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Edge Computing-Based Digital Twin Framework Based on ISO 23247 for Enhancing Data Processing Capabilities

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Abstract: Digital Twin (DT) technology has evolved to contextualize real-time interactions between the physical and digital worlds. It has gained increasing attention in various research areas and industries, including the manufacturing, aerospace, and automotive industries, while facing challenges in processing and analyzing large datasets. To address these challenges, this paper proposes an edge computing-based DT (E-DT) framework and elaborates on its functional and informational aspects. The functional aspect is represented using ISO 23247 as the reference architecture, while the informational aspect is elaborated by introducing a data fusion model. Then, an E-DT for Wire+Arc Additive Manufacturing (WAAM) is developed, its performance is evaluated, and the benefits of edge computing in enhancing real-time processing and decision-making are verified. In addition, a typical non-edge computing-based DT for WAAM is implemented according to ISO 23237 for comparison. The results show that the proposed E-DT for WAAM achieved reduction in latency through faster data processing, smaller data upload volume, and more consistent data upload speed.



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Keywords: digital twin; edge computing; ISO 23247; Wire+Arc additive manufacturing

1. Introduction

Digital twins (DTs) were initially developed to simulate aerospace systems used in the American military. DTs connect the real world to the digital world and realize real-time interactions between them [1]. They play a crucial role in modern industry as virtual replicas of physical systems. According to Grieves [2], DT technology enables real-time monitoring and simulation of an actual system's operations and conditions, facilitates decision-making and system management, and optimizes product and process development to increase efficiency. Consequently, DTs have been applied in various fields, including the manufacturing, aerospace, and automotive industries, and have been employed for predictive maintenance and product lifecycle management [3]. Furthermore, quality monitoring using DTs in manufacturing processes is increasingly employed, and according to Tjahjono et al. [4], this can lead to long-term efficiency and profitability.

However, DTs have significant limitations. Tao et al. [5] indicated that DTs must process and analyze a large amount of data to reflect the state of physical systems in real time and perform predictive analytics, which poses challenges regarding computing resources and data storage. Kritzing et al. [6] emphasized that the DT framework must rapidly process the vast amounts of data generated by physical systems to maintain accuracy.

Integrating DTs and edge computing is a viable approach for addressing this challenge. Edge computing processes data at or near a data source, effectively reducing the latency and bandwidth required for real-time data analysis. Shi et al. [7] highlighted that edge computing is particularly useful for Internet of Things (IoT) applications, in which immediate processing and responses are essential. This technology can be applied to industries where rapid data analysis and decision-making are critical, such as smart city infrastructure, automated industrial processes, and smart manufacturing systems.

To fully realize the advantages of integration, a systematic framework that serves as a standard needs to be developed. For this purpose, ISO 23247 [8], provided by the International Organization for Standardization (ISO), can be utilized. ISO 23247 provides a reference architecture for DTs in manufacturing and offers a consistent approach for implementing and integrating DTs through data management and communication protocol guidelines. However, to the best of our knowledge, no previous study has been conducted on the development of a reference architecture for DTs in which edge computing is integrated.

Accordingly, this paper proposes a framework for edge computing-based DT (E-DT) utilizing ISO 23247 and delves into its specific functionalities. The primary goal of this study was to outline, implement, and validate the operation of a DT framework for edge computing. To accomplish this, functional and informational elements were designed and presented as the framework's components. Subsequently, E-DT was implemented, and its performance was evaluated through a case study, demonstrating the significance and efficacy of the proposed framework. The contributions of the proposed method are as follows:

1. Proposing an edge computing-based DT framework grounded in ISO 23247 to enhance real-time data processing.
2. Introducing a data fusion module designed to improve data consistency and reduce network load.
3. Conducting a comparative case study demonstrating the advantages of the proposed framework over existing DT architectures in terms of latency, data processing speed, and data consistency.

The remainder of this paper is organized as follows. Section 2 explains the concepts of edge computing and DTs, summarizing relevant prior research. Section 3 focuses on the framework design and details its functional and informational aspects. In Section 4, the proposed framework is applied to Wire+Arc Additive Manufacturing (WAA) and its performance is validated. Finally, Section 5 concludes the paper.

2. Related Studies

2.1. Integration of DT Technology and Edge Computing

DTs connect the real and digital worlds and simulate their interactions in real time [1]. The initial DT concept emerged as a response to the need for the advanced simulation and optimization of manufacturing systems [9,10], and the community has increasingly recognized its significance. For example, Bazaz et al. [11] proposed the integration of manufacturing systems using DTs. Figueiredo et al. [12] adapted them to dynamic markets and customer demands. In addition, edge computing has emerged as a solution for addressing the latency and bandwidth limitations in cloud computing [13]. Edge computing has been recognized as a critical technology of Industry 4.0 to efficiently process massive amounts of data [14]. Furthermore, edge computing improves response times, reduces operating costs, and enhances data security in manufacturing environments [15].

Therefore, integrating edge computing and DTs has become increasingly interesting in the community. This integration enables real-time monitoring and control, facilitates predictive maintenance, and enhances operational efficiency [16]. Furthermore, previous studies have shown that edge computing can expedite data processing by integrating DTs with IoT devices, thereby accelerating responsiveness [17]. Zhou et al. [10] studied the application of mobile edge computing to enhance the resource and energy efficiency of DTs. Therefore, this area lacks a systematic framework for realizing the advantages of E-DT.

2.2. ISO 23247

ISO 23247 is the standard used for DTs in manufacturing [18]. It offers a consistent approach for implementing and integrating DTs through data management and communication protocol guidelines. The reference architecture of ISO 23247 consists of five entities: observable manufacturing elements (OMEs), a data collection and device control entity (DCDCE), core entity (CE), user entity (UE), and cross-system entity (CSE). OMEs represent items that require modeling in the manufacturing field. The DCDCE collects all OME changes and transmits commands and adjustment values, while the CE simulates physical objects. The UE refers to enterprise resource planning and product lifecycle management, which use DTs to make manufacturing more efficient. The CSE ensures effective communication and operation of DT components, such as sensors, IoT devices, and software systems. Each entity comprises sub-entities and each sub-entity consists of functional elements.

Regarding ISO 23247, Shao et al. [19] analyzed its impact on manufacturing, and Cabral et al. [20] discussed the implementation of a data-processing center for the DT architecture based on it and demonstrated the applications of DTs in manufacturing through actual cases. However, these studies did not discuss the integration of DT and edge computing. Qi et al. [21] and Protner et al. [22] investigated the integration of edge computing with DTs, targeting smart manufacturing and cyber-physical systems. However, their approaches were not based on ISO 23247. Wang et al. [23] indicated that DTs can have interoperability issues across various industrial sectors when standardized terminology and architecture are not employed. We believe that this is also true for integrated DTs; thus, we propose a new framework for E-DT using ISO 23247.

3. Proposed Edge Computing-Based Digital Twin Framework

ISO 23247 clearly defines five entities that must be considered when developing DTs: OMEs, DCDCE, CE, UE, and CSE [18]. Many DT studies have been developed based on this standard architecture, and it plays an important role in ensuring the completeness of DTs. However, as mentioned in Section 2, a growing number of studies have recently reported the importance of edge computing technologies in developing DTs that utilize large amounts of data, and there are examples of their use, but no standard architecture has been studied. Our research is significant in that it is the first to propose the standard architecture for DT development utilizing edge computing technology. We propose considerations to be taken into account when utilizing edge computing technology in the existing ISO 23247 from the perspective of function aspect and information fusion aspect.

3.1. Functional Aspect

ISO 23247 employs functional entities to define the functionalities of each element [18] and is the foundation of the proposed E-DT framework, as shown in Figure 1. This framework comprises four entities: OME, DCDCE, CE, and UE.

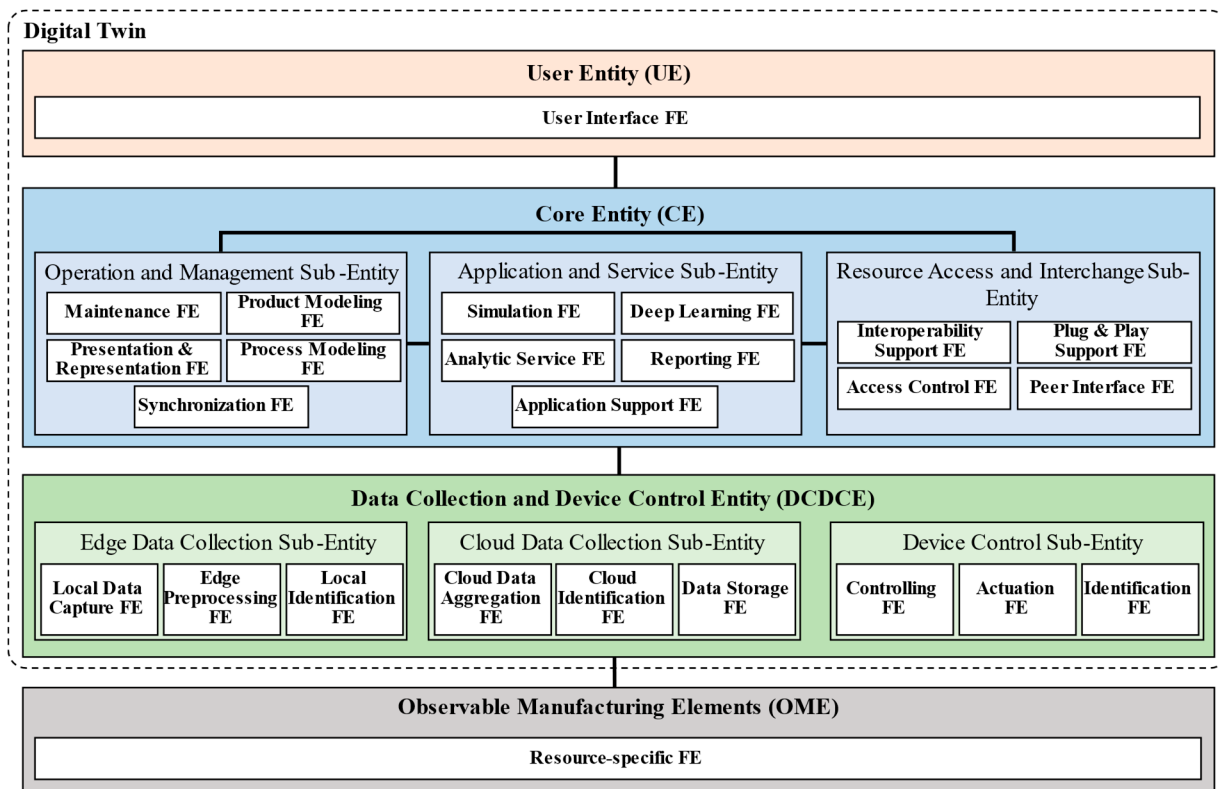


Figure 1. Architecture of the proposed E-DT framework.

The major differences from ISO 23247 are as follows. First, the role of the DCDCE is expanded, moving away from a centralized approach to distributed data processing and decision-making across the network. This minimizes bandwidth requirements and enhances data management efficiency. Second, the CSE is replaced by two new sub-entities in the DCDCE: edge and cloud data collection. This reduces the architecture's complexity, improves manageability, and simplifies operations in scenarios requiring rapid data processing and decision-making. Additionally, this change enables the protection of sensitive information within a more controlled range by processing data locally at the edge, instead of using a centralized model. Third, the functional entities (FEs) were modified and discussed in detail.

3.1.1. Observable Manufacturing Entity

According to ISO 23247, an OME represents the physical entities in a manufacturing environment that can be digitally represented within a DT framework [18]. It is essential for creating and operating a CE and plays a fundamental role in observing, monitoring, and analyzing process optimization and decision-making improvement. The introduction of edge computing has increased the efficiency of OME components by enabling faster and more efficient real-time data processing and analysis. However, it does not alter the fundamental structure or scope of the OME and maintains its definition and scope as outlined in ISO 23247.

3.1.2. Data Collection and Device Control Entity

The DCDCE collects data from sources within the manufacturing environment such as sensors, machinery, and operational systems. At manufacturing sites, it is common for a large volume of data to be acquired simultaneously and then gathered in an edge data cache awaiting preliminary processing. The edge data collected during the manufacturing process

can be categorized into five distinct types: sensor, device, actuator, log, and video/audio data, as detailed in Table 1.

Table 1. Five types of edge data.

Sensor	Device	Actuator	Log	Video/Audio
- Temperature - Humidity - Vibration - Air quality - Pressure	- Energy consumption data - Production data - Status data - Efficiency data	- Robotic arms data - Valve position data - Speed control data - Positioning data	- Maintenance logs - Error logs - Operational logs - Quality control logs - Downtime logs	- Machine images - Product images - Area views - Alarm sounds

Given the variety and volume of data flowing to edge servers, processing these data primarily at edge servers offers the following advantages:

- (1) By preprocessing the data at the edge, the amount of data that must be sent to central servers or the cloud can be minimized, thereby reducing bandwidth usage and enabling the development of responsive E-DTs.
- (2) The decrease in bandwidth usage can reduce maintenance and management costs.
- (3) Local processing of sensitive data reduces security risks.
- (4) Edge computing can operate reliably even when cloud or central server connections are unstable, facilitating a stable environment for model operations.

Therefore, to maximize the capabilities of edge computing, the original data collection sub-entity defined in ISO 23247 was modified into the edge and cloud data collection in the proposed framework. These two sub-entities facilitate the integration of DT and edge computing and enable the integrated E-DT to work based on the real-time status of the edge, where large volumes of data are generated. Details of the two sub-entities are discussed next.

In the edge data collection sub-entity, there are three FEs: local data capture, edge preprocessing, and local identification. The local data capture FE collects real-time data from multiple edge devices and sensors, effectively replacing the initial data-collection stage typically managed by the CSE. The edge preprocessing FE handles the initial processing of the source data collected at the edge, which includes filtering out noise, normalizing the data, and compressing large datasets into more manageable forms. The local identification FE assigns unique identifiers to aggregated data or events occurring at the edge, allowing for the marking of data origins and context tracking for later analysis. This replaces the role typically performed by the CSE in centralized environments.

The cloud data collection sub-entity focuses on managing and processing data at the cloud level. It is designed to act as a central point for integrating and storing the data collected and initially processed at the edge, and consolidating information in databases for further analysis and implementation. Cloud data collection can be classified into three types: cloud data aggregation, cloud identification, and data storage.

Cloud data aggregation involves the collection and integration of preprocessed data from the edge. Cloud identification is responsible for identifying and authenticating data sources, registering new data sources, and adding relevant metadata to incoming data. It also manages access control for data from the edge data collection, permits only authorized access, ensures data-source security, and detects anomalies or errors during identification. The data storage FE supports data retrieval, backup, and recovery, and optimizes storage efficiency through data compression, encryption, and duplication checks. It acts as a data repository that facilitates remote access to the cloud databases.

Device control operates the physical devices and commands the DT framework. However, the proposed framework takes on the role of real-time management of edge device operations, ranging from command transmission to monitoring the status of actuators and sensors. In the proposed framework, this sub-entity comprises three FEs: control, actuation, and identification.

The controlling FE is responsible for regulating and managing operational commands. It processes inputs from the E-DT system to determine appropriate commands. With increased edge devices and the resulting larger volume of edge data, the controlling FE manages more complex operational commands and uses algorithms to adjust the parameters for optimal task execution. Additionally, the actuation FE physically executes the commands received from the controlling FE more frequently. It acts as a messenger, relaying commands and converting digital decisions into actual mechanical or electrical responses. Finally, the identification FE identifies the physical components and their corresponding digital representations in order to receive these commands.

3.1.3. Core Entity

The CE has several essential characteristics in scenarios where edge computing is required. First, it is equipped with an algorithm that analyzes additional data to improve the quality and production of the manufacturing process. The CE can perform predictions using deep learning or advanced machine-learning technologies. In addition, as data sources are distributed and the role of the DCDCE is emphasized because of the edge computing paradigm, the CE focuses on data coordination among multiple edge devices. It also utilizes data in cloud databases for analysis, synthesis, and decision-making using enhanced computing power that can manage higher throughput and quickly perform complex calculations. The CE includes three sub-entities: operation and management, application and service, and resource access and interchange.

The operation and management sub-entity oversees the functions and performance of the CE, which results from the edge. It integrates the transmitted data and coordinates E-DT components. This sub-entity includes five FEs: maintenance, presentation and representation, product modeling, process modeling, and synchronization. The maintenance FE checks the reliability, performance, and lifetime of the E-DT by conducting system improvements in advance, such as software updates. The presentation and representation FE visualizes data and information. Compared with ISO 23247, many objects must be visualized owing to the increased edge data. Accordingly, this FE creates a user interface, graphic representation, and interaction visualization that allows data to be accessed. The product and process modeling FEs digitally model products and manufacturing processes, respectively. The synchronization FE is responsible for real-time data synchronization such that changes in the physical environment are reflected in the E-DT in real time.

The application and service sub-entity serves as a central storage and operating platform for applications and services that enhance the functionality of the DT. It includes five FEs: deep learning, simulation, analytical service, reporting, and application support. The simulation FE tests scenarios in an environment through virtual representations of physical processes. The analytical service FE analyzes the collected data and provides the necessary analyses and predictions. The reporting FE organizes the analysis results in a certain format to convey information. Finally, the application support FE provides infrastructure and support for applications.

The existing ISO 23247 standard overlooks the importance of rapidly developing machine-learning algorithms that can perform various tasks, such as recognizing complex patterns from data and performing predictive analyses [24]. The deep-learning FE applies deep-learning algorithms to tasks, such as predictive analysis, complex pattern recognition,

and advanced decision-making processes. It utilizes algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to process large amounts of data and make predictions. This can improve the functionality of the E-DT in predictive maintenance, anomaly detection, and manufacturing process optimization.

Although the deep-learning FE can be considered under the category of analytical service or simulation FEs, it is regarded as an independent FE because it includes algorithms that require expertise and increased computational power. It has unique technical requirements beyond simple data processing or existing analysis methods such as GPU allocation. Second, continuous development and research are required. This FE learns based on the data collected from the cloud data collection sub-entity and recognizes complex patterns. In addition, the analytical service FE establishes decisions and strategies through the predictive information obtained from the deep-learning FE.

The resource access and interchange sub-entity facilitates resource exchange and access between system components. This includes four FEs: interoperability support, plug-and-play support, access control, and peer interface. The interoperability support FE integrates components to interact with systems and other manufacturers or protocols. The plug-and-play support FE adds new devices and components to the system, automatically detects the device, identifies its functions, and automatically sets its configuration. The access control FE manages security and controls access to data and functions through user authentication and authorization. The peer interface FE is responsible for communication and data exchange between systems or components.

3.2. Informational Aspect

Information collected from data sources during the manufacturing and quality inspection processes is in multiple forms. Therefore, data fusion integrates visual inspection images, sensor values, operating parameters, and environmental data into a single dataset. This lays the foundation for analyzing the variables that may occur during the manufacturing process. For example, quality management is possible using real-time data, and the early detection and response to potential defects or quality deviations can contribute to the establishment of proactive maintenance and quality management strategies [25]. As shown in Figure 2, the proposed data-fusion module consists of three configurations: data preprocessing, formatting, and grouping.

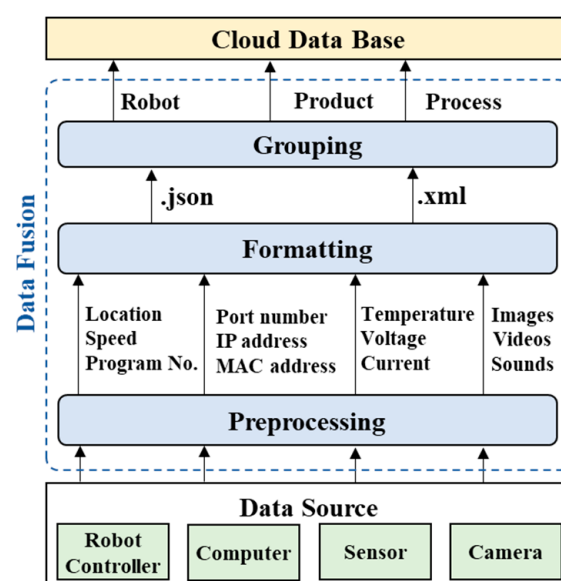


Figure 2. Data fusion model of the proposed E-DT framework.

Data pre-processing is an early stage of data fusion. It refers to cleaning tasks, such as noise removal, error correction, and normalization, which adjust data to a specific range or format. Data formatting is a common standard for all data. This includes data type conversion, date format standardization, and categorical data alignment. At this stage, the metadata are stored in JSON or XML format. Data grouping is the process of organizing data into meaningful categories or clusters and is based on specific attributes, such as time, location, sensor type, and data source. This step is used for future analysis or prediction by processing and managing the data within a logically divided group. Finally, the processed data are stored in a cloud database and later used to derive information.

To ensure data consistency within the proposed data fusion module, we integrate a data cache and adopt an event-driven consistency model. The data cache temporarily stores data from multiple sources, reducing the load on the cloud server and enabling faster, localized access to data during preprocessing. This design prevents delays associated with remote data fetching and minimizes potential inconsistencies caused by data latency. Furthermore, an event-driven consistency model is employed to manage synchronization between real-time data and digital representations. This model triggers consistency checks and updates whenever a new event—such as a significant process change or anomaly—is detected, maintaining real-time alignment between the physical and digital environments. By combining the data cache with an event-driven approach, the proposed data fusion module achieves both high data fidelity and robust responsiveness, ensuring data consistency across all digital twin operations.

4. Case Study

For validation purposes, the proposed E-DT framework was implemented for quality monitoring in a Wire+Arc Additive Manufacturing (WAAM) system; this is an extension of the work conducted by Kim et al. [26]. First, the WAAM process is introduced; then, we explain how the E-DT is implemented through the proposed framework.

4.1. Wire+Arc Additive Manufacturing

WAAM is a type of three-dimensional (3D) printing technology that uses an electric arc to melt metal wires so as to manufacture metal parts layer by layer and uses an arc between two non-consumable tungsten electrodes. According to Zhou et al. [27], WAAM can efficiently produce complex forms and is adaptable to industrial applications. It has the advantage of manufacturing large metal parts in a quick and efficient manner, providing flexibility for mixing with other metals.

However, because part quality is difficult to manage owing to complicated thermal cycles, WAAM faces important quality issues in terms of geometrical accuracy. Figure 3 shows a typical WAAM process and bead formation. As shown in Figure 3a, the filler metal melts at the center of the arc and forms droplets that move under the arc to create molten pools on the bead metal, resulting in a continuous droplet transition. When the heat input per unit length decreases because of a lower current or higher travel speed, the molten pool size and deposition area decrease, as shown in Figure 3b. This reduction causes the molten pool to move rearward, leading to the repeated formation of balling beads.

Besides the quality issues associated with bead formation, several other quality problems have been reported in WAAM. Xiao et al. [28] described the difficulty of predicting and controlling laminated geometric shapes, while Baier et al. [29] emphasized the importance of quality monitoring. They stated that responding to the process quickly was necessary to solve quality issues. Tang et al. [30] studied the geometric characteristics of the surface quality and found that the shape can be controlled using laser-based topography measurements with field monitoring. Binaei et al. [31] emphasized the importance of monitoring

and detecting pollutants such as Tungsten in the WAAM process in real time and discussed the role of monitoring in identifying and preventing defects such as pores in aluminum alloy parts. The authors also explained the effects on the quality of the final product.

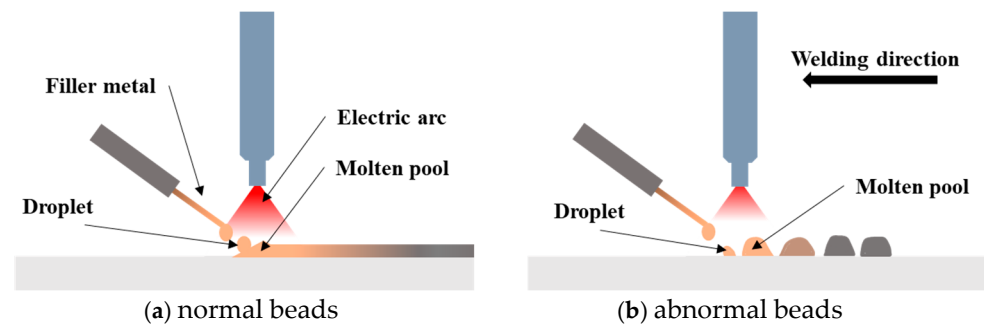


Figure 3. WAAM process with normal and abnormal beads.

With the proven importance of quality monitoring in WAAM, the need for DT technology has gained increased attention. Waldschmitt et al. [32] proposed a method for integrating DT models into the design and manufacturing of complex geometric structures using WAAM. Kyevelou et al. [33] used computer simulations and DTs to verify the structural performance of the first metal 3D-printed bridge manufactured using WAAM. These previous studies emphasized the importance of in-depth analysis and process optimization provided by DTs in WAAM and defined their role in solving manufacturing tasks. Despite these efforts, WAAM struggles to design responsive DTs because of the large amount of data generated during the process, which is more prominent when manufacturing complex shapes or large parts [34]. Additionally, Reisch et al. [35] explored the monitoring of situational awareness processes using DTs in additive manufacturing to manage and analyze large-scale data for real-time defect detection in WAAM, and emphasized the importance of processing vast amounts of data for faster real-time monitoring. Therefore, a solution could be the introduction of edge computing, which reduces latency and enables real-time data analysis and process monitoring by moving data processing locations to manufacturing sites. This can detect problems that may occur during the WAAM process in real time and improve quality via process parameter adjustments.

4.2. E-DT for Quality Monitoring in WAAM

This case study aimed to use the proposed E-DT framework for quality monitoring in WAAM by analyzing bead images. Figure 4 shows the normal and abnormal beads during and after processing.

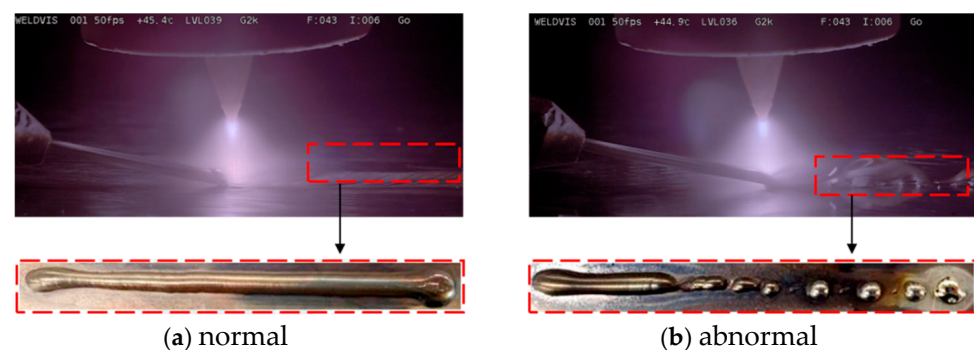


Figure 4. Welding beads in normal and abnormal state.

As shown in Figure 4, the normal beads are characterized by a consistent width and height and a uniform surface texture. In contrast, abnormal beads exhibit irregular shapes, abnormal size changes, irregularities, and surface defects. These defects may be caused by factors such as thermal instability, welding conditions, and imbalances in material supply. Several image-based methods have focused on real-time monitoring and quality management of WAAM processes. For instance, recently, Cho et al. [36] improved the efficiency of the process and the quality of the final product by evaluating the quality of each bead in real time using a high-resolution camera and a CNN-based image-processing algorithm.

4.2.1. Functional Aspect for Quality Monitoring in WAAM

The E-DT architecture for quality monitoring in WAAM is shown in Figure 5. It comprises four layers: OME, DCDCE, CE, and UE. Each of these entities is explained in detail below. Figure 6 shows the OMEs for this case study. A Fanuc 120ic robotic arm performs the WAAM, a Fanuc R-30iA controller controls the robot's behavior, and a Miller Dynamic 400 GTA provides the power required for the WAAM. Molybdenum, argon, and SS613L were used as the feed, shielding gas, and base material, respectively. Weld cameras were used to collect video data on the beads formed during the process, and the robot movement and operator location were checked through a webcam.

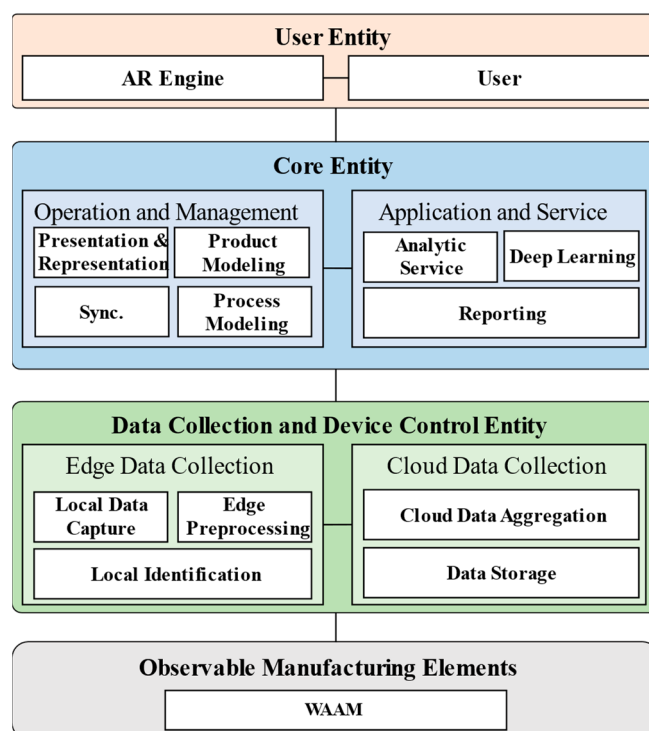


Figure 5. E-DT architecture for quality monitoring in WAAM.

The collected WAAM process images were stored on Edge Computer 1 with an Intel i7-12700H CPU processor, 32 GB DDR5 RAM, and an NVIDIA RTX 3070Ti GPU processor. Edge Computer 2 has the following configuration: Intel i7-12700H CPU processor, 16 GB DDR4 RAM, and NVIDIA RTX 3070Ti GPU Laptop. The DT server running the DT is built with an Intel i7-12700K, 128 GB DDR4 RAM, and NVIDIA RTX 4800A GPU. The operator is equipped with a Hololens2, allowing him to work in an artificial intelligence (AI) environment. Microsoft Azure was used as the cloud database server. The data stored in the cloud can be accessed and downloaded from the user's desired location, and the user who performs the process using Hololens2 downloads the data.

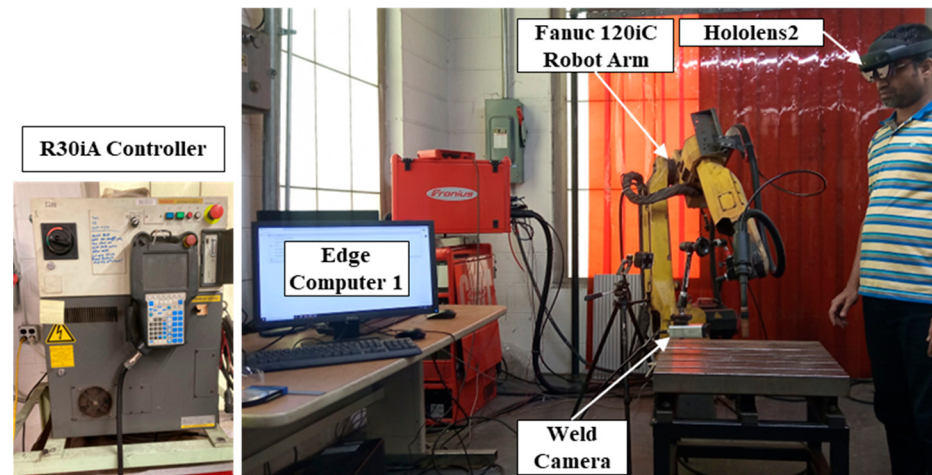


Figure 6. OMEs of the WAAM process.

The DCDCE collects and processes data from various sources in WAAM. Compared to the architecture described in Section 3, the device control is omitted because there is no bidirectional communication. Furthermore, the DCDCE has edge and cloud data collection sub-entities. Edge collection consists of local data capture, edge preprocessing, and local identification FEs. The local data capture FE collects the data. For this, a C# application was implemented to collect key operating indicators, such as the location, speed, and torque of the Fanuc 120iC robotic arm, using the OPC Unified Architecture (OPC UA) protocol. Simultaneously, a program was developed to collect and process video streams from the camera in real time using Python and OpenCV libraries to obtain image data from the camera. The edge preprocessing FE uses Numpy and OpenCV to normalize the operational data, including indicators such as the robotic arm location, speed, and torque. It also filters noise and processes a selection of frames based on video data using Gaussian blurred noise reduction. The local identification FE indicates the data source by storing it in a folder in JSON and XML format.

The cloud data collection sub-entity includes cloud data aggregation and data storage FEs to integrate and assign each data item an identifier for cloud storage. Microsoft Azure Event Hubs were used as the cloud data aggregation platform to divide the units generated from the source and process them in parallel. For the metadata and relational data in the data storage FE, Azure Blob Storage and Azure SQL Database were used, respectively. The cloud identification FE processes the identification and authentication of data sources, registers new data sources, and adds relevant metadata to incoming data.

The CE comprises the operation management and application and service sub-entities. Compared with the architecture proposed in Section 3, the resource access and interchange sub-entities were omitted to save computing resources. Computing resources must be saved because implementing deep-learning FEs requires significant computing resources. Complex data analysis and learning processes greatly increase GPU and CPU usage, which affects the overall efficiency of the E-DT. In addition, the DCDCE requires additional resources because it uses edge computing. Finally, implementing an augmented reality (AR) environment requires additional computational resources. AR enriches the user experience and helps intuitively understand complex manufacturing processes; however, it also requires significant processing power from GPUs and CPUs.

The product-modeling FE models the robot using computer-aided design (CAD), and the process-modeling FE models the logical structure of the process in C# code. The analytical service FE analyzes the collected data and provides relevant information, as shown in Figure 7. The images captured by the weld camera are divided into frames.

The fixed area is then cropped (red box in Figure 7). Subsequently, the cropped image is processed in black and white, and the edges are extracted using the Canny edge-detection algorithm. After extracting the line, the number, angle, and thickness of the line segments they are extracted via Hough transformation. As a result, the analytic service FE extracts the rod wire slope, arc size, and bead width through the frame extracted from the video. The deep-learning FE performs predictive analyses, complex pattern recognition, and advanced decision-making processes. Cho et al. [36] demonstrated that MobileNetV2 exhibited the highest performance in detecting abnormal bead images. Accordingly, in this FE, MobileNetV2 is trained using Pytorch and the current process state and arc shape are predicted. The reporting FE collects information derived from the analytical service and deep-learning FEs. The presentation and representation FE shows WAAM information derived from the analytical service and deep-learning FEs to users through a user interface (UI), as shown in Figure 8.

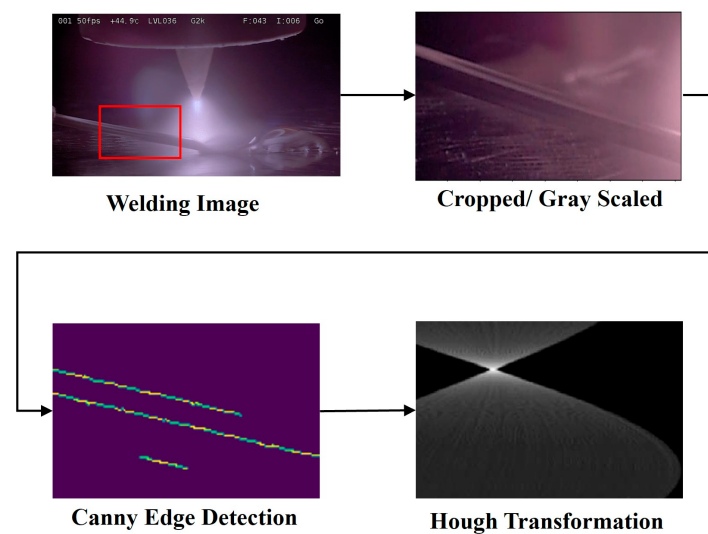


Figure 7. Analytic service FE.



Figure 8. Presentation and representation FE.

The UE consists of AR engine and user sub-entities. The AR engine creates an AR environment based on the information from the DCDCE. In this case, it was developed using Unity 3D, OpenXR, and the Mixed Reality Toolkit (MRTK), as shown in Figure 9. Unity 3D, a game engine with the ability to integrate AR, is used for DT visualization and UI construction [37]. OpenXR is a royalty-free standard that aims to simplify AR development by providing a common API that supports hardware devices [38]. MRTK is an open-source project developed by Microsoft and consists of a collection of tools and functions used to develop extended reality applications. The developed AR engine delivers AR information to users and enables them to virtually experience WAAM using Hololens2.

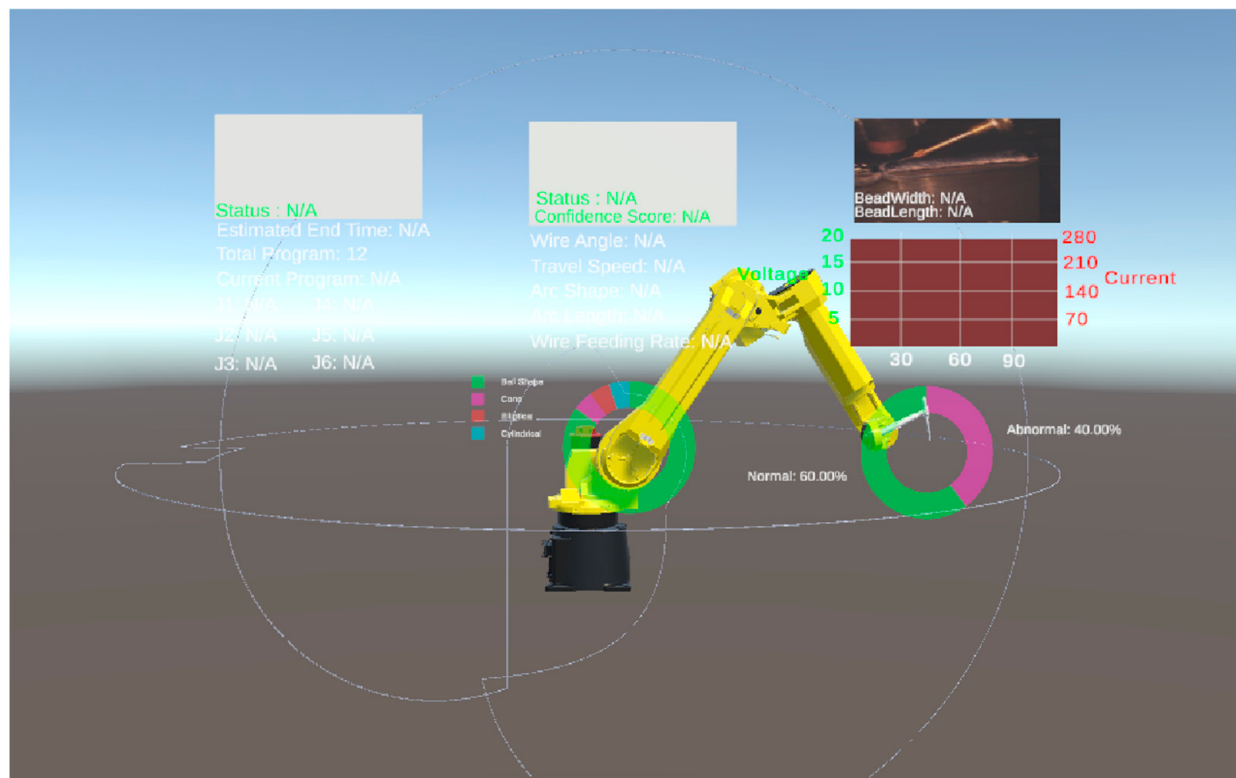


Figure 9. User entity developed using Unity 3D.

4.2.2. Informational Aspect for Quality Monitoring in WAAM

The information generated from WAAM flows into the computer during edge processing, is stored in the cloud database, and is finally distributed to the user and the E-DT. The information flow for this case study is shown in Figure 10. The information generated from the robot, welding camera, and webcam is fed to edge computers 1 and 2 for processing purposes. The input data characteristics are listed in Table 2. These computers function as edge data collection sub-entities. Data generated at the edge enter the data fusion model and undergo preprocessing, forming, and grouping processes, and additional JSON and XML file formats are created.

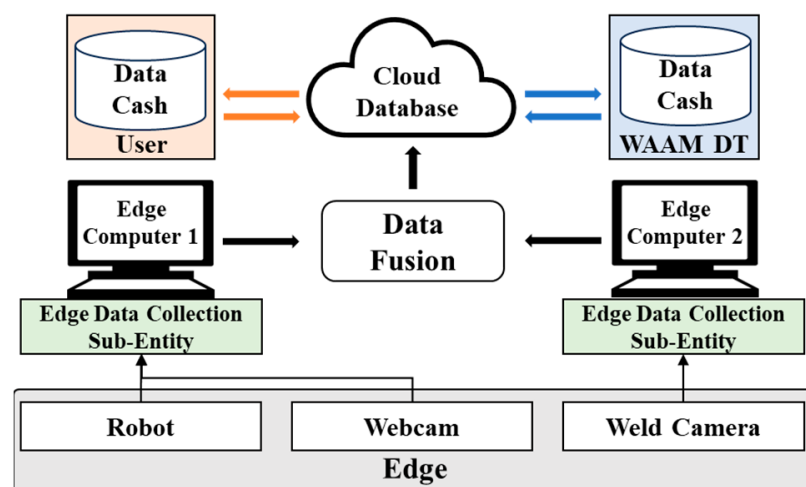


Figure 10. Information flow based on the proposed architecture.

Table 2. Edge data format and capacity of the case study.

Type	Format	Size per s	Processing Location
Robot Data	csv	5 KB	Edge Computer 1
Webcam Data	mp4	5 MB (30 fps)	Edge Computer 2
Weld Camera Data	mp4	25 MB (50 fps)	Edge Computer 2

The data input to the edge computer are stored in the cloud database after data processing. After passing through data fusion, the dataset is stored in a folder and transmitted to and stored in the Microsoft Azure cloud. The stored data are then sent to a cache, and a digital copy of the WAAM is generated. Conversely, when there is a change in the robot's movement, the digital objects are changed, and this information is stored in the cloud server. When the cloud database stores and transmits these changes to the user, the cache receives the changes and changes the AR environment. However, when a user changes the AR environment, the AR is stored in the user's data cache and transmitted to the cloud database.

4.3. Case Study Results

Figure 11a shows a snapshot of the UI showing the bead formation process in an AR environment. This demonstrates the robot monitoring state. It displays the product manufacturing process and the current quality state, which is classified as 'Normal' or 'Abnormal'. Additionally, information for checking process parameters, such as the arc shape and wire speed, can also be observed. Immediately after completing one bead, its entire appearance is checked, as shown in Figure 11b. The voltage and current values when creating the beads are also shown in the graph. The arc distribution, abnormal bead ratio, and movie clip of the process are also available at the end of the process.

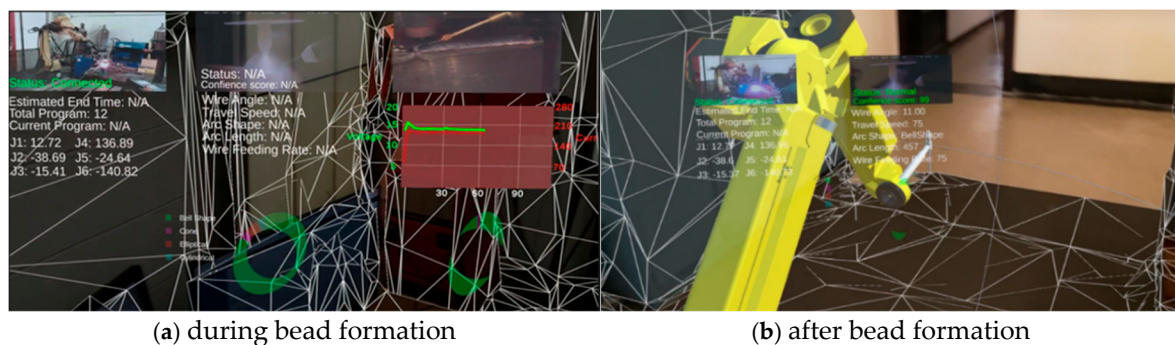


Figure 11. UI snapshot showing the WAAM during and after bead formation (click "https://o365skku-my.sharepoint.com/personal/dhee_o365_skku_edu/_layouts/15/stream.aspx?id=/personal/dhee_o365_skku_edu/Documents/2.%20EB%85%BC%EB%AC%B8/01%20EC%8B%AC%EC%82%AC%EC%A4%91/03%20EA%B0%95%EB%AF%BC%EC%88%98%20EC%A0%81%EC%25" to watch the video).

4.4. Performance Comparison with ISO 23247

Next, let us evaluate the performance of the existing DT framework (ISO 23247) and the proposed E-DT framework. The comparison criterion is data processing, which refers to the speed at which a system or technology can process, analyze, and transmit data, and it shows that fast data processing significantly reduces the power and time consumed for monitoring in edge computing [39]. The flow of information in the existing framework was also studied, as shown in Figure 12.

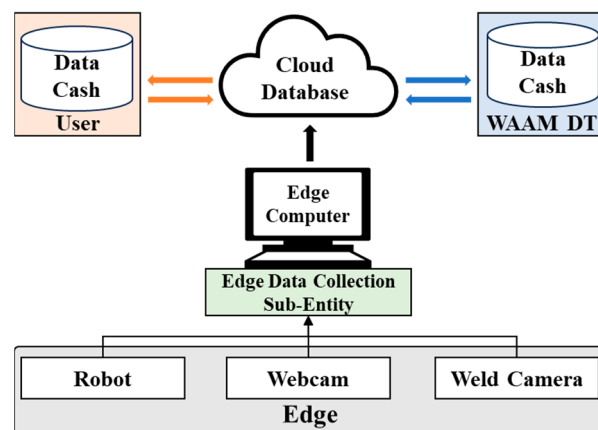


Figure 12. Information flow of the ISO 23247-based DT.

Notably, there is one edge computer here, whereas two edge computers exist in the proposed E-DT. In the information flow based on ISO 23247, one edge computer receives all data from the robot, weld camera, and webcam. Additionally, the received data are transferred to the cloud without data fusion. Furthermore, the DCDCE edge and cloud data collection sub-entities in the proposed framework are omitted. Instead, a data collection sub-entity was implemented.

The data throughput of the edge computers was measured for 10 s to determine the data-processing speed; the results are shown in Figure 13, where the data processed by the proposed and existing architectures are compared. The data-processing speed of the proposed framework outperforms that of the existing framework. On average, the data-processing speeds of edge computers 1 and 2 were 5.005 and 25 MB/s, respectively, and their sum was 30.005 MB/s, whereas that of the existing framework was 28.005 MB/s. This means that not all the real-time data collected by the edge computer in the existing framework were processed.

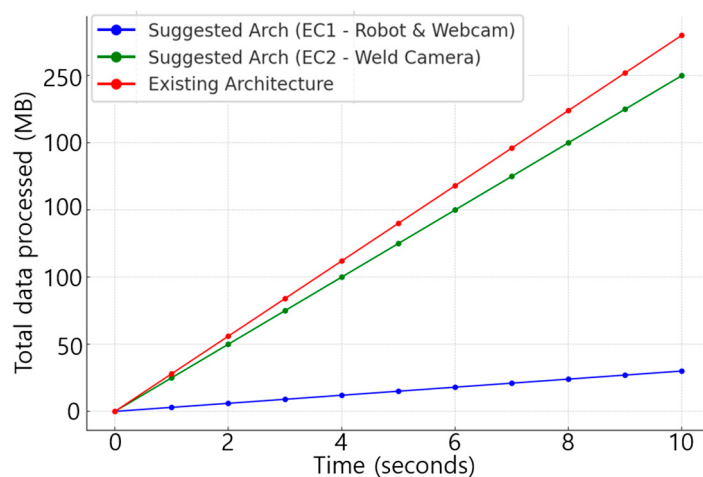


Figure 13. Data-processing speeds of the proposed and existing frameworks.

Also, the proposed edge computing-based architecture reduces network load compared to existing architectures, as illustrated by Figure 14, which often exceed network overload thresholds in data-intensive environments. By leveraging the data fusion module for preprocessing at each edge computer, the system effectively categorizes and compresses raw data locally before transmission, leading to a smaller overall data output. This approach not only minimizes bandwidth requirements but also stabilizes computational fluctuations, as each edge device processes only relevant, pre-filtered data. The resulting

streamlined data flow prevents bottlenecks and ensures consistent, real-time data handling across the network, contributing to more stable and efficient digital twin operation in high-volume manufacturing environments.

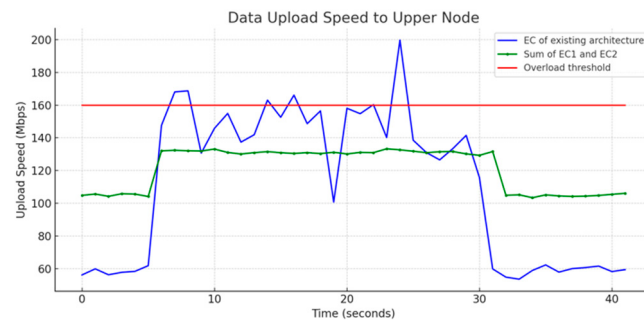


Figure 14. Data upload speeds of edge computers.

Furthermore, the proposed architecture achieves a reduction in latency for digital twin operations, as illustrated by Figure 15, primarily due to the smaller data upload volume and consistent upload speed. By preprocessing and categorizing data at each edge computer through the data fusion module, the system minimizes the amount of data that must be transmitted to the central network. This reduction in data volume, combined with a stabilized upload process, significantly decreases the time required for data to travel from the physical environment to the digital twin. Consequently, the digital twin can more effectively maintain real-time synchronization with the manufacturing process, enhancing the responsiveness and accuracy of decision-making in data-intensive scenarios.



Figure 15. Latencies of the proposed and existing frameworks.

The effect of the unprocessed data can be seen in Figure 16 which shows video frames captured by the weld camera. The frame with data loss accounted for only 30% of the capacity of the original frame, indicating a 70% data loss. This loss can be seen in Figure 16a. This limits the ability to divide and store the images captured by the weld camera in real time.

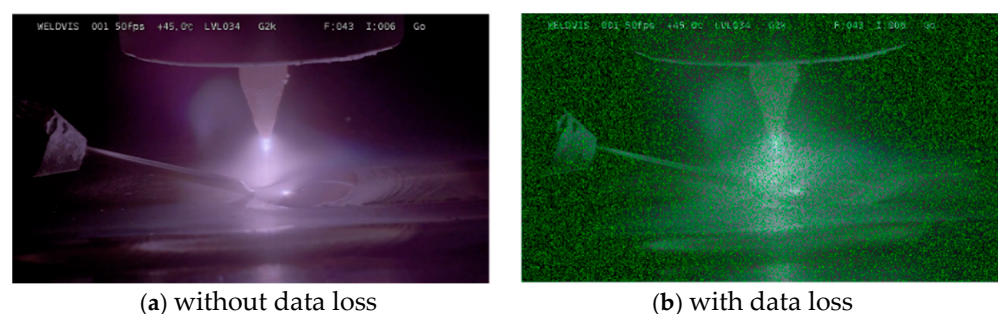


Figure 16. Video frames without and with data loss.

5. Conclusions

This paper proposes an edge computing-based DT (E-DT) framework using ISO 23247. To maximize computational power, the edge and cloud environments were built separately from the DCDCE, and the functional elements were defined. Additionally, data fusion is proposed to realize a DT framework that can respond to real-time changes. The proposed E-DT framework was implemented on a WAAM system as a case study, and it was observed that it exhibited a higher data-processing speed than the existing ISO 23247-based framework. This can enable real-time monitoring, autonomous decision-making, and interactive services for manufacturing processes, eventually leading to cost and downtime reduction and product quality improvement. Furthermore, more advanced DT technologies can be adopted to increase efficiency.

This paper proposes an edge computing-based digital twin (E-DT) framework using ISO 23247, designed to address the challenges of real-time data processing in data-intensive manufacturing environments. By decentralizing data processing through edge computing and utilizing a data fusion module for localized data categorization and compression, the proposed architecture offers several key benefits. First, it reduces network load by minimizing the volume of data transmitted to the central network, which in turn decreases latency and enhances the responsiveness of the digital twin system. Second, it ensures stable computation with fewer fluctuations due to consistent, localized data handling at each edge computer. Third, the architecture's event-driven consistency model maintains data fidelity while avoiding the computational burden of strong consistency models, allowing the digital twin to effectively support real-time decision-making in high-frequency, large-scale data environments.

Also, the reliance on edge computing introduces potential challenges in resource allocation, as the edge computers must have sufficient processing power and storage capacity to handle local data preprocessing. Additionally, while the event-driven consistency model enhances efficiency, it may not be suitable for applications that require absolute data synchronization, as it prioritizes responsiveness over strict consistency. Future research should focus on optimizing resource management in edge environments and exploring hybrid consistency models to support a broader range of manufacturing applications.

In future work, the proposed framework could be enhanced to meet industrial demands. First, the E-DT framework must be verified using a more complex system and more edge processors to verify its applicability. This study was conducted using three data sources and two edge computers. Second, it will be necessary to apply the model in additional cases involving actual industries and factories. Third, various types of data must be considered. In this study, quality monitoring was performed on image data from video frames. However, other types of data, such as numerical, textual, waveform, and sound data, can also be used in other industrial applications.

Meanwhile, the capabilities of current edge computing technologies are accompanied by several challenges, such as data security and privacy concerns, as well as resource management and scalability issues [37]. Further research should be dedicated to improving the energy efficiency of edge computing devices. Because edge devices operate in a resource-constrained environment, it is important to optimize the power consumption while maintaining high performance [40]. Accordingly, research on low-power high-performance computing models may contribute to the sustainability and scalability of edge computing for DTs. In addition, there are obstacles to integrating quality inspection processes within the DT framework, including, but not limited to, data accuracy, sensor calibration, and synchronization between virtual and physical systems [41]. Therefore, continuous research and development is required to improve the performance of DT technology. On the other

hand, the applicability of the proposed method for non-manufacturing industrial fields such as cultural heritage constructions [42] and buildings [43] should be considered.

In Section 4, we compared the network latency of the proposed and existing architectures as shown in Figure 15. It shows that the proposed approach significantly reduces the latency; however, no mathematical models have been proposed to explain the reduction of latency. Recently, Chekired et al. [44] proposed a queuing model to analyze network latency in hierarchical fog computing. Although their method primarily focuses on computing paradigms rather than on heterogeneous data integration, making it only partially relevant to our work, the concept of queuing models (mathematical models) for network latency could be referenced in the proposed method. The expected waiting time at low priority ($E[W_0]$) and high priority ($E[W_1]$) are given in Equations (1) and (2), respectively [44].

$$E[W_0] = \frac{\frac{\lambda_0}{\mu_0^2} + \frac{\lambda_1}{\mu_1^2}}{\left(1 - \frac{\lambda_1}{\mu_1}\right)\left(1 - \frac{\lambda_0}{\mu_0} - \frac{\lambda_1}{\mu_1}\right)}, \quad (1)$$

$$E[W_1] = \frac{\frac{\lambda_1}{\mu_1}}{\left(1 - \frac{\lambda_1}{\mu_1}\right)\mu_1}, \quad (2)$$

where $\lambda_0(\lambda_1)$ and $\mu_0(\mu_1)$ are, respectively, the arrival rate and the service rate of demands with (low) high priority. Since the proposed method does not assume low or high priorities, these equations cannot be directly applied to the proposed method. As future research, these equations should be modified to reflect the edge computing environment. Specifically, the arrival and service rates can be modeled as a function of system configurations based on the proposed architecture, and then the new queuing model for latency can be represented as a function of arrival and service rates.

Finally, DT frameworks with global standards, such as the OPC UA, must be comprehensively studied. The OPC UA is the main communication standard for industrial automation and can increase interoperability. However, this integration can be challenging, and compatibility and security between different systems cannot be ensured. Further research should explore ways to overcome these challenges.

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