A Digital Twin Implementation Architecture for Wire + Arc Additive Manufacturing based on ISO 23247

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Abstract

Digital twin (DT) is an enabling technology characterized by integrating cyber and physical spaces. It is well-fitted to additive manufacturing (AM) since it can benefit from digitalized assets and data analytics for the process control. Wire + arc additive manufacturing (WAAM) is being increasingly recognized, due to its fabrication of large-scale parts. Although many DT applications have been implemented in different industries, the applications for WAAM are unexplored. This paper proposes a generalized DT implementation architecture for WAAM based on ISO 23247 to address integration and interoperability issues. A case study of machine learning-based anomaly detection for WAAM is peformed.

Keywords: Digital Twin; Wire + Arc Additive Manufacturing; ISO 23247; data analytics

1 Introduction

As a large-scale, metal additive manufacturing (AM) process, wire + arc additive manufacturing (WAAM) consists of wire as the feedstock, a welding arc as the energy source, and robot arms or a computer numerical control (CNC) router for the movement. WAAM has the advantages of inexpensive initial setup, high deposition rates, and cost-efficient fabrication [1]. However, WAAM suffers from inherent uncertainties and complexities related to non-equilibrium thermal cycles caused by the layer-upon-layer nature of the process, which is similar to other metal AM processes [2]. Defects (e.g., voids and cracks) and unwanted features (e.g., heterogeneous microstructures) can deteriorate mechanical properties and surface roughness.

The AM community has been seeking viable solutions to these problems based on the digital twin (DT) concept [3]. The idea is to embed the knowledge gained from advanced sensor technologies into DTs to monitor and control WAAM operations. DT can be used to respond to variabilities that impact process repeatability, part reproducibility, and quality assurance [4]. Definitions of DT have been provided by NASA [5] and other researchers [6-8]. In this paper, we adopted the one defined by ISO for "Digital twin in manufacturing" as "a fit-for-purpose digital representation of an observable manufacturing element (OME) with synchronization between the OME and its digital representation [9]." In this context, OMEs are WAAM-related equipment and products. The digital representations are physics-based and data-driven models and simulations to help make adaptive and responsive control decisions.

Considering the means of digital representation, data analytics (e.g., physics-based, data-driven, and physics-informed data-driven modeling) have become effective tools for implementing the digital twin concept with two reasons [10,11]. First, the increasing availability of cost-effective and accurate sensing technologies (e.g., machine vision) that can be easily integrated into production plants has facilitated process monitoring and control [12]. Second, the advances in computing capabilities have made real-time/remote data analysis more feasible. DT can address the WAAM complexities, inherent uncertainties, instabilities, and defects through data analytics by enabling real-time analysis and control of the process. However, two obstacles need to be addressed. First, performing multidisciplinary modeling and simulation requires iterative analyses based on a vast, structural-and-material, design-space exploration. In addition, the abundance of process parameters demands an exponentially increasing number of input data samples, called the "curse of dimensionality". Second, implementing a DT for the WAAM process and parts involves integrating multiple systems across different platforms, the interoperability issues [3].

An approach to reducing the large computational effort in physics-based modeling is to use an inexpensive but less accurate model, called a surrogate model. Various surrogate modeling techniques can be applied, such as polynomial chaos models, Kriging (or Gaussian process), and neural networks [13], resulting in the interoperability issues. In order to address them, a system architecture that enables the use of appropriate technologies and standards is necessary. Building a bridge by creating a DT will reduce the number of trial-and-error tests, mitigate defects, reduce the time between the design and production, and make manufacturing metallic products cost-effective.

In this paper, a DT implementation architecture for WAAM is proposed based on ISO 23247 and the digital thread concept [14,15]. It aims to enable manufacturers to leverage DTs for real-time decision-making and control of the WAAM process. It provides a means to navigate the complex set of standards, technologies, and procedures that can support the implementations. The architecture is designed to be generic, reusable, and customizable irrespective of implementation to support relevant AM use cases. The remainder of this paper is organized as follows. Section 2 introduces the proposed DT implementation architecture. Section 3 demonstrates our case study based on the architecture: anomaly detection in the WAAM process. Section 4 presents the discussion and conclusion.

2 DT Implementation Architecture for WAAM

Figure 1 shows the proposed DT implementation architecture for WAAM processes. It includes features required by DTs, such as connectivity, adaptability, predictability, intelligence, real-time process monitoring and control, and humans-in-the-loop [16]. It consists of a digital twin (DT) and a physical twin (PT). Each layer has one or multiple entities, each comprises sub-entities, and the sub-entities are made from modules. The entities are the observable manufacturing elements (OME), data collection and device control entity (DCDCE), core entity (CE), and user entity (UE). The proposed architecture allows users to (1) represent the characteristics and real-time status of the WAAM process, (2) monitor and control using data analytics , and (3) collect and transfer the shop floor data to provide efficient decision-making support.

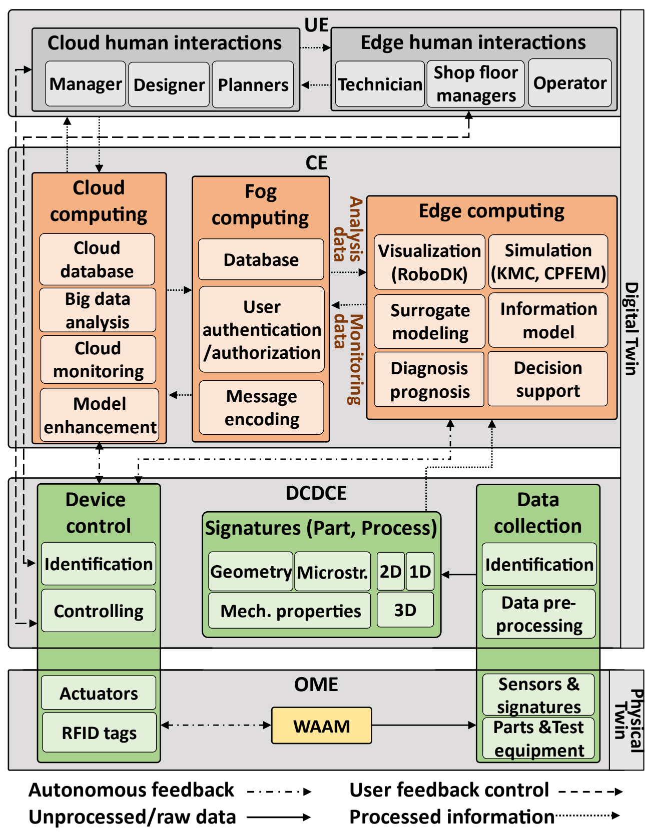

Figure 1 Digital twin implementation architecture for a WAAM process.

The flow of information in this architecture is as follows. The data from the WAAM setup, including the process and part signatures, are acquired through sensors and test equipment. After being identified and pre-processed in the data collection sub-entity, they are fed to the part and process sub-entity. This data can be geometrical, mechanical properties, and one-dimensional (1D), 2D, and 3D signatures. In the edge computing environment, different data processing can occur. If required, extra processing on the data can be performed in other computing environments, such as fog and cloud, where the data will be used by cloud- or edge-based users for decision-making based on models and simulations. The information flow is bi-directional throughout the entire architecture to enable real-time process monitoring and control. The PT and DT layers, their entities, and sub-entities will be discussed in the following subsections.

2.1 Physical Twin

The PT layer consists of the OMEs composed of the WAAM experimental setup and four sub-entities that support data collection (i.e., (1) sensors and signatures and (2) parts and test equipment) and device control (i.e., actuators and radio frequency identification (RFID) tags). The sensors can be (1) built-in (e.g., power measurement and the position tracking systems for a robot) and (2) attached ones (e.g., a pyrometer, a high dynamic range (HDR) camera, a thermocouple, and voltage/current). In addition, the OMEs in the WAAM setup are responsible for carrying out the tasks and transmitting the real-time data to the DCDCE entity. This real-time communication will enable the detection of failures to be corrected or compensated for by changing and sending additional process-parameter commands in a timely manner, i.e., as the parts are being produced in a closed-loop control system structure.

2.2 Digital Twin

The DT layer consists of three entities, i.e., DCDCE, CE, and UE. The DCDCE comprises three sub-entities: data collection, signatures (part, process), and device control. In the data collection sub-entity, the collected data is pre-processed. This may include data augmentation, classification, feature extraction, data cleansing, data integration, and data reduction. The signatures (part, process) sub-entity includes modules for geometrical accuracy, microstructure, and mechanical properties of the manufactured part. The form of signatures can be (1) 1D, such as current and voltage, (2) 2D, such as the data extracted from an HDR camera, and (3) 3D, such as the data from a coordinate measuring machine (CMM). The device control sub-entity includes data identification and process control modules.

The second and most influential entity is CE, which is responsible for the overall operation and management of DT in WAAM. It consists of three computing environments: edge, fog, and cloud. The edge computing environment has six main modules to help represent the OMEs: (1) Visualization of the process can be used to avoid a collision or unwanted robot movements. (2) Simulation approaches (e.g., Kinetic Monte Carlo (KMC), and Crystal Plasticity Finite Element Modeling (CPFEM)) can be used to understand the underlying physics and simulate the process. (3) Surrogate models, simpler versions of the process that mimic the mechanisms of complex models, can be used to reduce the time required for computation and decision-making. Using the design of experiment (DOE) and machine learning (ML)-based surrogate modeling, the AM community has characterized the relationships among process-structure-property-performance. But identifying these relationships is highly challenging due to the cost of obtaining sufficient data. To address this issue, physics-informed, data-driven WAAM models, which focus on the mechanical behavior of the parts, are used to derive a near-optimal design strategy and optimize the WAAM performance. (4) Information model is also employed to organize the flow of information, (5) diagnosis and prognosis, and (6) decision support that enables process alteration based on execution results of simulations and models. The fog computing environment, a means of secure communication between the edge and cloud computing environments, includes three modules: (1) user authentication/authorization, (2) message encoding that can be performed to limit the information access to specific users, and (3) database. The cloud computing environment comprises four different modules: (1) big data analysis enhances the accuracy of the modeling and simulation, e.g., in data-driven surrogate models, transfer learning can be used to train the models in a source domain and use it in a target, preferably related, domain; (2) remote monitoring and control enable process alteration and observation from remote locations; (3) model enhancement can also be performed; and (4) cloud databases can also be generated for future applications.

The last entity in the proposed hierarchical architecture is UE, where various human and system interactions can occur. In the UE, the interaction can be either on the cloud or edge. Technicians, shop floor managers, operators on the edge, and designers, planners, and managers on the cloud can use the processed data received from computing environments to send control commands. These commands can update process parameters such as current and voltage to obtain near-optimal part properties and process signatures. These include better surface roughness, fewer defects, higher mechanical performance, and geometrical accuracy.

3 Application scenario: real-time anomaly detection for WAAM

The proposed architecture can be employed for real-time anomaly detection to improve process repeatability, part reproducibility, and model interoperability in WAAM, as shown in Figure 2. In this application scenario, the communications are based on Open Platform Communications United Architecture (OPC UA). It is embodied based on the server-client concept, where the server publishes, and the client subscribes to data content. In terms of information, the structure consists of an address space model, base information model, domain-specific information model, and data layers.

The sensors are used to acquire voltage and current data from the process, and cameras are employed to collect HDR and thermal images from the experimental setup [17]. The data from WAAM parts are also extracted using the tensile test and CMM. The DCDCE entity receives the process and part signatures, including 1D data including current and voltage, 2D including HDR and thermal images, and 3D data including CMM and surface roughness data. In addition, test data such as the strain-stress curve is provided to this entity. These data are correlated to the nodes in the address space of OPC UA data and grouped with their corresponding components in the information model on the servers. When other clients require data, the server encodes it into standardized messages (e.g., Binary or XML) and sends them to the clients.

The OPC UA data is then pre-processed, and the convolutional neural network (CNN)-based, real-time anomaly detection and prediction DTs are generated. Then employing the standard approach defined in [9] and demonstrated in [17], the model is converted to DeepNetwork Predictive Model Markup Language (PMML) file format. The data will be fed into the server through the transport mechanism, where the model is converted to an OPC UA object and stored in a model repository [18]. Online analysis is performed to check any abnormality; if needed, the correction-process parameters will be obtained and fed back to the OME.

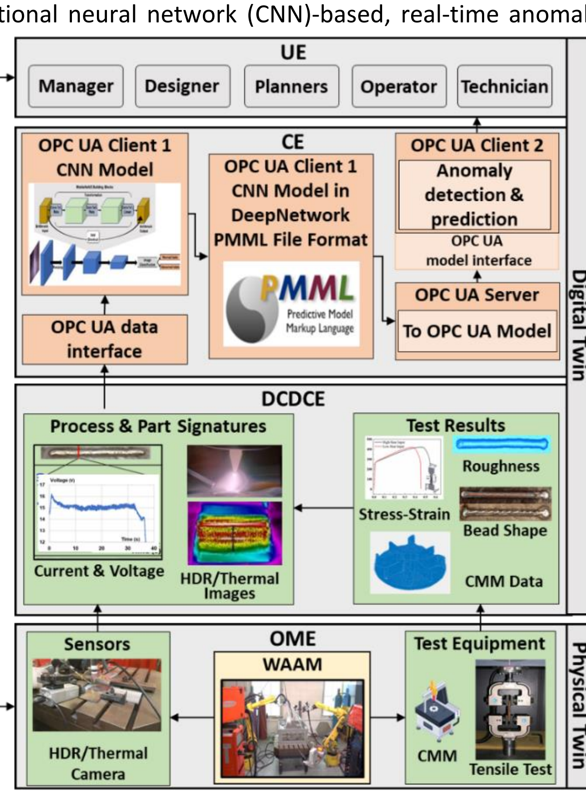

Figure 2. Flowchart of anomaly detection and process control in WAAM based on PMML and OPC UA.

The approach used in this study is compared to other approaches [6,19] that have not used OPC UA and PMML for digital twin implementations in Table 1. OPC UA addresses the interoperability and data sharing issues of integrating the models and information in different platforms since it is known as a cross-platform, open-source standard for data exchange. It is designed as a real-time communication standard that provides open, deterministic, real-time communication between automation systems, enabling real-time anomaly detection. Since it is a client-server-based communication secured through user authentication and authorization, it can ensure data security. In addition, PMML provides analytic applications to describe and exchange predictive models produced by data mining and machine learning algorithms. It supports common models such as logistic regression and feedforward neural networks.

Table 1. Comparisons between the proposed approach and the other approaches.

Criteria	Proposed approach	Other approaches
Interoperability	OPC UA enables better integration of different platforms.	May need a customized interface for model transactions on different platforms.
Real-time Anomaly Detection	OPC UA allows near real-time use of the as-processed data to detect anomalies and address them a timely manner.	Anomaly detection can only be done by a predictive model developed using historical datasets.
Data Sharing	Seamless data sharing through OPC UA data transfer and PMML model sharing.	May need to develop customized system interfaces.
Security	Vulnerabilities need to be analyzed, and new risk mitigation strategies are required.	Vulnerabilities and risk mitigation strategies are well-defined.

4 Summary

In this paper, a generalized DT implementation architecture for WAAM is proposed based on ISO 23247 and the digital thread concept. The implementation architecture will enable manufacturers to leverage DTs for real-time decision-making and control of WAAM applications. It also provides the means to navigate the complex set of standards, technologies, and procedures that can be used for digital twin implementations. A case study for real-time anomaly detection was also performed to demonstrate the applicability of the proposed architecture. In the near future, a practical case study will be performed, based on this architecture.

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