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A framework of welding digital twin for steel structures

Ke CHEN[1]*, Weixun DUAN[2], Guichen ZHOU[3], Gang WANG[4], Linzi ZHENG[5]

[1] *National Center of Technology Innovation for Digital Construction, Huazhong University of Science and Technology, China,* E-mail address: chenkecm@hust.edu.cn
[2] *National Center of Technology Innovation for Digital Construction, Huazhong University of Science and Technology, China,* E-mail address: duanweixun24@163.com
[3] *National Center of Technology Innovation for Digital Construction, Huazhong University of Science and Technology, China,* E-mail address: zgc_0317@hust.edu.cn
[4] *National Center of Technology Innovation for Digital Construction, Huazhong University of Science and Technology, China,* E-mail address: m202371906@hust.edu.cn
[5] *College of Public Administration, Huazhong University of Science and Technology, China,* E-mail address: 2019010228@hust.edu.cn

Abstract: The significance of welding quality cannot be overstated in ensuring the structural integrity of steel constructions. However, welding operations are inherently intricate, influenced by numerous variables. This paper introduces a novel welding digital twin framework grounded in a dynamic knowledge base. This framework serves to visualize the welding procedures and forecast optimal welding parameters. Such insights facilitate informed decision-making by operators, thereby enhancing both the quality and efficiency of welding processes. Furthermore, the study employs the welding of H-beam steel as an example, wherein a digital twin welding model is established, based on which the overall welding quality can be improved.
Key words: digital twin, steel structure, welding knowledge, framework

1. INTRODUCTION

Steel structural construction is a popular industrialized construction method employed worldwide. This method predominantly incorporates steel beams, columns, trusses, and various other components fabricated from steel sections and plates. Unlike traditional concrete construction, steel structural construction replaces reinforced concrete with steel components known for their exceptional strength and resistance to earthquakes [1]. Moreover, steel structural construction presents apparent advantages, including architectural design flexibility, simplified connectivity, and reduced construction waste generation [2]. Consequently, steel structural construction finds applications in commercial buildings, warehouses, bridges, and industrial facilities.

Welding represents a pivotal joining technique in steel structural construction, which offers flexibility to meet specific architectural or engineering requirements [3]. Welded joints demonstrate the ability to withstand significant loads and stresses, thereby ensuring the robustness of steel structural components. Welding different steel components requires adherence to specific criteria such as current, welding speed, arc length, and torch orientation, all within dynamically changing work environments [4]. It is crucial to recognize that the quality of welding directly impacts the overall structural integrity of the entire building. Consequently, continuous monitoring and precise adjustment of operating parameters are essential for both manual welding and welding robots [5]. However, existing methods rely on direct observations and limited sensing devices, which do not provide an intuitive understanding or dynamic control of the welding status.

Numerous digitalized solutions have emerged to enhance the production process of steel structural construction [6]. Among these solutions, digital twin (DT) has gained considerable attention and practical implementation due to its unique attributes of virtual-real integration and real-time interaction. A DT model refers to a digital replica of physical products, assets, processes, and systems, which serves to describe and model the corresponding physical counterpart in a digital format [7]. In construction, DT integrates data from various sources, including Building Information Modeling (BIM) and Internet of Things (IoT) devices, to generate a precise and dynamic representation of the entire project or specific project elements throughout its entire life cycle [8]. However, when it comes to the application of DT in the welding of steel structural components, limited research endeavors have focused on leveraging DT's capabilities for analyzing, predicting, and optimizing welding processes and operations, creating a gap in this domain.

Hence, this study seeks to propose a framework for a welding DT designed for steel structural construction. This framework extends the conventional DT paradigm, ensuring the appropriate configuration of welding parameters and enhancing the automation level in steel construction.

2. THE PROPOSED FRAMEWORK

Figure 1 presents the proposed framework of welding DT. Within this framework, the welding process for steel structures is orchestrated through a DT model, complemented by a dynamic knowledge base. This amalgamation of DT model and knowledge base (KB) enhances the production efficiency and provides real-time visual aids to refine the welding process. The framework delineates five key components:

(1) The physical entity embodies the tangible welding production system comprising essential production equipment such as welding equipment, raw materials, worktables, sensors, and environmental conditions [9]. This entity encapsulates a plethora of dynamic and static data pivotal to the welding process of steel structures.

(2) The virtual model leverages data gleaned from the physical layer to craft highly authentic simulation models [10]. I It entails the comprehensive modeling of the welding process for steel structures from a multi-physics and multi-scale perspective, encompassing component models, manufacturing process models, and attribute information.

(3) Welding DT requires real-time sensing during actual welding operations, necessitating the collection of data from varied dimensions and perspectives. The collected data spans three primary categories: process data, material data, and equipment data.

(4) The Knowledge Discovery in Database (KDD) layer serves as the linchpin of the entire framework, driving knowledge processing through the extraction, classification, and storage of collected data within a KB. Furthermore, it entails conducting similarity calculations between repository knowledge and input data from entity production, thereby furnishing matching parameters to the virtual model. Feedback loops enable the optimization of the KB through data from the virtual model.

(5) The application layer encompasses modules such as the monitoring module, data processing module, and dynamic optimization module. Its primary functions entail monitoring welding quality, visualizing real-time sensing data, preprocessing process parameters, optimizing the welding process, and dynamically updating the knowledge base of DT.

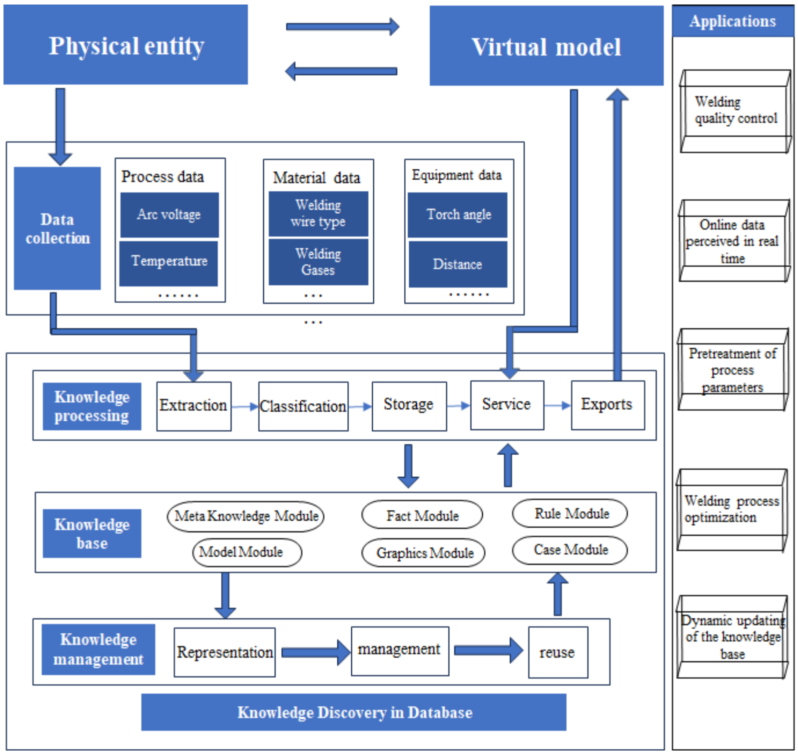


Figure 1. Welding digital twin framework

3. ENABLING TECHNIQUES

3.1. Development of knowledge base

The knowledge base is structured into three fundamental categories: meta knowledge, objective knowledge, and case-based knowledge. Meta knowledge is instantiated through meta-rules, constituting the Meta Knowledge Module. Objective knowledge manifests in diverse forms, including production rules and object-oriented representations, and is organized across the Fact Module, the Rule Module, the Model Module, and the Graphic Module. Case-based knowledge, represented through frame networks, shapes the Case Module.

(1) Meta Knowledge Module: This module governs the reasoning process for specific objectives, including the determination of problem-solving sequences, problem decomposition methods, and candidate rule set selection. Meta-knowledge, reflecting logical knowledge relations, is formalized through production rules, mimicking the human reasoning processes [11].

(2) Fact Module: This module houses a substantial corpus of knowledge concerning process procedures and parameters. This knowledge is decomposed into individual ontologies, wherein each welding process ontology serves as a knowledge object, enabling an object-oriented knowledge representation approach. Semantic connections and constraint relationships among object classes organize knowledge objects into a coherent structure [12].

(3) Rule Module: This module stipulates provisions for steel structure welding, encompassing information on welding objects, processes, quality inspection, and associated aspects. These provisions imply various constraints guiding proper welding execution, facilitating the formulation of rules using a specific formatted approach. The logical relationships among these rules necessitate the adoption of production knowledge representation.

(4) Model Module: This module comprises welding process models tailored to diverse scenarios, such as H-beams, box-section steel, and circular tube steel. Each scenario features multiple welding node models, each composed of a three-dimensional model. These models facilitate a comprehensive understanding of welding processes and associated parameters.

(5) Graphics Module: This module encompasses images, videos, scanned documents, and other non-structured data captured at welding sites. Knowledge in this module is organized according to scene classification, employing an object-oriented knowledge representation for effective management and retrieval.

(6) Case Module: This module categorizes welding scenarios, each comprising varying working conditions subdivided into sub-scenes. These sub-scenes contain various model information, attribute parameters, etc., each stored in their respective modules. The interconnection between different sub-scenarios is established through attribute relationships, forming a coherent frame network stored in the case module. Frame representation, adept at expressing structural knowledge and facilitating inheritance, enables the comprehensive representation of object relationships [13].

3.2. Knowledge storage for welding process

The repository of knowledge primarily stems from external and internal sources [14]. External knowledge collection centers around standard specifications, technical documents, and construction manuals. Internal knowledge acquisition necessitates the establishment of data interfaces within completed production management systems, facilitating the periodic gathering of production data and cases to enable knowledge updates. Given the multifaceted nature of welding practices, the asscociated knowledge inherently exhibits a complex logical relationship. The adoption of a relational database management system (RDBMS) emerges as a logical choice, ensuring data consistency [15]. Consequently, the knowledge storage database in this study predominantly employs RDBMS.

3.3. Knowledge usages for welding process

The implementation mechanism of knowledge primarily entails the utilization of intelligent algorithms to approximate production information with cases in the knowledge base, sorting them based on case similarity. The most suitable cases are selected, and their parameters are exported to the digital twin for simulation modeling. Concurrently, an appropriate welding quality evaluation system is established. Parameters meeting quality standards are subsequently output to the welding equipment.

(1) Retrieval of cases based on process similarity

The process similarity entails the alignment of both geometric and non-geometric information, which is calculated by two methods, i.e., topological structure similarity calculation and process concept similarity calculation [16]. The topological structure pertains to geometric details and model specifications within a given case, while the similarity of process concepts encompasses non-geometric information, including descriptions of welding processes, operation steps, and other parameters. For a welding process, both the topological structure and process concept are deemed equally influential in determining case similarity. Thus, the calculation formula for welding process similarity, denoted as *SimP(W),* is established to appropriately capture the combined impact of topological structure and process concept:

$$SimP(Wi)=0.5*SimT(Ti)+0.5*SimS(Si) \quad (1)$$

Where *SimT* is the similarity of topological structure, and *SimS* is the similarity of process concept.

A hierarchical topological structure can be adopted to represent the geometric information of welding processes. This structure aids in retrieving knowledge from the knowledge base. Categorization of different steel structures, their dimensions, and equipment further diversifies into various sub-scenes. Within the hierarchical topological structure, these sub-scenes, referred to as leaves, exhibit associative relationships. Solid lines within this structure denote connections between leaves and sub-leaves, as well as among different leaves. Based on these leaves and solid lines, a hierarchical structure of welding cases and new welding scenarios is delineated, as illustrated in Figure 2.

The diverse hierarchical scenarios within the topological structure are delineated as distinct computational targets. For instance, in Figure 2, the hierarchical levels of cases (B, C) and (D, F, G) represent two independent computational objectives. *SimT(T)* is computed as the weighted sum of *SimG*(g_i).

$$SimT(T_j) = \sum_{i=1} w_i * SimG(g_{i,} T_j(g_i)) \quad (2)$$

where $\sum w_i = 1$, the weights associated with higher levels are more than those linked to lower levels.

$$SimG(g_i T_j(g_i)) = \sum_{u=1} w_u * SimE(e_{u,} G_i(e_u)) \quad (3)$$

where $\sum w_u = 1$.

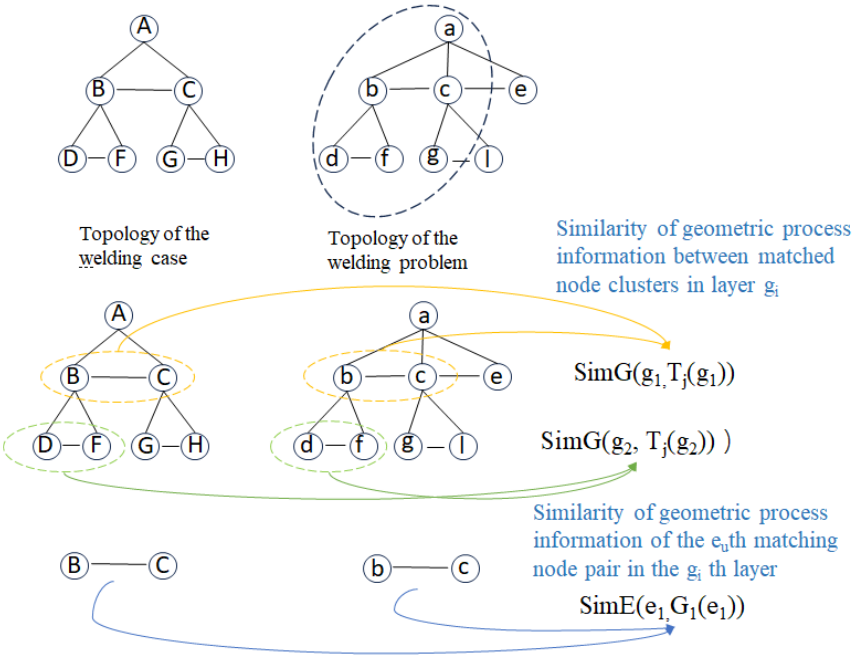


Figure 2. Topology matching

The calculation of welding process concept similarity is conducted through a weighted bipartite graph. By considering the non-geometric process information of both new welding tasks and welding process cases as distinct sets, a similarity matrix is generated between the new welding tasks and the cases. The maximum similarity pair determines the non-geometric process information similarity.

Let N represents the welding process concept in the new welding task, and C denotes the welding process concept in the knowledge base:

$$N=\{n1, n2, \ldots nq\} \tag{4}$$

$$C=\{c1, c2, \ldots cl\} \tag{5}$$

The similarity matrix for the two welding processes is denoted as S:

$$S=\begin{bmatrix} s_{11} & \cdots & s_{1q} \\ \vdots & \ddots & \vdots \\ s_{l1} & \cdots & s_{lq} \end{bmatrix} \tag{6}$$

where s_{ij} is the similarity between the non-geometric process concept n_i in the new welding task and the welding process concept c_j in the knowledge base. $m_{si,xi}$ refers to the maximum similarity value in the ith row of the similarity matrix S. Therefore, the welding process concept similarity is calculated as:

$$SimS(S_i) = \left(S\frac{\sum_{i=1}^{l} \mathrm{ms}_{i,xi}}{l}\right) \tag{7}$$

The cases are organized in descending order based on their process similarity. The case that best suits the new welding task is selected according to the similarity ranking, and the parameters are input into the model.

(2) Simulation of welding processes

In welding processes involving diverse entities such as workers, equipment, and materials, achieving an accurate mapping from the virtual to the physical realm necessitates the establishment of high-fidelity models. The proposed DT model is developed from both geometric and logical modeling. Geometric modeling encompasses the 3D representation of entities existing in the physical space, such as equipment, welding wires, and materials. These models are created using 3D modeling software like CATIA, SolidWorks, Tekla, etc., with the objective of offering comprehensive representations that accurately reflect the physical state of entities. The logical model precisely reflects how welding parameters influence the welding quality.

(3) Welding quality evaluation

By simulating the welding process with matched welding parameters input into a virtual model, the neural network algorithm can generate the geometric dimensions of the welding seam. The quality of the weld is assessed using decision attributes from the rule database in the knowledge base. Based on the quality assessment results, parameters are interactively adjusted through human-machine interaction to optimize the selection of process parameters. The optimized results are then reintroduced into the knowledge base as new cases.

4. ILLUSTRATIVE EXAMPLE

The study uses the welding of H-shaped steel structure as an example to illustrate the application of the framework. The example adopts Tekla to build the target digital model. A knowledge base is tailored specifically for welding H-shaped steel, orchestrating the welding procedure through the DT model driven by knowledge.

4.1. Developiment of welding digital twin for H-beam

The welding process applied to H-shaped steel is delineated into ten sequential steps, as illustrated in Figure 3. Corresponding models are developed based on the requisite materials and equipment involved in these steps, thereby encapsulating the geometric attributes of the entity. Properties are thoughtfully assigned to each component within the model, as demonstrated in Figure 4. This allocation encompasses both welding product properties, such as material size and equipment dimensions, and process properties, including welding temperature, arc voltage, etc.

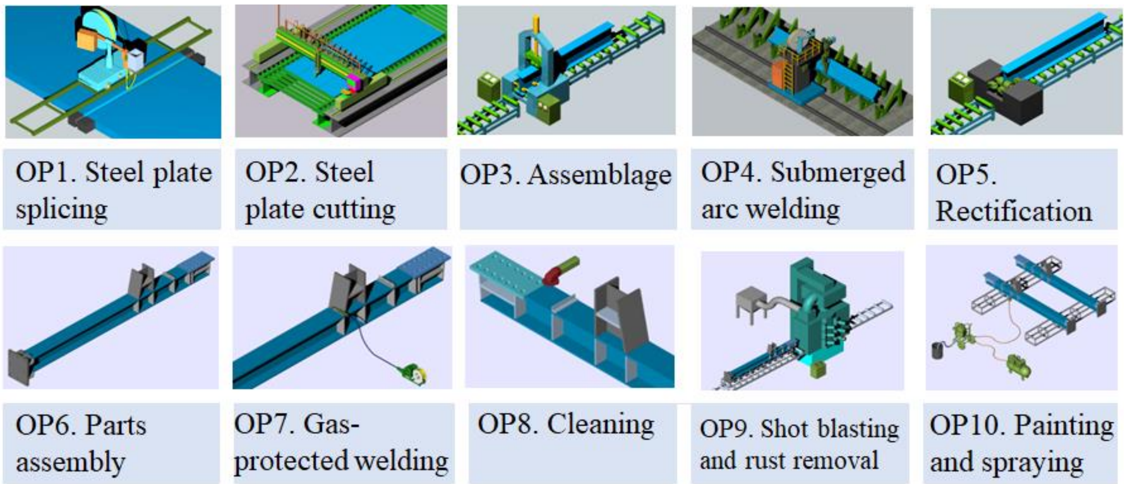
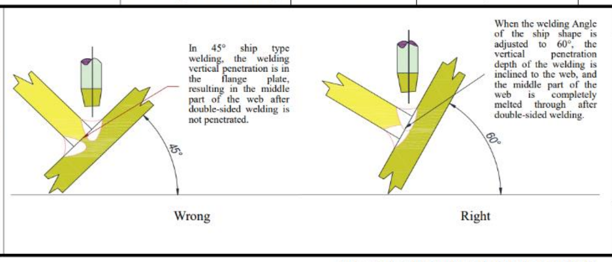


Figure 3. Digital twin modeling of H-beam welding

TECHNOLOGY	Process name	Process number	Material designation	Thickness of steel plate	Document number
	Submerged arc welding	5	Q355B	≤12mm	HLGXGYK-5-1

Process diagram



Classification	Name	Model
Equipment	Automatic submerged arc welding machine	MZ1250
	Flux dryer	
Welding material	Welding wire brand	H10Mn2
	Specification	Φ4.0mm
	Grade of flux	SJ101
	Baked condition	250~300℃/2h
Detection tool	Angle square	
	Flaw detector	

Process requirements and operation methods	
1、Implementation standard: GB50205 steel structure engineering construction quality acceptance code.	6、During the welding process, the welder can observe the temperature color brightness on the back of the web to determine the size of the current and whether the welding is thorough.
2、According to the requirements of the node diagram, the length of the point solid weld shall be ≥40mm, and the spacing shall be 200 ~ 300mm.	7、During the welding process, pay attention to the dry extension length of the wire and the flux coverage (25~30mm), and do not stop the arc in the middle.
3、Before welding, the current and voltage are adjusted on the debugging board and the welding speed is adjusted at the same time.	8、Without carbon planing, the tilting member is directly welded by submerged arc welding with high current to achieve full penetration of the weld.
4、Before formal welding, both ends of the weld should be installed with the same thickness as the base metal arc quenching plate, the length of which is not less than 150mm.	9、In order to prevent the distortion of the component, the four welds should be welded according to the same direction welding principle.
5、To ensure the penetration depth and Angle, weld the flange plate at an Angle of more than 60 degrees between the flange plate and the floor to obtain a complete penetration weld.	10、Cut off the arc extinguishing plate and mark it with welder's steel mark after the welding is completed and the appearance is qualified.

Welding parameter											Inspection requirement
No	Bead	Welding method	Power supply polarity	Groove spacing(mm)	Welding current(A)	Arc voltage(V)	Wire extension(mm)	Welding speed(cm/min)	Length of arc welding seam(mm)	Length of arc quenching seam(mm)	Appearance UT- Flaw detection
1	Front	SAW	reverse /DC	0~1	750~800	30~38	30~40	30~40	80~100	80~100	According to drawing design requirements and process requirements
2	contrary	SAW	reverse /DC	-	750~850	30~38	30~40	30~40	80~100	80~100	
3	front	SAW	reverse /DC	0~1	750~800	30~38	30~40	30~40	80~100	80~100	
4	contrary	SAW	reverse /DC	-	750~850	30~38	30~40	30~40	80~100	80~100	

Figure 4. Properties assigned to individual components

4.2. Knowledge-enabled welding process

Data concerning dimensions, equipment specifications, and other pertinent attributes related to the H-shaped steel are collected through various sensors. Subsequently, this data undergoes preliminary screening and matching within the knowledge base. Welding cases sharing similar information regarding base material quality, joint type, and welding posture are amalgamated to mitigate issues stemming from excessive data volume.

The subsequent phase involves rough matching of welding parameters, wherein cases meeting predefined criteria based on recognized features identified in the DT model are selected. This process then transitions to fine-tuning matches, encompassing individual calculations of the correlation between existing weld characteristics in the cases, with a filtering mechanism applied to exclude cases falling outside a specified error range. The parameters derived from the filtered cases are then incorporated into the model to simulate the welding process, as depicted in Figure 5.

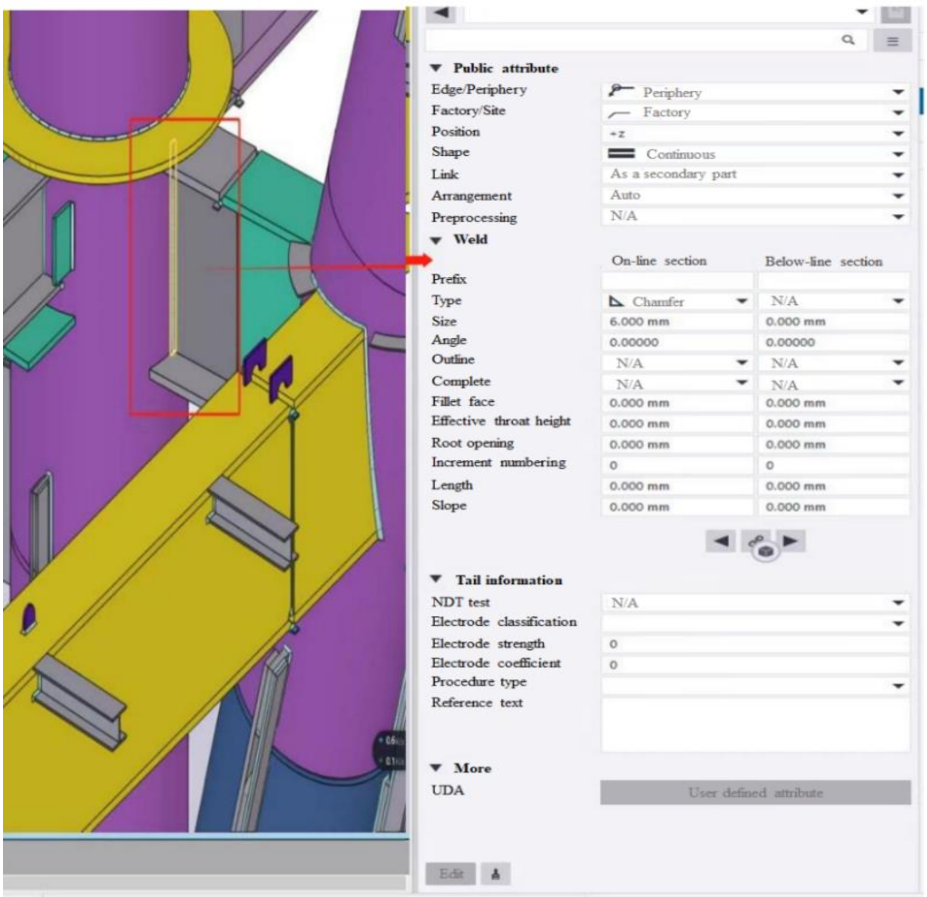


Figure 5. Parameters incorporated into the model

Leveraging the knowledge base, the welding DT can process welding parameters, mitigating quality variations attributed to manual welding through case process similarity calculation. The parameters derived from knowledge base preprocessing are then input into the DT model, where a neural network algorithm predicts welding quality, facilitating the refinement of parameters to enhance welding quality. Furthermore, the optimized parameters are extracted to update the knowledge base, thus closing the loop in welding knowledge management. This iterative process ensures the continuous refinement of welding practices.

5. CONCLUSION

This study proposes a framework of welding digital twin for steel structures. The framework facilitates the monitoring and optimization of the welding process, ultimately enhancing welding quality. The contributions of this study can be summarized as follows:

(1) The establishment of a knowledge-driven DT system for welding steel structures. This framework effectively leverages existing knowledge, thereby enhancing the decision-making capabilities of DT.

(2) Refinement of the welding knowledge base. The knowledge base is organized into six modules, which support welding process parameter preprocessing, quality assessment, and optimization strategies. All these modules act as the driving force behind the DT model. Additionally, the knolwdge base can be continually updated through case analyses and integration.

(3) Taking the welding of H-beam steel as an example, it shows the integration of geometric and non-geometric characteristics of steel components into the DT model. The case information stored in the knowledge base is used for matching, and the matched parameter information is input into the digital twin model to complete quality prediction and parameter optimization.

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