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CONCEPTUAL ARCHITECTURE OF DIGITAL TWIN WITH HUMAN-IN-THE-LOOP -BASED SMART MANUFACTURING

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ABSTRACT

This paper proposes a conceptual architecture of digital twin with human-in-the-loop-based smart manufacturing (DH-SM). Our proposed architecture integrates cyber-physical systems with human spaces, where artificial intelligence and human cognition are employed jointly to make informed decisions. This will enable real-time, collaborative decision-making between humans, software, and machines. For example, when evaluating a new product design, information about the product's physical features, manufacturing requirements, and customer demands must be processed concurrently. Moreover, the DH-SM architecture enables the creation of an immersive environment that allows customers to be effectively involved in the manufacturing process. The DH-SM architecture is well fitted to those relatively new manufacturing processes, such as metal additive manufacturing, since they can benefit from using digital twins, data analytics, and artificial intelligence for monitoring and controlling those processes to support non-contact manufacturing. The proposed DH-SM will enable manufacturers to leverage the existing cyber-physical system and extended reality technologies to generate immersive experiences for end users, operators, managers, and stakeholders. A use case of wire + arc additive manufacturing is discussed to demonstrate the applicability of the proposed architecture. Relevant development and implementation challenges are also discussed.

Keywords: Digital Twin, Smart Manufacturing, Human-in-the-loop, Collaborative Decision Making, Non-contact Manufacturing, Industrial Metaverse.

1. INTRODUCTION

Manufacturing is the backbone of economic development in the U.S. [1]. The COVID-19 pandemic crisis disrupted the manufacturing industry in many countries, resulting in (1) major upheavals in their production networks, (2) substantial reductions in new product demands, and (3) negative impacts in both their local and global supply chains [2,3]. Moreover, new lessons for manufacturing to successfully tackle these pandemic impacts are still being learned [4]. One of those new lessons is the "non-contact manufacturing" paradigm [5], which is based on remotely controlling a system, a process, and a part with minimal physical interactions.

Before the pandemic, several strategic plans such as "Smart Manufacturing (SM)" in the USA and "Industry 4.0" in Germany [6-8] have helped advance manufacturing industries. SM brings smart technologies such as smart sensors, high-performance computing, industrial internet of things (IIoT), artificial intelligence (AI), and data analytics to traditional production processes and manufacturing systems. However, various manufacturing operations still remain manual, where humans can perform them better than machines. To enable human operators to better use SM technologies and also support the non-contact manufacturing concept, a new concept of Digital Twin with Human-in-the-Loop-based Smart Manufacturing (DH-SM) is introduced.

Metaverse enables the integration of a "virtual world" with the "physical world" [9]. The resulting integration is based on an extended reality (XR) that combines augmented reality (AR), virtual reality (VR), and mixed reality (MR) technologies. Currently, the "virtual world" can be the "Digital Twin (DT)", which may be used for various purposes such as analyzing health conditions of equipment for predictive maintenance, managing the whole lifecycle of a physical asset, and improving decision-making through engineering and numerical analysis [10]. In addition to the functionalities provided by DTs [11-14], the metaverse will add auditory, visual, and haptic realism to achieve the embodiment. It will change the way humans interact with the future virtual, physical, and pandemic worlds. Also, the metaverse has a great potential to positively change the manufacturing landscape by taking advantage of (1) immersive experiences, (2) freedom from a physical distance called "telepresence," and (3) interconnection.

In this paper, we propose an architecture that supports DH-SM. This architecture is intended to enable integrability, interoperability, interactivity, and immersivity. The architecture includes three modules: Cyber-Physical System (CPS), Avatar-User System (AUS), and Collaborative Decision-Making Engine (CDME). Collectively, these modules can support future human-in-the-loop research, demonstrations, and case studies in SM. The proposed architecture can also support non-contact manufacturing by allowing users to remotely access a shop floor through immersive simulation to realize real-time monitoring and control.

The remainder of this paper is organized as follows: Section 2 provides some background information about various manufacturing paradigms. Section 3 introduces the conceptual architecture of digital twin with human-in-the-loop -based smart manufacturing. Section 4 discusses a use case in wire + arc additive manufacturing (WAAM) to demonstrate the applicability of the proposed architecture. Section 5 discusses the relevant development and implementation challenges, and Section 6 concludes the paper and discusses the future work.

2. AUGMENTING SM WITH DH TECHNOLOGIES

Manufacturing paradigms have been evolving for decades. Figure 1 shows the evolution, which includes traditional, intelligent, concurrent, and smart manufacturing. In traditional manufacturing, human workers use their senses to monitor, operate, and update the process and inspect the final workpiece. To reduce the roles of humans and speed up fabrication and inspection, intelligent manufacturing was introduced to automate formerly human-made decisions. Concurrent manufacturing involves a systematic approach to simultaneously design the product and develop its manufacturing process. That approach, based on a Japanese idea called Kansei engineering, included feelings, impressions, and emotions from stakeholders in concrete design parameters [15].

SM includes transformative technologies for managing the interconnections among physical assets, their DTs, and related computational capabilities. A CPS generally consists of a collection of DTs of physical assets, including (1) material inputs, (2) manufacturing processes, and (3) final products [16-18]. The idea is to embed data gained from advanced sensor technologies into DTs of all three to improve process control and part quality. For example, in additive manufacturing (AM), DTs can be used to model the variabilities that impact process repeatability, part reproducibility, and quality assurance [19]. These DTs can be comprised of "surrogate models" such as physics-based, data-driven, and physics-informed, data-driven models [12,14].

In this paper, we view the conceptual DH-SM architecture as a framework that can help enhance SM to achieve convergent, collaborative, and non-contact manufacturing. It consists of multidisciplinary domains, such as advanced manufacturing capabilities, digital technologies, and cognitive engineering. This enables highly optimized processes/supply networks, customized products, and resilience for unexpected and manufacturing-unfriendly situations. The DH-SM concept and its information flow are depicted in Figure 2. This paper focuses on AUS and CDME since the concept of CPS is well-established. The AUS supports better decision-making by creating an immersive and interactive user experience across the entire product life cycle. It comprises an enhanced user (EU) and human digital twin (HDT). EU generates data, information, and knowledge and provides them to the other modules for analysis, decision-making, and control. The HDT, the digital replica of the EU, can analyze, accumulate, and synthesize the data and knowledge acquired from the DT and EU modules to support collaborative decision-making. Each module is explained in detail in Section 3.

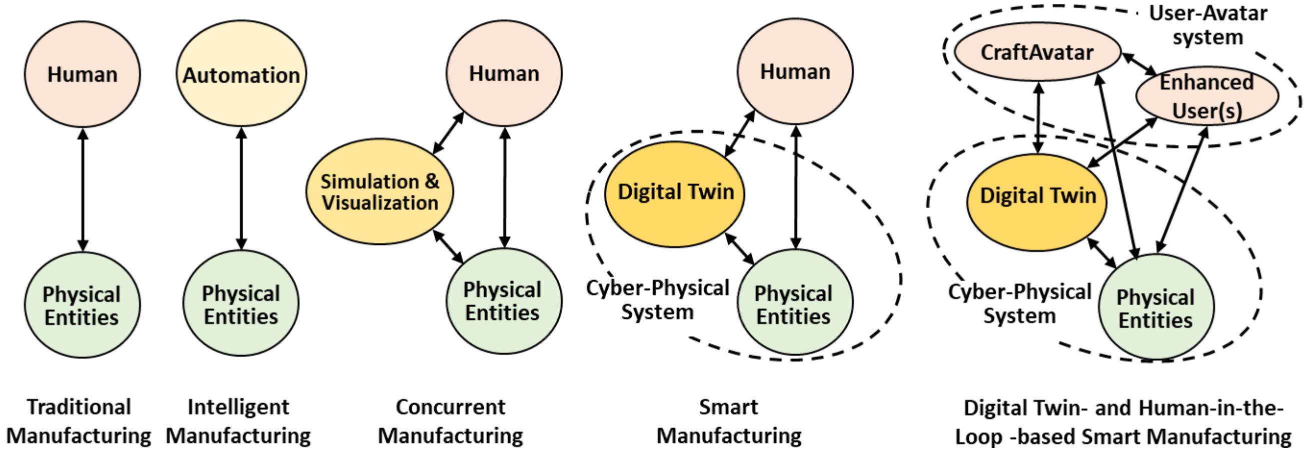


FIGURE 1: MANUFACTURING FROM TRADITIONAL TO SMART MANUFACTURING AND THE PROPOSED PARADIGM OF DH-SM

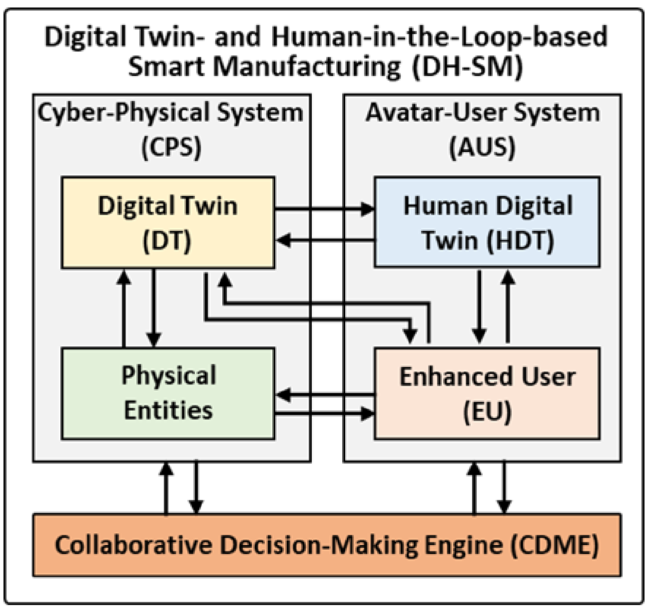


FIGURE 2: THE CONCEPT AND INFORMATION FLOW OF DIGITAL TWIN WITH HUMAN-IN-THE-LOOP -BASED SMART MANUFACTURING.

3. A CONCEPTUAL ARCHITECTURE OF DIGITAL TWIN WITH HUMAN-IN-THE-LOOP- BASED SMART MANUFACTURING

Figure 3 shows the detailed modules and the information flow in the proposed DH-SM architecture based on the previous studies [6,20]. Physical Entities comprise Process Parameters, Experimental Configuration, Observable Manufacturing Elements (OME), and Data Acquisition Devices. DTs include Data Preparation, Information Models, Modeling and Simulation, and Digital Twin Models. EU consists of User Experience Plans, Immersive Environments, User(s), and Sensory Realism. The user experience plans are based on the actual manufacturing requirements and case scenarios. For example, given a customer's product, its surface-appearance of a product can be evaluated virtually using a Likert scale [21]. Immersive environments provide real-time interactive immersion to the user(s). They can interact with the immersive contents of a product via metaverse technologies (e.g., XR: VR/AR/MR). The realistic interaction among those inputs can be achieved via multi-modal senses in Sensory Realism. Based on their results, users can generate their desired experiences, which can be inputs to HDT for further analysis.

HDT consists of four components: Data Preparation, Information Model, Immersive Analysis, and CraftsAvatar. In the Data Preparation component, both quantifiable and unquantifiable data from the EU can be stored and preprocessed. The two prepared data types will be formalized and transferred to other modules in the Information Model. Immersive Analysis can analyze the different information models, and CraftsAvatar is a digital replica of the enhanced user(s) that can perform simulations, acquire data, perform data analysis, and semi-independently make decisions for better performance. Ultimately, CraftsAvatar can continuously evolve into a "Virtual Master" in a domain-specific area. CDME includes Verification, Validation, Uncertainty Quantification (VVUQ), and Multi-Criteria Decision Making (MCDM). In VVUQ, analytical models estimate the uncertainties of the process and the parts. Those uncertainties can be due to the lack of knowledge (epistemic) or intrinsic randomness (aleatoric) [22]. MCDM includes scaling, normalization, weighting, and aggregation components for the final decision-making [23]. The following subsections will explain the information flows in DH-SM and its issues.

3.1 Cyber-Physical System

Cyber-Physical System includes two modules, Digital Twin and Physical Entities. The process parameters are first decided in the Physical Entities, and then the experimental configurations are set, considering the available OMEs. Data acquisition devices are then employed to obtain signatures to establish a relationship among the process, structure, property, and performance (PSPP) [24]. The signatures are divided into

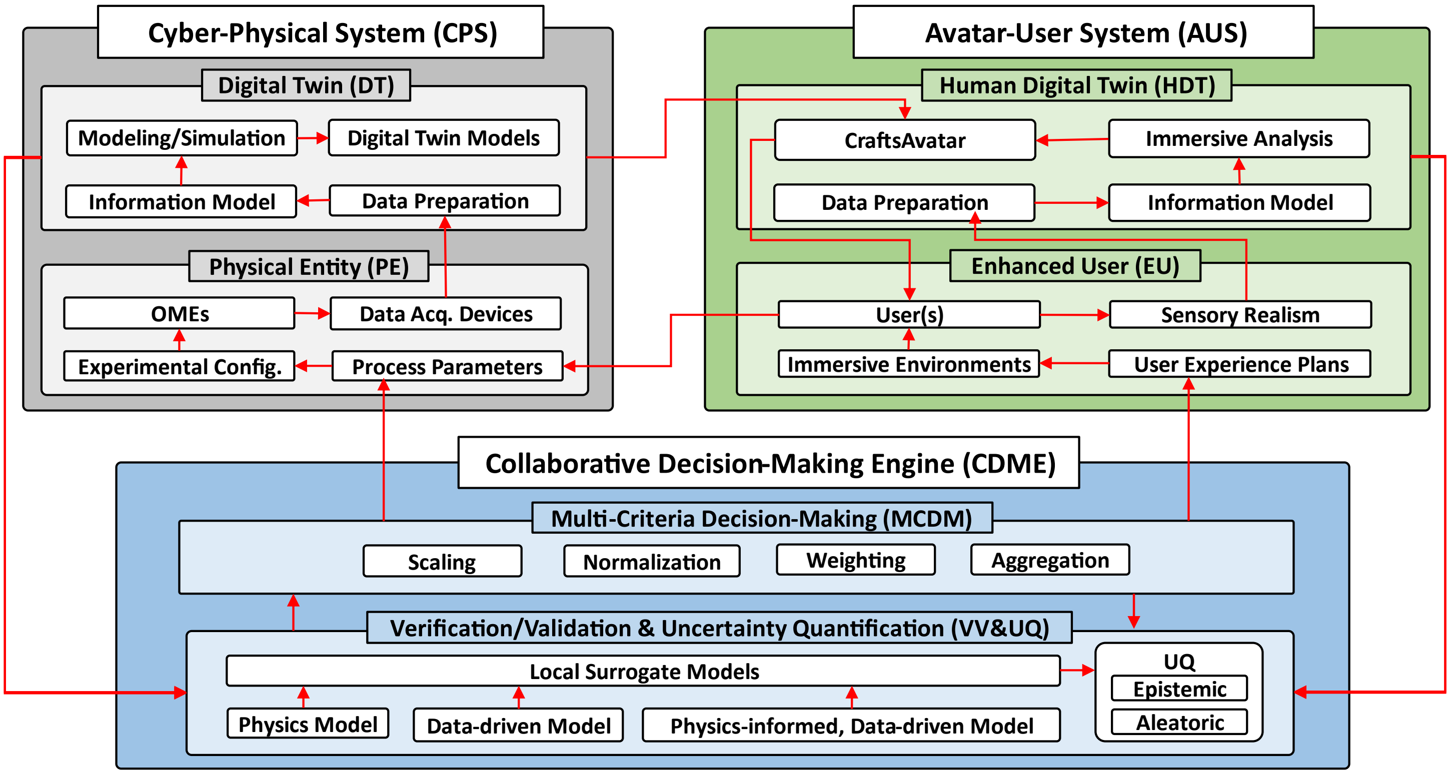


FIGURE 3: THE MODULES AND INFORMATION FLOW OF DIGITAL TWIN WITH HUMAN-IN-THE-LOOP -BASED SMART MANUFACTURING

process signatures and part signatures. The process signatures can be 1D, such as current and voltage; 2D, such as the data extracted from a charge- coupled device (CCD) camera, high dynamic range (HDR) camera, and high-speed camera; and 3D, such as the data from the profilometer. 1D process signatures are much easier to handle and store, while 2D and 3D signatures contain more information and can be used in different data structures.

On the other hand, the acquired part signatures in the architecture can be classified into three types. The first type is the signatures based on the microstructure of the part, obtained through material characterization techniques such as optical microscope image, scanning electron microscope (SEM), and electron backscatter diffraction (EBSD). These signatures can shed light on the anisotropic and heterogeneous behavior of AM parts. The second type is mechanical properties extracted by tests such as tensile that can be used to obtain the stress-strain curve for the materials. Finally, the third type is signatures based on the part geometry obtained using a coordinate-measuring machine (CMM), which measures geometrical accuracy and surface roughness. The part signatures can be used to validate the physics-based and data-driven models.

The data acquisition devices can be (1) internal or built-in sensors such as welding power measurement and the position tracking systems for the robot and (2) external sensors such as pyrometers, HDR cameras, high-speed cameras, thermocouples, and CCD cameras. In the proposed architecture, the process monitoring, and control should be simultaneously addressed in a unified system. This governs that the system responsible for controlling the AM system must also communicate with the software to run online diagnostics during manufacturing. Through this approach, any detected failures could be corrected or compensated by modifying or sending additional commands to the system. The framework is constructed to allow quick adaptation to new manufacturing conditions and the incorporation of multiple diagnostic tools.

The other module in CPS is the Digital Twin, which aims to create a digital replica of the physical entities and phenomena through different modeling and simulation approaches, including but not limited to physics-based, data-driven, physics-informed data-driven, and surrogate models. Surrogate models are simpler versions that mimic the mechanisms of complex models. Their purpose of surrogates is to reduce the computation time. In the proposed architecture, surrogate models can be generated for processes and parts. The design of experiment (DOE) is widely employed to create surrogate models due to its effectiveness and efficiency.

Nevertheless, (1) DOE cannot be used for real-time monitoring and control, and (2) a considerable number of experiments have to be carried out, which requires significant resources. To overcome the two limitations, machine learning (ML) surrogate models based on process signatures for real-time monitoring and control have gained increasing attention due to low cost, less time consumption, and high accuracy. ML, specifically the semi-supervised learning algorithm and generative adversarial network (GAN), has been extensively employed for anomaly detection as in AnoGAN [25] and MAD-GAN [26]. In addition, ensemble learning (EL) has been used to improve classification, prediction, and/or function approximation [27]. EL systematically generates and combines several models, such as classifiers or experts, to solve a computer intelligence problem. Despite their advantages, ML-based surrogate models demand massive data, thus hindering their widespread application.

3.2 Avatar-User System

The avatar user system includes two main modules: Human Digital Twin and Enhanced User. In Human Digital Twin, the Data Preparation component stores and preprocesses both quantifiable and unquantifiable data, while the Information Model component formalizes them. The Immersive Analysis component analyzes and synthesizes the data sets. CraftsAvatar has domain-specific data demonstrating how to perform a task and give advice based on the user's skill levels or professional maturity. CraftsAvatar can access, analyze, and synthesize manufacturing domain-specific data, information, and knowledge through the DT module. This will lead to domain-specific wisdom and intuition after further analysis and synthesis of information from DT and EH.

There are several research and technical issues. First, the knowledge needed to digitize and formalize the data types is significantly lacking. For example, how to formalize human knowledge and intuition should be investigated as part of the Data Preparation and Information Model. Second, the concept and the implementation of Immersive Analysis are still in the initial stage. Third, detailed case studies should be performed to demonstrate the effectiveness of a semi-autonomous CraftsAvatar.

The second module in AUS, the Enhanced User module, provides immersive interactions with other physical entities based on the human's visual, auditory, and touch senses (taste and smell are excluded due to the current technological limitations). Photorealistic visualization plays the most crucial role in immersion since humans collect up to 80 % of their surrounding information through vision. The auditory and tactile senses greatly enhance the immersion by hearing (e.g., 3D sound) and providing a touch feeling of an object (e.g., the texture of a car shift knob and handlebar). This sensory realism can be implemented utilizing industrial metaverse technologies for remote virtual training, concurrent design, and remote monitoring. Users can then generate the two types of data already discussed: (1) the quantifiable (e.g., Likert scale of customers' preference) and (2) the unquantifiable (e.g., description of customers' perception).

Implementing this module, however, demands solutions to several research and technical issues. First, as the number of data modalities increases, the user's immersive experience will improve; but more complicated integration tasks will be required. To address these issues, new open-source software tools and interface standards will be needed. Second, the implementations will require huge computational costs. For example, photorealistic visualization of an object by rendering tools is the result of complex interactions among light (e.g., spectrum), 3D models (e.g., texture), and viewing (e.g., direction) conditions. For this, an affordable high-end graphics process unit (GPU) should be available. Third, new types of user-friendly interfaces are required. For example, head-mounted displays are reported to cause discomfort, pain, or visual fatigue after use [28].

3.3 Collaborative Decision-Making Engine

The resulting data will enable "collaborative decision-making" based on a multi-criteria optimization approach that can improve the performance of the process and the quality of the parts. The analytical models should be verified, validated, and uncertainty must be quantified for accurate analyses. Then, different analytical models must be composed into a single, aggregated, integrated analytical model. Figure 4 conceptually shows the composability task using three different models (A: response surface model, B: artificial neural network, and C: Kriging model). Then, the composed model needs to characterize its component's uncertainties and their propagation in the aggregated model. Propagation requires careful consideration in scaling, normalizing, weighting, and aggregating methods. The decision will be transferred to the physical entities if a near-optimal solution is determined. If not, additional data must be collected, and further analysis must be performed.

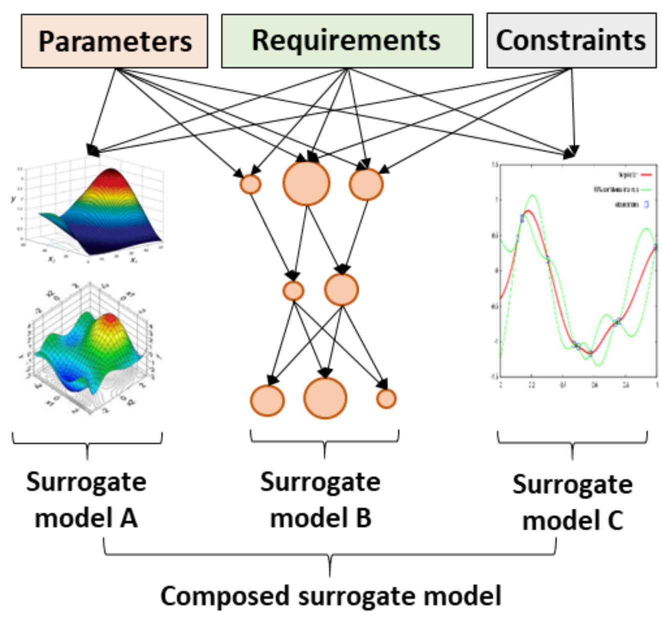


FIGURE 4: DIFFERENT TYPES OF SURROGATE MODELS

For this module, a robust approach is needed to compose individual analytical models and propagate the uncertainties that arise from disparate manufacturing resources. To develop this approach, four significant challenges must be overcome and/or managed: (1) high uncertainty, conflicting objectives, heterogeneous forms of data, multi-interests, and perspectives; (2) complex and dynamically evolving manufacturing processes and environments; (3) inherent interoperability issues in MCDM; and (4) requirements of verification and validation in aggregated/composed model [29].

4. A USE CASE IN WIRE + ARC ADDITIVE MANUFACTURING

Metal AM has attracted much attention since many complicated machinery components should be produced with metal, and other conventional manufacturing processes are much more time- and cost- intensive. Among various metal AM processes, Directed Energy Deposition (DED) uses a focused energy source where the material is melted and deposited by a nozzle. One of the representative forms of DED is WAAM, which uses metal wire as the feedstock and an arc as an energy source. Since the material in this process is deposited through metal wire, the amount of metal usage can be minimized. In addition, it benefits from a high deposition rate and is suitable for large and custom-made metal parts. To demonstrate a use case, we use the in-house WAAM system [30].

Although WAAM has many benefits, most companies still hesitate to adopt it due to some its drawbacks. The additive process based on arc welding can raise problems such as spatter, porosity, undercut, deformation, crack, and slag [31]. Moreover, the design space in the WAAM process is huge, and numerous parameters, directly and indirectly, influence the final part, therefore, choosing the near-optimal process parameters becomes of prime importance. To ensure that optimal parameters are selected, human cognition is kept in the loop with AI in the collaborative decision-making engine. In addition, in-situ process monitoring and control are ultimately lacking in the current WAAM systems.

To address these issues, we instantiated the DH-SM architecture for the WAAM problem. As shown in Figure 5, we generated the system architecture based on Figure 2. The use case consists of the physical entity, the digital twin, the human digital twin, and the enhanced users. In the following subsection, each of these components will be discussed.

4.1 Cyber-Physical System for the WAAM Case

In accordance with Section 3, the CPS comprises two main modules: Physical Entities and Digital Twin. The Physical Entities include a GTAW-based WAAM system, as shown in Figure 6. It also consists of a robot arm that moves to the coordinates designated by the controller. The tungsten inert gas (TIG) torch is attached to the hand of the robot arm and supplied with energy from the energy source. It deposits a feeding material provided by the wire feeder to generate weld beads on the substrate. Process parameters, including travel speed, Wire Feed Rate (WFR), and current, are determined by the controller input, wire feeder, and energy source, respectively. Current and voltage sensors measure the numerical values of the arc characteristics in real time. A data interface monitors and acquires the arc current and voltage data delivered from the sensor [32]. An HDR camera is attached to the torch to capture weld pool and bead images along with the movement of the torch [33]. This camera was optimized for arc welding with a dynamic range of 140 dB to capture high-quality video frames. Standard camera systems are inapplicable due to their low dynamic ranges and lightning interferences in arc welding. A camera data interface recorded the images and converted them into .jpg file formats.

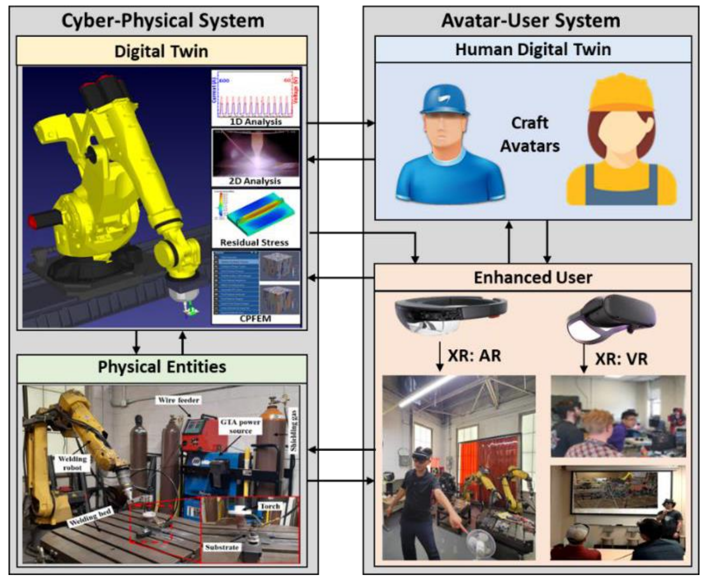


FIGURE 5: CONCEPTUAL ARCHITECTURE OF THE DH-SM FOR A WAAM CASE

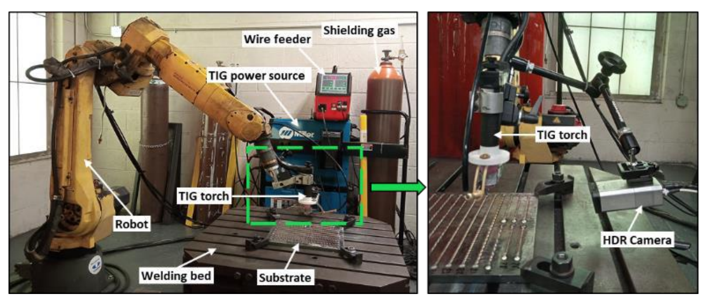
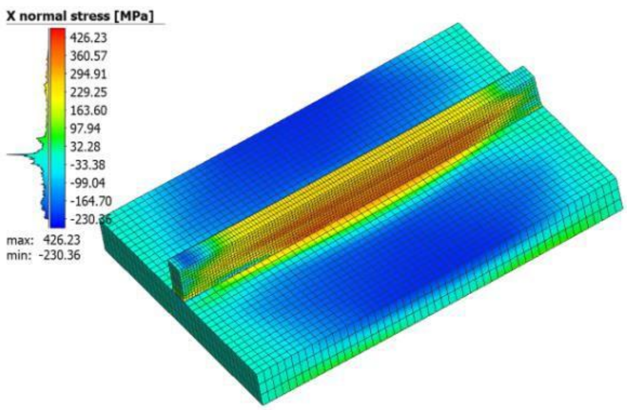


FIGURE 6: EXPERIMENTAL ENVIRONMENT INCLUDING WIRE FEEDER, SHIELDING GAS, TIG POWER SOURCE, TIG TORCH, ROBOT, AND HDR CAMERA

The other module in CPS is the Digital Twin. This module paves the way for creating a digital twin of the physical entities by applying 3D visualization, data analytics, physics-based models, data-driven models (machine learning), and surrogate models. A DT of the WAAM process was built to improve product quality and production efficiency. Real-time monitoring data was collected to consistently achieve the mapping and interaction between data and models to form the real-time interaction between the physical and digital twins. Then the process is analyzed. Firstly, a DT with 3D visualization of the WAAM process is implemented. Secondly, as shown in Figure 7, residual stress modeling and Crystal Plasticity Finite Element Simulation Method (CPFEM) are employed to model the physical phenomena and the microstructural evolution of the parts. Thirdly, data-driven approaches are employed for real-time process monitoring. Finally, surrogate models that aim to convert the computationally expensive models to a reduced-order model are employed to enhance the DT of the process. Figure 8 shows an example of real-time anomaly detection using machine learning.



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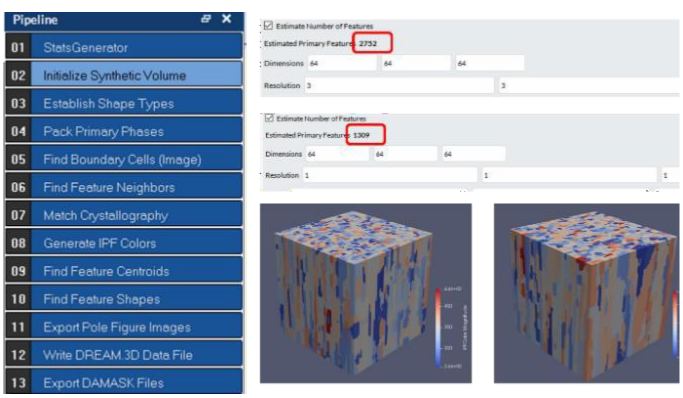


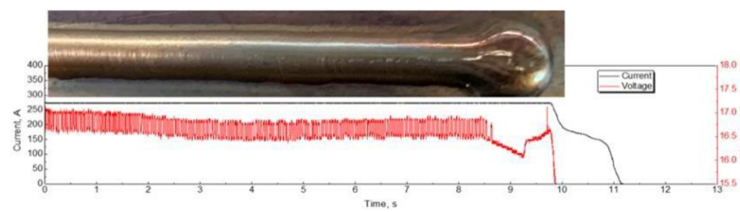
(b)

FIGURE 7: DT COMPONENTS FOR WAAM PARTS: (a) RESIDUAL STRESS AND (b) CPFEM

The data collection is realized by the sensors and data acquisition devices. By combining the real-time process, process design, and process simulation, the DT elements are constructed. Then, by combining the historical and real-time data, online process monitoring is enabled by data analysis. In case of any abnormality, the correction process parameters will be timely sent back to the physical entity. Thus, the quality prediction and control of welding of ship group products are realized.

4.2 Avatar-User System for the WAAM Case

In the AUS, the concept of Human-in-the-Loop is ultimately realized by the human DT and enhanced user modules. An enhanced user module can be categorized into edge users and cloud users. The edge EU benefits from AR technology through XR glasses and suits to perform remote inspection and training. Using the XR technology, the users can access real-time data such as the process parameters, online video of the process including high dynamic range images, thermal images and CCD cameras, simulations, and models. In remote locations, the users can have the same level of access to the system through XR and VR. The cloud-enhanced users at the cloud layer can modify the process where needed, change the process parameters based on their cognition and the real-time data acquired for the sensors, and perform a real-time inspection of the process and the parts. In addition, stakeholders of an enterprise can also have direct access to the physical entities and the process and investigate the possible enhancements. Figure 9 demonstrates the edge and the cloud-enhanced users. Both types of users can access to real-time process parameters, computational analysis of the process, and microstructural analysis of the parts. One of the significant advantages of EU at the edge and the cloud layer is that it enables easy training sessions for expert users to teach the process to beginners remotely and in real time.



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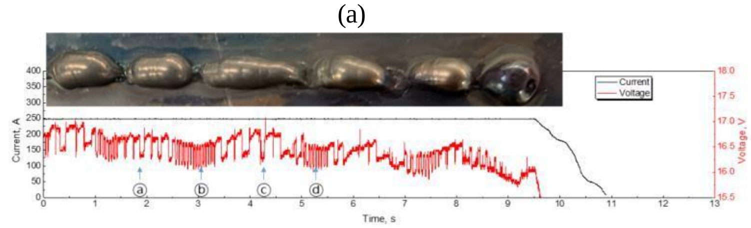
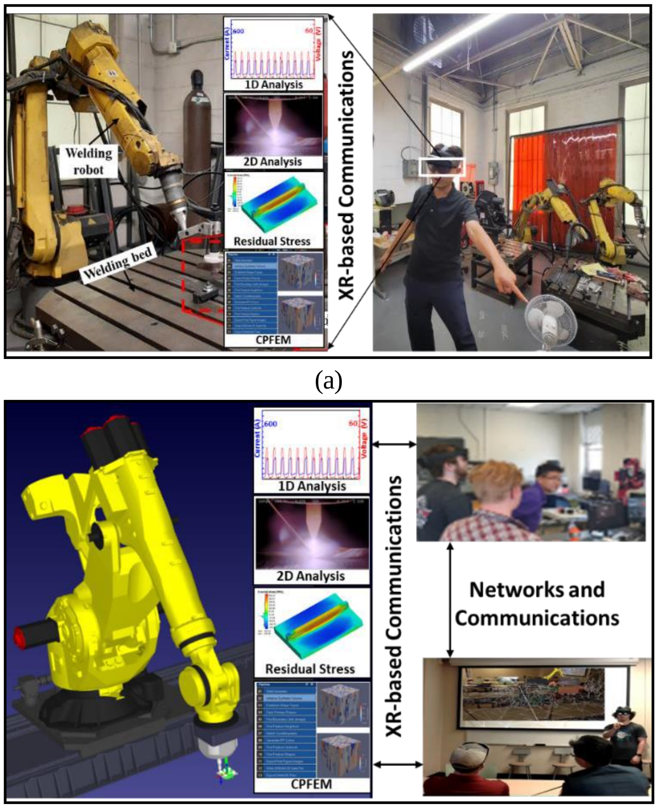


(b)

FIGURE 8: MACHINE LEARNING FOR REAL-TIME ANOMALY DETECTION (a) NORMAL AND (b) ABNORMAL BEADS [32]

The Human Digital Twin module includes a craft avatar for every individual, including operators, technicians, engineers, trainers, and trainees at the edge layers and managers and stakeholders at the cloud layers. These craft avatars can be used for different purposes, including but not limited to training, real-time monitoring, control, and maintenance. This becomes advantageous, particularly in the case of complicated processes like WAAM, where the window map is narrow, meaning that it is challenging to find the near-optimal process parameters. This is also true for most metal AM processes due to low process repeatability and part reproducibility [19]. As shown in Figure 10, three types of interactions are foreseeable, human, avatar, and human-avatar in the HDT module. Human interactions are already well-established and available in the industry; however, the other two types are still to be developed. These communications have numerous applications, such as training, where a beginner is taught fundamentals, and concepts of the WAAM process or an apprentice is trained to become an operator.



(a)

(b)

FIGURE 9: ENHANCED USERS AT (a) THE EDGE LAYER (b) THE CLOUD LAYER

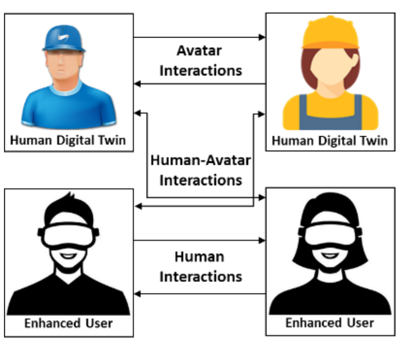


FIGURE 10: INTERACTIONS BETWEEN THE HDTS AND EUS

5. DISCUSSION

The architecture proposed in this paper, DH-SM, can be used to support the integration of physical assets with humans and digital twins. It will help enable real-time, collaborative decision-making between humans, software, and machines. For example, when evaluating a new product design, information about the product's physical features, manufacturing requirements, and customer experience must be processed concurrently [34]. Moreover, the DH-SM architecture can support the creation of an immersive environment that allows customers to be effectively involved in manufacturing.

However, due to current standards and technology limitations, implementing the DH-SM architecture still has some challenges. First, realizing the real-time bidirectional information flow is demanding. For example, the 3D-rendered object of a human in an immersive environment must take place in real time, currently, however, implementing such a real-time interaction is challenging because of the huge amount of data that must be collected and processed. In addition, since these interactions occur in a wireless environment, the low data transmission rate is another issue. Advanced wireless techniques (e.g., 5G and 6G) should be investigated and developed. To achieve this, the interfaces between the architecture modules must be implemented. Second, the concept of "Plug and Play" is difficult to achieve. Software or devices need to work perfectly when first used or connected without the need for reconfiguration or adjustment by the user. Interoperability standards are required to support these functionalities and integration. The interface specifications and communication protocols are not yet well developed. Third, cybersecurity is an ongoing issue that must be linked to those interoperability standards because the abundance of personal data and immersive content is prone to cyber threats [35]. Fourth, many manufacturers, especially Small and Medium-sized Enterprises (SMEs), lack the infrastructure needed to use cloud-based standards such as open platform communication unified architecture (OPC-UA).

To provide a sense of realism to users, new immersion methods will also be needed. These methods will provide users with a more accurate perception of real manufacturing activities with comfort and intuition. For this to be realized, immersive modeling techniques should be advanced. Common interactive technologies include XR and human-computer interface. Current issues with these technologies include (1) the interactive devices are not lightweight and transparent enough, (2) the cost of the devices is high, and (3) there are also associated costs for learning and using these devices. In addition, the user's mental/physical health and socio-economic impacts must also be considered. We believe the existing sustainable and smart manufacturing guidelines can be extended and updated for DH- SM.

One of the main incentives for DH-SM is realizing the concept of non-contact and remote manufacturing, which is one of the fast-paced advancing technologies. Metaverse technology adds an immersive experience to the configuration layer of cyber-physical systems. In manufacturing, the Industrial Metaverse's purpose would be to speed up processes like repairs, maintenance, starting new manufacturing lines, remote monitoring, control, and new user/manager training through simulation. [36]. More efforts will be needed to ensure the seamless and secure communication and synchronization between digital twins, remote human users, and physical systems for non-contact manufacturing.

6. CONCLUSION

We believe that the DH-SM concept and the proposed architecture are particularly relevant today, especially for manufacturing processes that require human intervention. Since these manufacturing processes include humans at every level, taking advantage of the human's perception, cognition, and intuition is essential. We believe the DH-SM architecture will provide real industrial impacts by managing a user's involvement in the evolving, complex, and dynamically changing manufacturing environment. Accordingly, it will change the manufacturing landscape and can guide future research directions for developing standards, reference architectures, technologies; researching necessary components; and implementing case studies. In further studies, we aim to develop the presented conceptual framework with different experimental plans and physical entities to demonstrate the capabilities and efficacy of the proposed DH-SM architecture.

DISCLAIMER

Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose. No approval or endorsement of any commercial product by NIST is intended or implied. This material is based upon work supported by the National Science Foundation under Grant No. 2015693.

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