normal and abnormal.

DT manufacturing data model hyperparameters		
Hyperparameter category	Nylon sample data	Fiber sample data
Hidden layer size	419	406
Layers	1	1
Dropout probability	0.351	0.417
Learning rate	0.005788	0.000137
Weight decay	1.32×10^{-6}	2.44×10^{-4}
Batch size	64	32
Bi-directionality	No	No
Training wheels	50	50
Training output results		
Accuracy	0.9302	0.9199
Precision	0.8824	0.8634
Recall	0.9930	0.9929
F1 Score	0.9344	0.9236

Table 3: Digital twin manufacturing data model training hyperparameters and results.

If the same batch of products is produced again, gathering new manufacturing data and applying the trained model for identification is essential. The confidence level of the five distinct samples, as indicated by historical identification results, warrants consideration. The levels should be organized within a window, removing the initial element and appending the new data's confidence level at the window's end. The threshold is established by calculating the position index. If the confidence level of the latest data surpasses the existing threshold, it can be concluded that a software defect exists in the manufacturing process. The origin of the defect can be identified through a visualization

interface, allowing relevant personnel to locate the defect quickly. Defects commonly arise from nylon and fiber breaks, geometric shape irregularities, overflow boundaries, and absent components, as demonstrated in Figure 11. Manufacturing experience indicates a strong relationship between these defects and the software's process parameters and control logic.

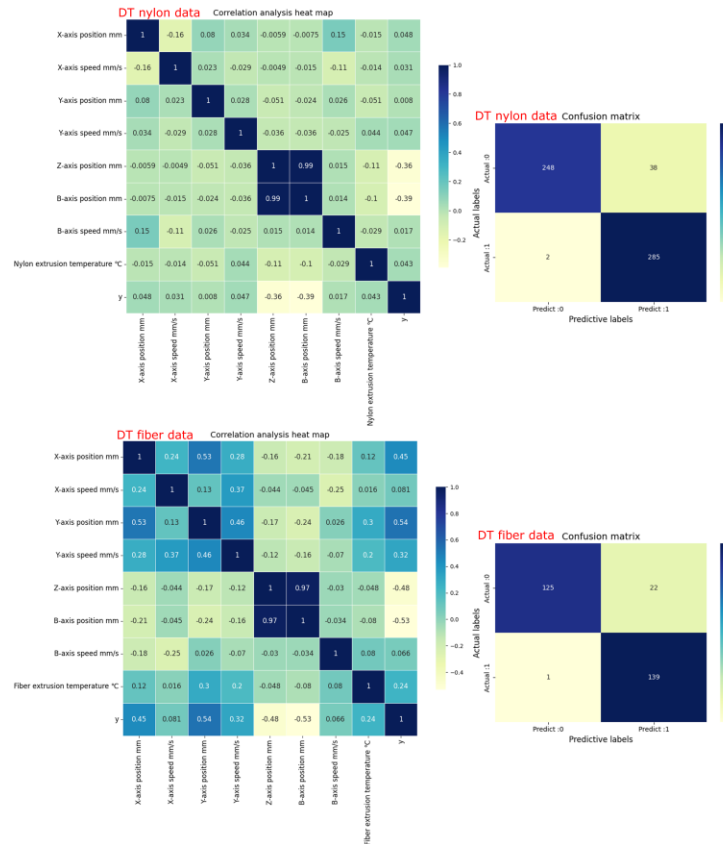


Figure 10: Correlation heat map and confusion matrix of the digital twin manufacturing data model.

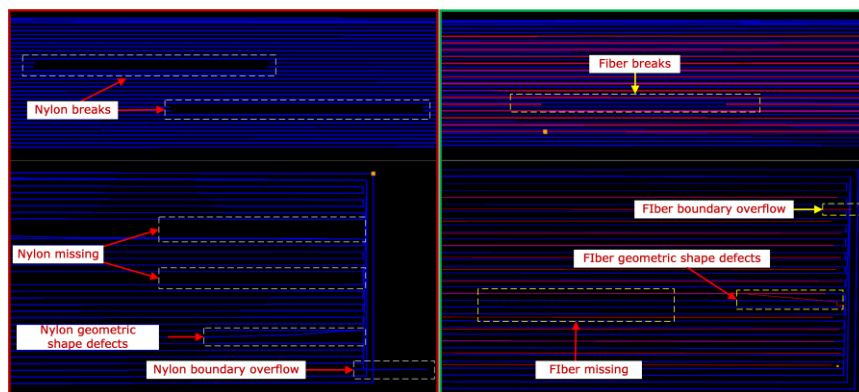


Figure 11: Common software defects.

4.3.2 Physical manufacturing data traceability

The methodology for tracing physical manufacturing data aligns with tracing DT data. The distinguishing factor relates to the source of the extracted data: DT manufacturing data originates from software, while physical manufacturing data comes from hardware. An analysis of the physical manufacturing process indicates that nylon and continuous carbon fiber extrusion motors and nozzles demonstrate a greater likelihood of abnormalities. An analysis of the defects associated with physical actuators is essential, as these defects can significantly affect the quality of the final product. Sensors enable sample data collection, while the generation of abnormal data is triggered by detecting physical actuator anomalies through sensor feedback loops and threshold-based diagnostics. Table 4 presents the hyperparameters and test results for physically manufacturing nylon and continuous carbon fiber data models. Figure 12 presents the changes in the training indicators of the physical manufacturing nylon and fiber data LSTM classification model, the confusion matrix, and the correlation analysis heat map. The confusion matrix is a statistical instrument that presents the outcomes of a machine learning model evaluation, offering insight into prediction accuracy and error types. The correlation analysis heat map visually represents the relationship between input features and output values, helping identify dominant influencing factors. The input comprises the gathered feature data, while the output consists of label values of 0 and 1, representing normal and abnormal states, respectively.

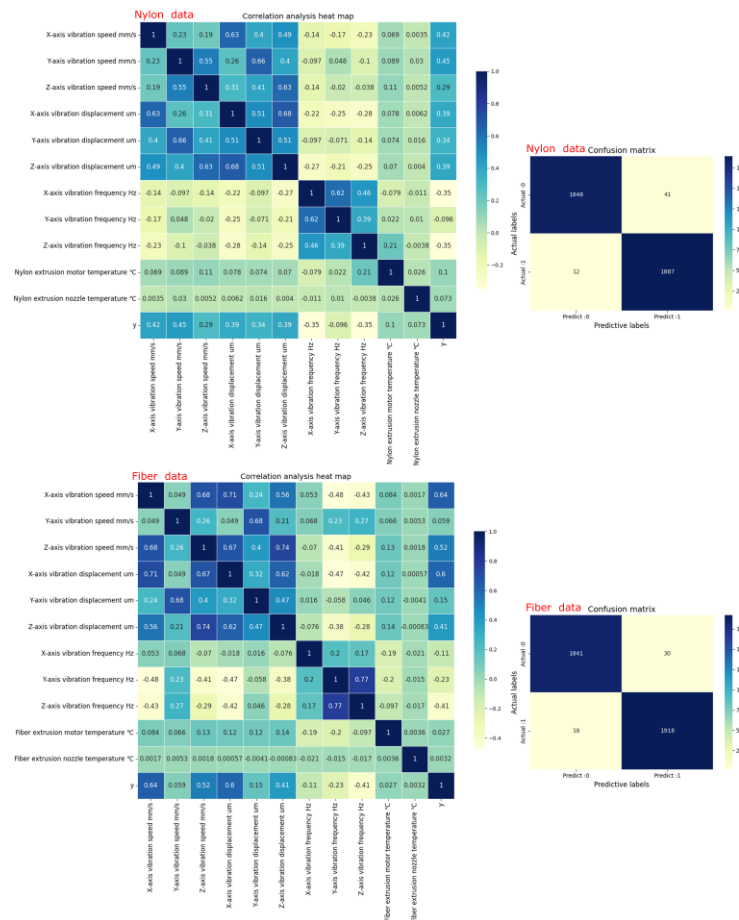


Figure 12: Correlation heat map and confusion matrix of the physical manufacturing data model.

Physical manufacturing data model hyperparameters		
Hyperparameter category	Nylon sample data	Fiber sample data
Hidden layer size	462	318
Layers	4	2
Dropout probability	0.210	0.012
Learning rate	0.00193	0.00892
Weight decay	5.52×10^{-5}	1.38×10^{-5}
Batch size	100	100
Bi-directionality	No	No
Training wheels	50	50
Training output results		
Accuracy	0.9860	0.9874
Precision	0.9787	0.9846
Recall	0.9937	0.9907
F1 Score	0.9862	0.9876

Table 4: Training hyperparameters and results for the physical manufacturing data model.

If the same batch of products is produced again, gathering new manufacturing data and applying the trained model for recognition is crucial. If the confidence level of the latest data surpasses the existing threshold, it can be concluded that a hardware defect exists in the manufacturing process. Consistent sensor calibration is crucial during model implementation to prevent data bias. The hardware actuator is associated with common defects such as extrusion motor overtemperature, abnormal vibration, and abnormal nozzle temperature. Figure 13 illustrates that, according to manufacturing experience, the origin of these defects is closely associated with the hardware actuator and motor.

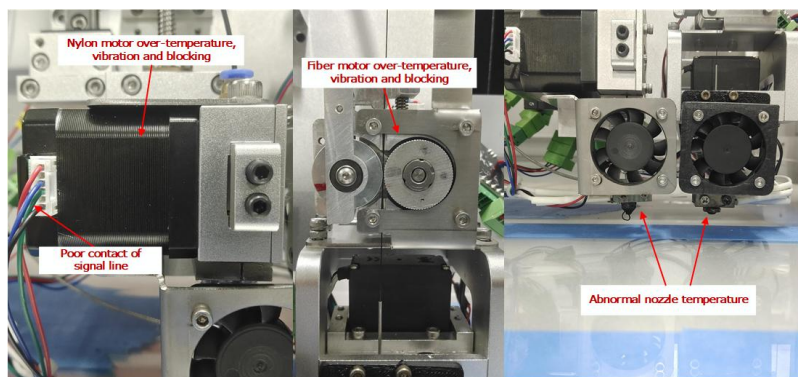


Figure 13: Common hardware defects.

4.4 Cloud Management

The processes are managed centrally by a cloud-based system. In the product design phase, the cloud-based management system obtains the designed product dimensions and the finite element method analysis results, subsequently storing the data in the designated file. The cloud facilitates centralized management of product design, manufacturing, and data traceability processes. It enables the monitoring of manufacturing data and its subsequent visualization. DT and physical

manufacturing are conducted via a cloud management system during the product manufacturing phase. The cloud management system employs edge computing devices to monitor subordinate computers and gather DT and physical manufacturing data in a specified file directory. In the data tracing phase, the cloud management system employs an edge computing device to retrieve the manufacturing data stored in the specified file. The system utilizes a Bayesian optimization LSTM algorithm to identify data and subsequently stores the identification results. The product is simultaneously subjected to tensile strength testing, with the resulting tensile strength value stored in the cloud. After completing this process, the product's unique identification number is generated. This number includes relevant information such as manufacturing time, pass/fail status, predicted tensile strength, and actual tensile strength. Figure 14 presents this information. Implementing a cloud management platform facilitates the oversight of the product life cycle in its entirety. The established cloud platform offers support for remote access.

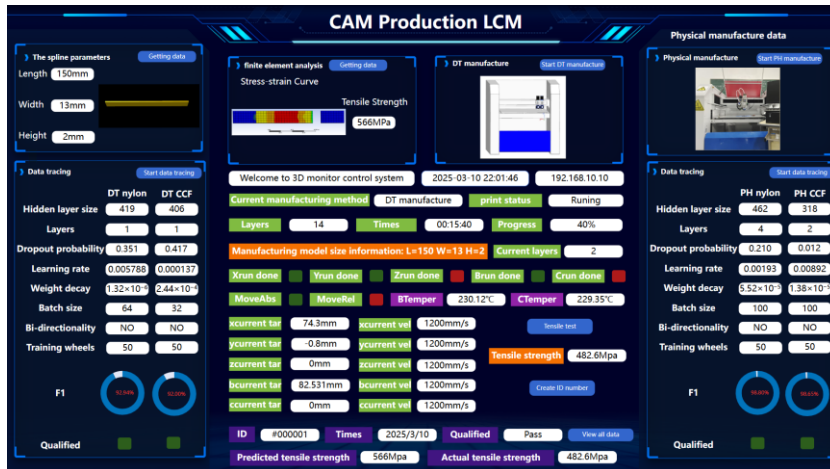


Figure 14: Cloud-based product lifecycle management system.

5 CONCLUSIONS

The adoption of CAM products has significantly increased in the aerospace and automotive sectors due to their unique benefits, such as high strength, low weight, rapid production processes, and cost efficiency. The traditional production technique is marked by complexity, limited quality control, and a lack of systematic verification of its relationship with the manufacturing process, hindering its widespread use. This paper proposes a DT-driven AM framework for composite materials to address the issues above. It assesses the framework's efficacy through a case study of AM of continuous carbon fiber-reinforced nylon composites. The experimental results demonstrate that the AM framework of the composite material can facilitate the realization of the entire LCM of the product, thereby ensuring its quality reliability. A comparison of the traditional manufacturing process with the introduction of DT technology for simulation manufacturing reveals the verification of process parameters and control logic of the software. A Bayesian optimization LSTM algorithm is introduced to trace DTs and physical manufacturing data, enabling the rapid identification of defects, i.e., distinguishing between software and hardware defects. A cloud-based management system is proposed to oversee the entire manufacturing process and ensure the traceability of product manufacturing data.

Integrating cloud management and edge computing resources facilitates efficient data interaction and processing within the three main domains of design, manufacturing, and traceability,

thus improving the system's adaptability and migration capabilities. The proposed framework applies to the AM process of various composite products. The research findings suggest that a DT-driven LCM framework can improve manufacturing processes and provide innovative, practical solutions for the AM of composite materials.

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REFERENCES

- [1] Zhang, L.; Chen, X.-Q.; Zhou, W.; Cheng, T.-B.; Chen, L.-J.; Guo, Z.; Han, B.; Lu, L.-X.: Digital Twins for Additive Manufacturing: A State-of-the-Art Review, *Applied Sciences-Basel*, 10(23), 2020. <https://doi.org/10.3390/app10238350>
- [2] Naser, A.-Z.; Defersha, F.; Xu, X.; Yang, S.: Automating life cycle assessment for additive manufacturing with machine learning: Framework design, dataset buildup, and a case study, *Journal of Manufacturing Systems*, 71, 2023, 504-526. <https://doi.org/10.1016/j.jmsy.2023.10.009>
- [3] Naser, A.-Z.; Defersha, F.; Pei, E.-J.; Zhao, Y.-F.; Yang, S.: Toward automated life cycle assessment for additive manufacturing: A systematic review of influential parameters and framework design, *Sustainable Production and Consumption*, 41, 2023, 253-274. <https://doi.org/10.1016/j.spc.2023.08.009>
- [4] Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W.: Digital Twin in manufacturing: A categorical literature review and classification, 16th IFAC Symposium on Information Control Problems in Manufacturing (INCOM), Bergamo, ITALY, 2018, pp. 1016-1022.
- [5] Chen, Z.-J.; Surendraarcharyagie, K.; Granland, K.; Chen, C.; Xu, X.; Xiong, Y.; Davies, C.; Tang, Y.-L.: Service oriented digital twin for additive manufacturing process, *Journal of Manufacturing Systems*, 74, 2024, 762-776. <https://doi.org/10.1016/j.jmsy.2024.04.015>
- [6] Garrido, J.; Sáez, J.: Integration of automatic generated simulation models, machine control projects and management tools to support whole life cycle of industrial digital twins, 9th IFAC/IFIP/IFORS/IISE/INFORMS Conference on Manufacturing Modelling, Management and Control (IFAC MIM), Berlin, GERMANY, 2019, pp. 1814-1819.
- [7] Kong, H.-Y.; Sun, H.; Wang, J.; Wang, L.; Sun, L.; Shen, J.: Life cycle assessment of ammonia co-firing power plants: A comprehensive review and analysis from a whole industrial chain perspective, *Advances in Applied Energy*, 14, 2024. <https://doi.org/10.1016/j.adapen.2024.100178>
- [8] Manco, P.; Caterino, M.; Rinaldi, M.; Fera, M.: Additive manufacturing in green supply chains: A parametric model for life cycle assessment and cost, *Sustainable Production and Consumption*, 36, 2023, 463-478. <https://doi.org/10.1016/j.spc.2023.01.015>
- [9] Cardeal, G.; Sequeira, D.; Mendonça, J.; Leite, M.; Ribeiro, I.: Additive manufacturing in the process industry: A process-based cost model to study life cycle cost and the viability of additive manufacturing spare parts, *Procedia CIRP*, 98, 2021, 211-216. <https://doi.org/10.1016/j.procir.2021.01.032>
- [10] Ma, J.-F.; Harstvedt, J.-D.; Dunaway, D.; Bian, L.-K.; Jaradat, R.: An exploratory investigation of Additively Manufactured Product life cycle sustainability assessment, *Journal of Cleaner Production*, 192, 2018, 55-70. <https://doi.org/10.1016/j.jclepro.2018.04.249>
- [11] Gong, H.-F.; Su, D.; Zeng, S.-Q.; Chen, X.-S.: Advancements in digital twin modeling for underground spaces and lightweight geometric modeling technologies, *Automation in Construction*, 165, 2024. <https://doi.org/10.1016/j.autcon.2024.105578>

- [12] Yu, X.-Y.; Sun, X.-Y.; Ou, L.-L.: Graphics-based modular digital twin software framework for production lines, *Computers & Industrial Engineering*, 193, 2024. <https://doi.org/10.1016/j.cie.2024.110308>
- [13] Karkaria, V.; Goeckner, A.; Zha, R.-J.; Chen, J.; Zhang, J.-J.; Zhu, Q.; Cao, J.; Gao, R.-X.; Chen, W.: Towards a digital twin framework in additive manufacturing: Machine learning and bayesian optimization for time series process optimization, *Journal of Manufacturing Systems*, 75, 2024, 322-332. <https://doi.org/10.1016/j.jmsy.2024.04.023>
- [14] Poojara, S.-R.; Dehury, C.-K.; Jakovits, P.; Srirama, S.-N.: Serverless data pipeline approaches for IoT data in fog and cloud computing, *Future Generation Computer Systems-the International Journal of Escience*, 130, 2022, 91-105. <https://doi.org/10.1016/j.future.2021.12.012>
- [15] Helu, M.; Sprock, T.; Hartenstine, D.; Venketesh, R.; Sobel, W.: Scalable data pipeline architecture to support the industrial internet of things, *Cirp Annals-Manufacturing Technology*, 69(1), 2020, 385-388. <https://doi.org/10.1016/j.cirp.2020.04.006>
- [16] Akin, Ö.; Deniz, H.-F.; Nefis, D.; Kızıltan, A.; Çakır, A.: Enabling Big Data Analytics at Manufacturing Fields of Farplas Automotive, *Intelligent and Fuzzy Techniques: Smart and Innovative Solutions*, Springer International Publishing, Cham, 2021, pp. 817-824.
- [17] Jin, L.; Zhai, X.; Wang, K.; Zhang, K.; Wu, D.; Nazir, A.; Jiang, J.; Liao, W.-H.: Big data, machine learning, and digital twin assisted additive manufacturing: A review, *Materials & Design*, 244, 2024. <https://doi.org/10.1016/j.matdes.2024.113086>
- [18] Mali, R.; Pise, U.: Modeling elastic properties of biocomposites using various analytical models and ansys material designer, *Materials Today: Proceedings*, 72, 2023, 1372-1378. <https://doi.org/10.1016/j.matpr.2022.09.334>
- [19] Peng, S.-M.; Wang, Y.-J.; Tang, A.-H.; Jiang, Y.-X.; Kan, J.-R.; Pecht, M.: State of health estimation joint improved grey wolf optimization algorithm and LSTM using partial discharging health features for lithium-ion batteries, *Energy*, 315, 2025. <https://doi.org/10.1016/j.energy.2024.134293>
- [20] Gupta, B.-B.; Gaurav, A.; Attar, R.-W.; Arya, V.; Alhomoud, A.; Chui, K.-T.: LSTM Based Neural Network Model for Anomaly Event Detection in Care-Independent Smart Homes, *Cmes-Computer Modeling in Engineering & Sciences*, 140(3), 2024, 2689-2706. <https://doi.org/10.32604/cmes.2024.050825>