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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 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. This paper proposes a generalized DT implementation architecture for WAAM based on ISO 23247 to address integration and interoperability issues. It will enable manufacturers to leverage DT for the real-time decision-making and control. An application scenario of machine learning-based anomaly detection for WAAM is used to explain the architecture.

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, it 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/or data-driven models and simulations to help make adaptive and responsive control decisions.

Considering the means of digital representation, for two reasons, data analytics (e.g., physics-based, data-driven, and physics-informed data-driven modeling) has become an effective tool for implementing the digital twin concept [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 manage the WAAM complexities, inherent uncertainties, instabilities, and defects through data analytics, 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, several tens of process parameters demand 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 and dealing with 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

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techniques can be applied, such as polynomial chaos models, Kriging (or Gaussian process) models, 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 can minimize the trial-and-error tests, defects, and production lead time, consequently leading to a cost-effective approach.

This paper proposes a DT implementation architecture for WAAM based on ISO 23,247 (Digital Twin Manufacturing Framework) and the digital thread concept [3,14,15]. 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 to support relevant 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

Fig. 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 comprising multiple sub-entities, and the sub-entities in turn 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 condition of the WAAM process, (2) monitor and control using data analytics, and (3) collect and transfer the shop floor data to provide decision-making support.

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 transferred to the part and process sub-entity. This

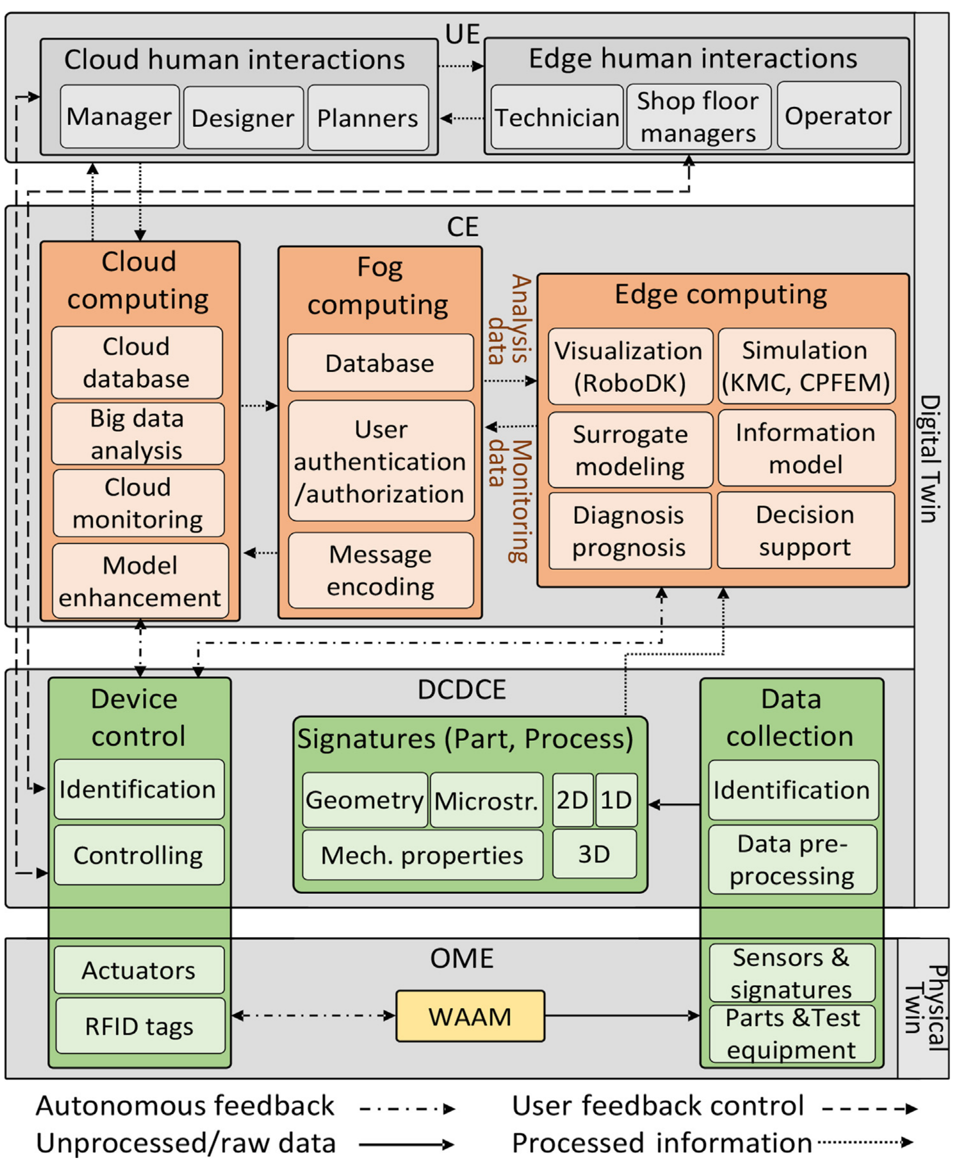

Fig. 1. Digital twin implementation architecture for a WAAM process.

data can be geometrical accuracy, 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 are 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 sensor). In addition, the OMEs in the WAAM setup are in charge of 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 by changing and sending additional process-parameter commands in a timely manner, such 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 (e.g., part and 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 sub-entity includes modules for geometrical accuracy, microstructures, and mechanical properties of a part. The form of signatures can be (1) 1D (e.g., current and voltage); (2) 2D (e.g., images from an HDR camera); and (3) 3D (e.g., 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. 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 collisions 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 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) An 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; (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 Fig. 2. In this application scenario, the communications are based on Open Platform Communications Unified Architecture (OPC UA). It uses a server-client concept. While the server provides data content, the client subscribes.

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 (e.g., current and voltage), 2D (e.g., HDR images), and 3D data (e.g., surface roughness). In addition, test data such as the strain–stress curve is provided to this entity. These data are correlated to nodes in an address space of OPC UA data and gathered with respect to the corresponding components in an information model on a server.

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.

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 describes and exchanges analytical predictive models generated by machine learning and data mining. Compared to other approaches [6,19], the proposed approach is carefully designed to have the better features in terms of interoperability, real-time anomaly detection, data sharing, and security, as explained in Table 1.

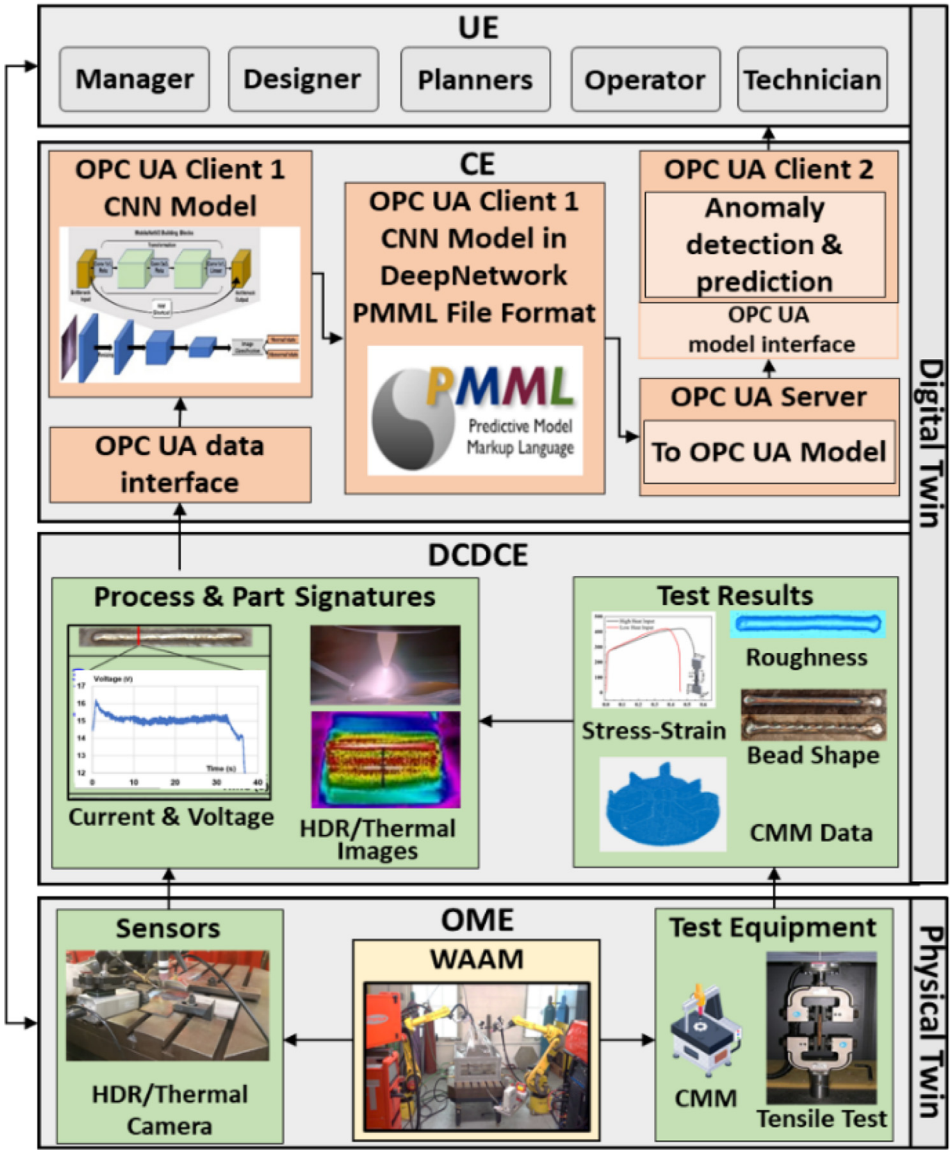

Fig. 2. Flowchart of anomaly detection and process control in WAAM based on PMML and OPC UA.

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

Criteria	Proposed approach	Other approaches [6,19]
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 in 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 23,247 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. An application scenario for real-time anomaly detection was also analyzed to demonstrate the applicability of the proposed architecture. In the near future, three case studies will be performed based on this architecture, the WAAM setup [15], and the AM knowledge [3,4,14]. First, the application scenario described in Section 3 will be practically implemented, and its technological advances will be investigated. Second, a digital twin-based part qualification method, as a non-destructive evaluation method, will be studied by analyzing and synthesizing the different types of process signatures. Third, advanced technologies in extended reality (XR) will be integrated into applicable case studies to enhance the DT capabilities and consequently its benefits will be studied.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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