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

Authors:
Xiao Wei, wx15862390119sues@163.com, Shanghai University of Engineering Science
Jian Mao, jmao@sues.edu.cn, Shanghai University of Engineering Science

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Introduction:

Additive manufacturing (AM), a pivotal element of Industry 4.0, enables the fabrication of intricate structures through the layer-by-layer accumulation of materials. This procedure has specific benefits, such as the creation of intricate surfaces, the shaping of composite materials, the execution of integrated assembly, and the acceleration of manufacturing. AM has rapidly advanced in multiple industries, including aerospace, construction, medical technology, and automotive manufacturing. However, conventional cloud manufacturing has faced various hurdles, such as integrating resources across businesses, unified planning, and managing substantial volumes. The challenges encompass the lack of smooth access to diverse resources, excessive system load, and significant reliance on the cloud for the manufacturing process, which impedes the advancement of comprehensive product lifecycle management[1-3].

The advent of cloud-edge collaborative manufacturing has initiated a paradigm change by enabling the integration of cloud and edge computing through digital technologies such as the Internet of Things, digital twins (DTs), and big data processing. Cloud manufacturing is a service-centric manufacturing paradigm integrating the Industrial Internet of Things, facilitating on-demand access to a diverse array of configurable manufacturing services in the cloud under defined parameters and enhancing data traceability accuracy[4-6]. As shown in Fig.1, the lifespan of an additively made object comprises three phases: Design, Manufacturing, and Traceability. The three stages of data can interact with each other. A consolidated platform is established to oversee these steps, and once testing is completed, the data from the product manufacturing process may be tracked. The amalgamation of cloud-based manufacturing technologies and DTs can surmount the constraints imposed by data boundaries. The digital twin (DT) facilitates the validation of manufacturing parameters, forecasts manufacturing processes, and implements closed-loop lifecycle management. At the same time, the incidence of quality concerns due to human factors is markedly diminished. Integrating DT technology and deep learning has resulted in substantial advancements in the simulation and optimization of industrial processes. These advancements have been realized through the aggregation of state data and the promotion of cloud-based collaborative manufacturing. This advancement has resulted in more efficient, adaptable, and cost-effective production processes. Moreover, these advancements provide an innovative resolution for contemporary production[7-9]. Fig.2 illustrates the DT of the AM process. The imported CAD model undergoes a slicing procedure. Finite element analysis is employed to get material characterization data during the material processing step. The process parameters are verified using virtualized manufacturing, and the actual process flow is verified using semi-virtualized manufacturing. Relevant data is then collected. The virtualized manufacturing process is simulated at the DT platform, while semi-virtualized manufacturing is executed by connecting the DT platform to the physical entity equipment. During the concluding phase of production, the product is subjected to stringent testing to evaluate its tensile strength, flexibility, and adherence to design standards. Only items that meet these rigorous tests are considered appropriate for qualified products.

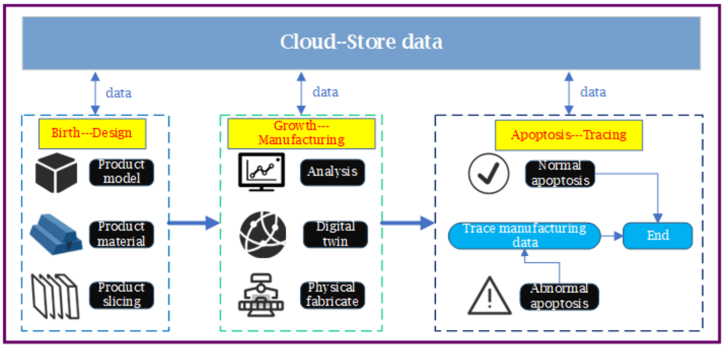

Fig. 1: AM product cycles.

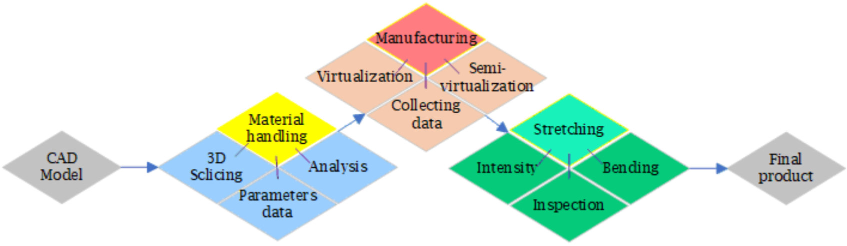

Fig. 2: DT AM processes.

Main Idea:

This paper examines the shortcomings of current DT systems in AM, explicitly focusing on migration capabilities and comprehensive lifecycle management. The proposed framework is a DT that manages the complete lifecycle of composite AM, utilizing cloud-edge collaboration. The framework encompasses three essential domains: design, manufacturing, and traceability. Integrating cloud management with edge computing resources facilitates efficient data interaction and processing, enhancing system adaptability and migration capabilities. Fig. 3 illustrates the life cycle management framework for composite AM. This approach utilizes a DT-driven manufacturing model supported by a cloud manufacturing management framework that includes five components: cloud management, material handling, Virtualized manufacturing, semi-virtualized manufacturing, and tensile testing. The cloud is categorized into client and server components within this framework. The client manages the manufacturing process in a unified manner, whereas the server is the principal repository for manufacturing data. Finite element analysis was employed in material handling to predict tensile strength. Virtualized Manufacturing is a process that simulates the product manufacturing process and verifies the manufacturing accuracy of the slicing parameters. The manufacturing of actual products is performed in a semi-virtualized manner, and tensile testing is conducted to ascertain the compliance of products from the same batch. The present study involves the aggregation of virtualized and semi-virtualized manufacturing data. The manufacturing data of virtualization and semi-virtualization are collected, and the manufacturing data are identified using the long short-term memory (LSTM) deep learning algorithm. This allows for the rapid identification of defects in the manufacturing product and the realization of traceability in the manufacturing data. For illustration, consider the DT model developed for carbon fiber-reinforced material products. This model was developed based on two fundamental concepts: the multi-coupling of AM equipment in physical space and the virtual reality mapping method[10]. Secondly, establishing a unified cloud-based management platform is essential for the comprehensive digital support of the entire process. The comprehensive lifecycle management of additively manufactured products has enhanced product quality and decreased.

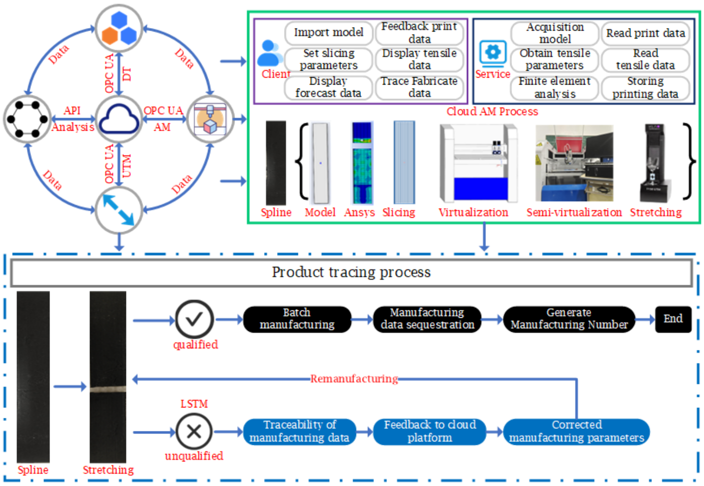

Fig. 3: The life cycle management framework for composite AM.

The session on manufacturing data traceability utilizes the LSTM algorithm to track both DT and physical manufacturing data. The LSTM memory cell consists of three gates: a forget gate, an input gate, and an output gate. The forgetting gate serves as the principal computational unit that dictates the degree of retention for long-term information C . The mathematical principle involves filtering irrelevant information by giving the incoming a weight between 0 and 1 C . From the previous time step. The input gate functions as the computational unit that assesses the degree of new information to be assimilated for later incorporation into long-term memory, referred to as C_{t-1} . This technique is mathematically based on assigning a weight between 0 and 1 to all incoming information at a specific moment. This process entails systematically screening incoming information to integrate new elements into long-term memory selectively C . The variable C_t represents the cumulative amount of new information acquired at the present step. The output gate operates as a computing unit responsible for filtering short-term information h_t from the newly obtained long-term information C_t to guarantee the optimal synchronization of the former with the current time step. The unit's mathematical foundations entail assigning a weight between 0 and 1 to the previously calculated long-term information C_t , thereby enabling the selection of the most pertinent information for the present time step, which is subsequently employed for predictive purposes. In this system, long-term memory C_{t-1} , short-term information h_{t-1} , and fresh information are at the current time step X_t , and the projected value is at the current time step $\hat{y}_t$. Eqn. (1.1) illustrates the mathematical of LSTM.

$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f) \tag{1.1}$$

$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i)$$

$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o)$$

$$C_t = tanh(W_C[h_{t-1}, X_t] + b_C)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t$$

$$h_t = o_t \odot tanh(C_t)$$

The input data for LSTM training is categorized into two types: virtualized manufacturing data and semi-virtualized manufacturing data. The virtualized manufacturing dataset includes the position and speed information of the XYZBC axis motors, with labels of 0 and 1, where 0 denotes a normal state and 1 indicates an abnormal condition. The semi-virtualized manufacturing dataset encompasses a broader range of sensor signals, including the position and speed of the physical XYZBC axis motors, vibration angles, velocities, displacements of the extruder along the XYZ axes, motor temperatures, and nozzle temperatures. This dataset is similarly labeled, with 0 representing normal operation and 1 indicating the presence of anomalies. Abnormal data is synthetically generated by introducing artificial faults to simulate defective conditions. Across both datasets, normal instances constitute 70% of the samples, while abnormal instances account for the remaining 30%. The combined dataset is randomly split into training and testing subsets, with 80% allocated for training and 20% reserved for testing.

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.

Conclusions:

This paper presents a DT designed to manage the complete lifecycle of additively manufactured composite materials through cloud-based collaboration. Integrating cloud management and edge computing resources within the framework facilitates efficient data interaction and processing across the three main domains of design, manufacturing, and traceability, enhancing the system's adaptability and migration capabilities. Experimental validation with carbon fiber-reinforced nylon demonstrates that the proposed framework enhances manufacturing efficiency, improves product quality, and lowers manufacturing costs. The study results indicate that DT drive cloud edge collaborative manufacturing can enhance smart manufacturing and offer innovative, practical solutions in the AM of composite materials.

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Xiao Wei, https://orcid.org/0009-0009-1034-2761
Jian Mao, https://orcid.org/0009-0006-2061-8395

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