Journal of Electrotechnology, Electrical Engineering and Management (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/jeeem.2023.060508
ISSN 2560-6697 Vol. 6 Num. 5

The Seamless Collaborative Operation Technology of Integrating Equipment Control for Intelligent Laser Welding Assembly Unit

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Keywords: Integrated equipment control, data management, quality analysis, RESTful API system collaboration technology

Abstract: In the process of laser complex thin-wall component welding, there are multiple stages of data monitoring before, during, and after welding. However, the data that had been collected cannot be effectively used for quality analysis and decision-making in real-time. That had been found, the existing archived and summarized relevant quality data during the welding process had not been carried out in the exploration of mass process data in the laser welding process, as well as the dimensions of quality data management were not standardized. This paper presents a new method which is a seamless collaborative operation technology of multiple systems integrating equipment control, data management, and quality analysis based on an intelligent laser welding assembly unit for complex thin-wall components to solve this problem. The quality process data of laser welding can be structured effectively according to the stage and model, and sort out the aggregation shape by using this technology. Furthermore, the method can form a relatively reliable quality judgment index to match the welding results. Data has been analyzed and processed by the application layer, and the processing results are fed back to the superior computer. Through experiments and tests, the technology proposed in this paper can realize the rational use of process quality data after sorting out and determining the quality analysis and decisions basis, realize the seamless coordination of multiple systems for equipment monitoring data, and upper computer program control with the help of upper application technology. Therefore, the system can obtain the reliability and real-time quality analyses and decisions.

1. Introduction

Nowadays, laser welding has a very important position in the industrial manufacturing system. [1-2] However, there are multiple stages of data monitoring and collection in the laser welding process, including pre-welding, welding, post-welding, as well as the collected data cannot be effectively used for quality analysis and decision-making in real time. Therefore, this research mainly realized the model design and structured processing of laser welding process data according to stages, and stores them in the database. The upper-layer application matches the quality data with information such as welding base metal and process parameters, as well as makes quality decision-making and process parameter adjustment based on the quality judgment based on the defect model in the application. The adjusted process parameters are sent to the host computer, and the host computer updates the process parameters in time to realize the self-adaptive adjustment of the laser welding process.

The method changes the parameters of the equipment through the host computer program, so as to control the equipment by using the new parameters. Simultaneously, structured storage and time-domain acquisition of process data for equipment operation will be implemented using data management pointers. Through the analysis of quality data, quality analysis can output quality judgment result information at various stages in data management; system collaboration is to integrate equipment monitoring, equipment control, data management, and upper-level quality analysis to achieve data sharing and collaboration.

Aiming at the welding defects such as unstable welding process caused by parameter mismatch, assembly errors and other reasons in the laser welding process, Gong Jianfeng et al. based on the coaxial image sensing technology, they have established a set of laser welding process Quality online monitoring system. This system collects and analyzes the molten pool image in the welding process and extracts the feature information of the molten pool. The experimental results of Gong Jianfeng et al. show that under the laser welding test conditions of unequal thickness stainless steel sheets with a laser power of 1500 W, the instability, collapse defects, and welding deviation during the welding process have a certain correlation with the change of the characteristic information of the molten pool shape. The proposed feature information can be combined with BP neural network algorithm for data analysis. Based on the LabVIEW software platform, the automatic identification and alarm functions of corresponding defects can be realized.[3]

Currently, most of the coaxial monitoring is carried out based on experimental research, and it is extremely rare for mature industrial products to be applied in production. Germany's FILT (fraunhofer institute for laser technology) combines multi-component optical mirrors to integrate the auxiliary light source and the visual monitoring system with a CMOS camera as the main body in the same laser welding head, and successfully developed a coaxial auxiliary light source visual monitoring system.[4] This system can provide functions such as weld seam tracking, weld pool and small hole shape observation for the staff, and obtain clear images and accurate sizes.[5] Prometec also introduced the coaxial vision sensing system PD2000 for laser welding quality monitoring. The image obtained by the system can directly obtain the size information of the keyhole and the energy intensity distribution information, and can intuitively judge the defects such as discontinuity and lack of penetration of the weld.[6]

In the domestic literature related to the research on the real-time monitoring system of the laser welding process, Wu Songping et al from Huazhong University of Science and Technology designed the corresponding signal conditioning circuit based on the optical and acoustic sensing information of the molten pool, and established a hardware system of multi-sensor data fusion.[7] Yang Yongbin et al chose to use the LabVIEW platform as the system development environment to study the penetration state of laser welding seam forming, analyze the signal characteristics under various penetration states, and realize the automatic identification of penetration modes. However, the research signals are blue-violet light signal, infrared radiation signal and audible sound signal, which leads to the acquisition of one-dimensional information, which is not intuitive, and has little analysis content.[8]

In the foreign related research, the laser welding coaxial real-time monitoring system can not only realize real-time online monitoring, but also complete the synchronous analysis and processing of signals. Its application system is relatively complete, and the monitoring system manufactured in Germany is mostly used in current industrial applications abroad. In contrast, most of the domestic researches show that the information processing of coaxial monitoring system is at the research level of the laboratory, and there is no independently developed product in industrial application. The processing of some image information needs to be completed offline, so it is difficult to achieve synchronous processing in the welding process. Some researchers use the LabVIEW development environment, although the human-computer interaction is well realized, the characteristic information is mostly based on the one-dimensional information of sound and light, and the amount of information is limited.

In summary, the real-time monitoring system of laser process quality at home and abroad mainly analyzes the quality data with the help of multi-dimensional sensors, visual monitoring components, and statistical analysis platforms. The emphasis of this paper is based on advanced sensors and hardware equipment, full real-time statistics on the quality data of all aspects of the laser welding process, and integration of the welding robot PLC controller to achieve pre-welding and welding analysis, decision-making and calibration, and post-welding quality data analysis and feedback welding parameters, providing effective data support for the optimization of laser welding process parameters.

2. Technical Solutions

Based on the differences between the different stages of robotic laser welding, it is divided into pre-welding, during welding, and post-welding.

The pre-welding phase forms a pre-welding quality database with the help of the laser welding robot, tooling, bars, wall plates, and other positional information.

During the welding phase, the quality data collected in real-time at each point is uploaded to the application layer through equipment acquisition, which analyses and identifies quality problems in combination with the welding quality database and the quality judgment basis. The quality problems information can be fed back to the operator, and the robot welding can be dynamically adjusted by human-machine coordination to the workstation.

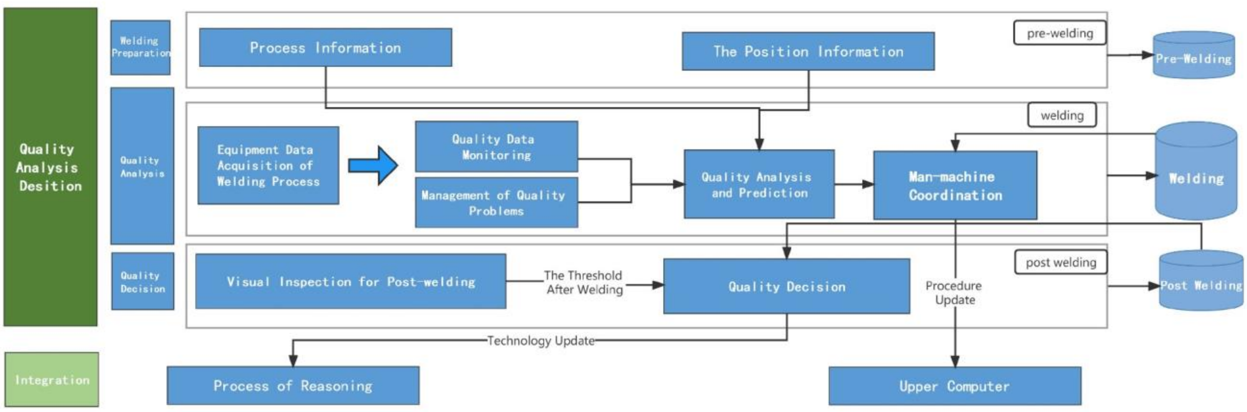

Figure 1: Business flow chart

In the post-welding stage, structural analysis is made on the information of weld, weld foot and defect collected by different butt forms with the help of external visual inspection, and quality judgment is made with the help of post-welding quality database and post-welding threshold. The judgment result is used as an effective guide to update the process in reverse, and is used to update the process knowledge base. After the knowledge base is updated, when the new base metal is welded by the welding robot, the new process is automatically obtained, and the convergence and optimization of laser welding quality problems are realized in the form of continuous iteration.

Finally, the quality data in the whole process of laser welding is effectively matched and correlated with the information of base material and process, providing effective and reliable quality data support for subsequent quality analysis and decision-making.

According to the existing laser welding quality data and quality management stage division, the pre-welding, welding and post-welding quality models are designed respectively as shown in Figure1.

3. Multi-system Seamless Collaborative Operation Technology Based on Integrated Equipment Control, Data Management and Quality Analysis for Intelligent Laser Welding Assembly Unit

3.1. Quality Model and Defect Pattern Construction Based on Expert System and Rough Set Theory Knowledge Modeling

Any text or material outside the aforementioned margins will not be printed. Expert systems emphasize the use of domain experts' expertise to solve real-world problems that require experts to solve them effectively.[9] The two core components of an expert system are the Knowledge Base (KB), which stores expertise, and the Inference Engine (IE) that uses the KB to solve practical problems. The basic structure of expert system consists of explanation mechanism, knowledge base, knowledge acquisition module, dynamic database of relevant information in solving process, data storage for specific problems, inference machine, and a human-machine interface for the system to exchange information with experts and users.

Rule-based expert system (ES) represented by MYCIN generally adopts the structure which is shown in Figure 2. This structure takes knowledge base and inference machine as the main part. The remaining part of it contains the human-machine interface, the database of knowledge acquisition procedures and the interpretation procedures. Nowadays, this structure developed from so-called generative systems is widely used in expert system development.

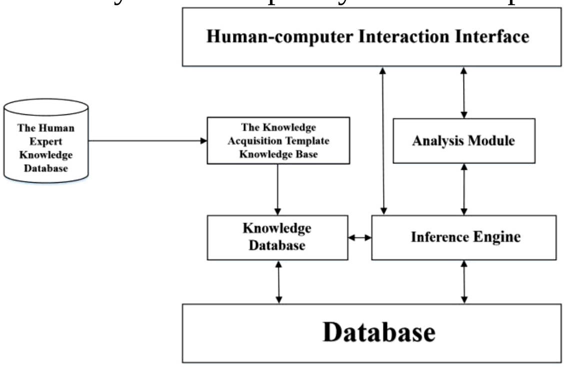

Figure 2: Expert system structure diagram

The quality judgment of the laser welding process is suitable for the development of the expert system. Because it relies on the process experience and the basic theory of laser processing technology to solve practical problems. The expert system for quality judgment of the laser welding process mainly involves welding CAD, visual recognition, welding defect or equipment fault diagnosis and so on. The problems of quality knowledge representation, quality knowledge base construction and quality knowledge management system (SWPKMS) development are solved by analyzing the real-time collection of quality knowledge data at various stages from multiple systems, and ideas such as quality analysis, data management and knowledge management. Furthermore, the ideas of quality analysis, data management and knowledge management are introduced to address the overall design, functional structure, establishment of quality knowledge base and knowledge reasoning methods of the quality defect assessment expert system.

It is difficult to find the internal laws of the system in detail from the mechanism, most of the systems have nonlinear, time-varying, time-delay and other characteristics, and neither the experimental method nor the mechanism analysis method can complete the modeling requirements. Therefore, non-mechanism modeling relying on knowledge is more suitable for quality judgment of laser welding process. Expert systems, neural networks, fuzzy modeling, genetic algorithms and other methods can be used to develop intelligent systems for quality judgment of the laser welding process. Because the laser welding process of ribbed thin-walled shell components is a complex process, it is difficult to find a unified rule, and it is difficult to obtain an accurate mathematical model. The knowledge of the laser welding process of ribbed thin-walled shell components can be obtained based on the fuzzy modeling algorithm.

To solve the problem which is difficult to obtain an accurate mathematical model of quality data during laser welding, a knowledge modeling method based on rough set theory (rough set knowledge modeling method) can be the solution. This method simplifies the decision table provided by rough set theory and obtains the system knowledge model from the experience data or experimental data of system operation. The rough set method used in modeling is completely based on the theory's understanding of knowledge. Therefore, the obtained model is called the knowledge model.

The rough set knowledge modeling method has the following six main steps:

1) Modeling data acquisition
2) Data pre-processing
3) Continuous attribute discretization
4) Conditional attribute reduction
5) Conditional attribute value reduction
6) Rule reduction

Among them, attribute value reduction rules, attribute reduction and reduction are the core parts of the model acquisition. Figure 3 is a schematic diagram of the process of acquiring knowledge model by rough set knowledge processing system:

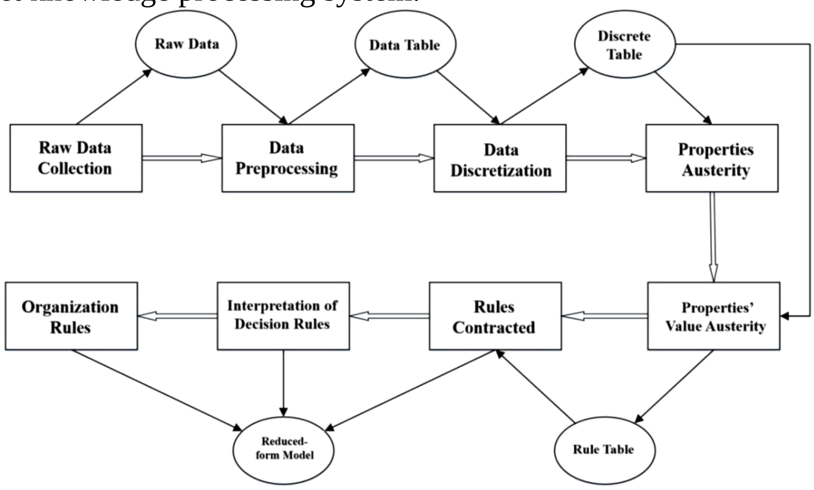

Figure 3: Basic process of RS modeling

Applied to the modeling of the laser welding process, the core concept of RS theory can be extended to the knowledge model of the fuzzy system by borrowing the identification method of the knowledge model. This method can effectively extract fuzzy models of complex processes in the case of incomplete and inaccurate data.

In this study, several attribute reduction algorithms were constructed for the laser welding of thin-walled shell members with ribs by using the welding dynamic process modeling method based on RS theory, and the solution effect was good. The knowledge model is obtained by using the modeling data of laser welding of thin-walled shell members with ribs.

The model obtained by the VPRS-based modeling method has better noise resistance and more stability than the model obtained by the classical RS modeling method. Moreover, the comprehensibility and ease of maintenance of the model are more advantageous.

In the model of different stages of laser welding process quality system, the system parameters are usually variables of some continuous value attributes, such as position of robot, position of tool, laser power, weld speed, weld leg height, weld width, etc. RS theory will discretize those continuous data, and then obtain knowledge through attribute reduction and attribute value reduction. However, the existing discretization method will lose part of the information, thereby reducing the accuracy of the RS model. To improve the accuracy of the knowledge model in the laser welding process, combining rough sets with other uncertainty sets (such as fuzzy sets, vague sets, etc.) can effectively process the fuzzy data in the system, and generating new uncertainty models.

Fuzziness is a kind of uncertainty existing in the actual structure of engineering. The so-called fuzziness refers to an objective property in that concept of the thing itself is unclear. There is no exact definition in essence, and there is no definite limit in quantity. In the objective world, the phenomenon of mutation is prone to conceptual division, but absolute mutation does not exist. The transformation of the attributes of things mostly presents a continuous form with intermediary transition, which shows that ambiguity generally exists in the objective world. The data objects of continuous-valued attributes are often ambiguous in complex information systems, and an object in complex systems may belong to different fuzzy concepts at the same time. The acquisition of fuzzy knowledge is also an important direction in the field of artificial intelligence. At present, the fuzzy rough set method is usually used to extract fuzzy rules. Generally, it need to go through the steps of (1) data collection, (2) data preprocessing, (3) data fuzzification, (4) attribute reduction, (5) rule extraction, and other steps to extract fuzzy rules. The third step of fuzzification means converting the raw data into fuzzy values. Thus, the information table of continuous attributes of laser welding is converted into a fuzzy information table. The attribute reduction of the fourth step is to define the fuzzy positive domain and dependence function of laser welding based on the given fuzzy rough set model. Then, the attribute reduction of laser welding is calculated according to a suitable algorithm. The fuzzy rough set method of laser welding which is obtained by this method has the characteristics of effectively acquiring fuzzy knowledge, reducing dependence on experience, and obtaining a simplified knowledge model. Therefore, the knowledge acquisition method based on fuzzy rough set theory is more suitable for laser welding process quality, which relies on empirical knowledge and manual teaching.

3.2. Laser Welding Real-time Perception and Equipment Interconnection Integration Common Technology for Multi-source Data Collection

This research has focused on the synchronous acquisition and networking communication structure of multi-heterogeneous systems in the laser welding process, and established a layered construction method of the Internet of Things in the workshop; This research also researched the hardware interface and communication protocol standards of related equipment, as well as that has designed and developed a universal and compatible interface docking and matching method. Through the construction of industrial fiber ring network, the interconnection between the laser welding site intelligent equipment and the upper business management system is realized.

The method is aiming at the problems of untimely acquisition of information collected in real-time in the laser welding process, incompatible protocols and the difficulty in data intercommunication. The research on multi-protocol adaptive industrial interconnection and intelligent data acquisition technology can be used to establish high-reliability equipment interconnection.

Multi-protocol adaptive industrial interconnection and intelligent data collection technology include three technical directions: multi-protocol adaptive analysis and adaptive connection technology, intelligent data collection and information modeling technology for high acquisition ratio, distributed edge computing framework-based technology for cloud-edge collaboration technology.

The efficient processing and decision-making technology based on embedded systems and deep learning, and the abnormal multi-objective optimization and decision-making technology caused by the defects of the laser welding process of deep learning and random process have formed the industrial mechanism model, data model and optimization decision-making algorithm model of the manufacturing site.

The edge intelligence-based precision control technology includes production equipment heterogeneous data aggregation and information association technology, data-driven edge control model construction technology, edge-side precision control technology based on parallel control and cloud-side collaboration. This technology can form edge equipment parameter models and real-time online control algorithm models.

3.3. Collaboration of Multiple Heterogeneous Systems based on RESTful API

The RESTful API interface can realize the universal HTTP common interface service without distinguishing the technology stack, and it can realize the human-machine interface system which is written by C/C++ to interact with this system for quality and process data; as well as it can realize the real-time data uploading and quality knowledge base data matching as the basis of judgment for the quality process data collection system based on QT/Python/C#/Java technology stack.

3.4. Quality Defect Prediction Based on Intelligent Analysis

By extracting laser welding quality data at each stage, real-time abnormality judgments are made on the quality data based on specified thresholds. In case of abnormal quality data, automatic analysis of defects can be performed to rapidly identify the causes of defects.

Through in-depth mining research of a large amount of welding quality data, a defect prediction model for laser welding is constructed. With the help of real-time analysis of pre-welding and in-welding data, the problem can be quickly and accurately located. The adjustments can be given before welding defects appeared, and achieved intelligent analysis of quality defect prediction.

Data cleaning, dimensionality reduction and denoising are carried out for the massive data collected, and invalid data are eliminated to extract the key data. A monitoring system is established for the key parameters in the laser welding process. Based on a large amount of cleaned historical data, the optimal mathematical model or algorithm is selected to predict the future operation of the equipment, so as to make intelligent early warning judgment. Figure 4 shows the quality prediction process based on reliable models.

Figure 4: Quality prediction process based on reliable models

4. Implementation

4.1. Common Data Pool Interface Design for Quality Data

4.1.1. RESTful API Interface

The RESTful API is a REST-style API, which works when a request is sent to the server from a terminal like mobile, tablet, or PC. If it is not applicable to the RESTful API, the data request for each platform has to define the appropriate return format to fit the front-end display. However, the RESTful API requires the front-end to send requests in a predefined syntax format, so the server only needs to define a unified response interface and does not have to parse all kinds of requests as before.

RESTful is an HTTP-based protocol which focuses on resources, unified interfaces, URIs, and statelessness.

Entities on the web such as text, images, audio, video are collectively referred to as resources. Resources always present themselves in a certain format. Text formats always use txt and html formats, images use JPG and JPEG formats, and RESTful APIs use JSON formats. CRUD and RESTful for business data use HTTP to correspond with them in order to unify the interface. Figure 5 describes the HTTP method set.

CRUD	HTTP Methods
Create	POST
Read	GET
Update	PUT
Delete	DELETE

Figure 5: HTTP method set

A URI is a Uniform Resource Identifier that can be used to uniquely identify a resource. a URL (Uniform Resource Locator) is a URI because it can uniquely mark a resource. However, URL! = URI, URLs are a subset of URIs. This is because URLs use paths to uniquely identify resources. It is also possible to use a unique number to uniquely identify a resource, such as example.html.fuce2da23, except that this approach is not widely used. In conclusion, it is important to make a conceptual distinction between URLs and URIs.

Stateless, which means that all resources can be located with a URI and changes to other resources do not affect changes to this resource. An idempotency concept is introduced here: whether an operation is executed once or multiple times, the effect after execution is the same. For example, a GET request is sent for a resource, if it is accessed once and if it is accessed ten times to obtain it.

The data collected from equipment before, during, and after welding are effectively extracted and effectively and uniformly controlled according to the structured model through publishing external RESTful API interfaces. The interfaces include pre-welding quality data synchronization, in-welding quality data synchronization, and post-welding quality data synchronization.

4.1.2. Interface Design

Combined with the differences in the quality data models of each stage of laser welding, the interface design is carried out respectively as shown in Figure 6, Figure 7, Figure 8.

Pre-welding interface:/moqm/preWeldingInfoSaveAll

Required Parameter

Parameter Names	Parameter Description	Request Type	Whether Must	Date Type	schema
Authorization	Token	header	true	string	
+ preweldingInfoList	preweldingInfoList	body	true	array	PreweldingInfo

Response Status

Status Code	Description	schema
200	OK	Result«List«PreweldingInfo»»
201	Created	
401	Unauthorized	
403	Forbidden	
404	Not Found	

Response Parameter

Parameter Names	Parameter Description	Type	schema
code		integer(int32)	integer(int32)
+ data		array	PreweldingInfo
msg		string	

Figure 6: Pre-welding interface documentation

Welding interface: /moqm/weldingInfoSaveAll

Required Parameter

Parameter Names	Parameter Description	Request Type	Whether Must	Data Type	schema
Authorization	Token	header	true	string	
+ weldingInfoList	weldingInfoList	body	true	array	WeldingInfo

Response Status

200	OK	Result«List«WeldingInfo»»
201	Created	
401	Unauthorized	
403	Forbidden	
404	Not Found	

Response Parameter

Parameter Names	Parameter Description	Type	schema
code		integer(int32)	integer(int32)
+ data		array	WeldingInfo
msg		string	

Figure 7: Welding interface documentation

Post-welding interface:/moqm/alfWeldingInfoSaveAll

Required Parameter

Parameter Names	Parameter Description	Request Type	Whether Must	Data Type	schema
Authorization	Token	header	true	string	
+ list	list	body	true	array	AlfWeldingInfo

Response Status

200	OK	Result«List«AlfWeldingInfo»»
201	Created	
401	Unauthorized	
403	Forbidden	
404	Not Found	

Response Parameter

Parameter Names	Parameter Description	Type	schema
code		integer(int32)	integer(int32)
+ data		array	AlfWeldingInfo
msg		string	

Figure 8: Post-welding interface documentation

4.1.3. Knife4j Interface Service Documentation Released

Knife4j is an enhanced solution for integrating Swagger to generate Api documents for the Java

MVC framework.

The predecessor of Knife4j was swagger-bootstrap-ui. In order to fit the development of the micro-service architecture, the original swagger-bootstrap-ui uses the back-end Java code + front-end Ui mixed packaging method. It is very bloated under the microservice architecture. Therefore, the project was officially renamed knife4j.

Main areas of focus after the name have been changed:

The front-end and back-end Java code and the front-end Ui module are separated, making it more flexible to use under the microservice architecture;

Providing an enhanced solution focused on Swagger is different from just improving the front-end UI part. The code of Knife4j configuration requirements is shown in Figure 9.

```
@Configuration
@EnableSwagger2WebMvc
@ConditionalOnExpression
@EnableKnife4j
public class Knife4jConfiguration{
     @Bean(value = "defaultApi2")
     public Docket defaultApi2(){
         Docket docket=new Docket(DocumentationType.SWAGGER_2)
                .apiInfo(new ApiInfoBuilder()
                         .title("Backsatge Frame  Interface File")
                         .description("Backsatge Frame")
                         .termOfServiceUrl("http://192.168.1.60:8081/")
                         .contact(new Contact("seven potato","http://192.168.1.60:8081","gongyueca@hotmail.com"))
                         .version("2.1.0")
                         .build())
                 .groupName("2.Xversion")
                 .select()
                 .apis(RequestHandlerSelectors.basePackage("com.zm.backstage.controller"))
                 .paths(PathSelectors.any())
                 .build();
         return docket;
      }
}
```

Figure 9: Knife4j configuration requirements

4.1.4. Post-Welding Quality Data Model and User Interface Development

Based on the Angular front-end development framework, the MVVM-based quality prediction model management function is quickly built.

1) Angular Development Framework

There are seven modules in the Angular framework: components, directives, data binding, modules, templates, services, and dependency injection [9].

Module is used to segment files, ensure the import sequence of JavaScript files, and load the corresponding class library correctly.

Directives extend the functionality of an element and add new behavioral features to a specific DOM element. Directives are used like HTML element attributes, except that they are customizable attributes.

Component: Another type of instruction, which builds a small organizational code unit, each code unit has a clearly defined responsibility and can be reused in multiple applications. In each angular application, there is a component tree, which consists of top-level root components, sub-components and sibling components, which can intuitively show the composition of the UI interface, and simultaneously show the data flow from one component to another.

Template and data binding can introduce Html through template or template URL to detail the interface content rendered by angular. Furthermore, the data binding mechanism can map data to the template or call data from the template.

Services and Dependency Injection: In Angular, if components are used to handle interface interaction, then services are where developers write and place reusable public functions (log management, permission management) and complex business logic. Services have shared functionality and can be reused by multiple components. In Angular, a service is a simple class used to perform data analysis and complete logic.

The application can be decoupled by adding “@Injectable” decorator to the class which implements the service and registering with the Provider.

Modules that depend on template views to interact with the user in the elements can make up the component. The role of the component class is to maintain the functional logic and data model of the component, and the component class is another element. Directives enhance a template's features and extend its syntax, and routes allow application interface switching. The service part encapsulates the unit of functional logic and can be introduced into the component. The angular framework is shown in Figure 10.

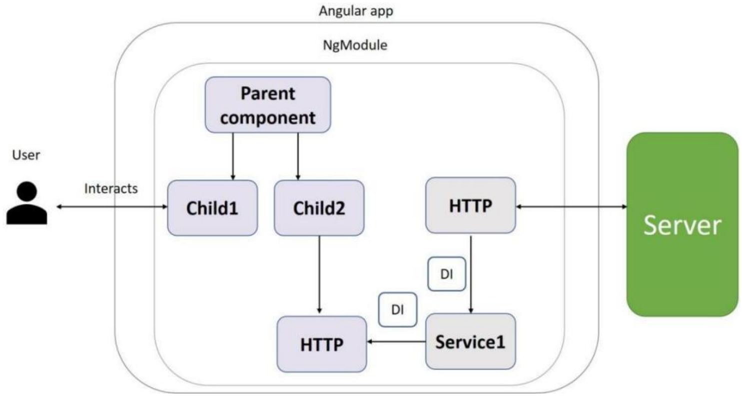

Figure 10: Angular framework

2) Quality Data Model, Defect Model Design

Establishing end-to-end quality data of laser welding process and process data association, monitoring each link of laser welding data are necessary. Once abnormal product quality or quality is found, the big data analysis system can automatically help technicians quickly analyze the main factors that may lead to the problem, and quickly locate the problem point and solve the problem in time. Through a variety of modeling methods, the correlation between data can be found, and the trigger point of quality problems can be pre-positioned to improve the efficiency of laser welding quality control.

The correct relationship between the data and product quality can be found via collecting all test data and attribute data related to the quality for each stage of laser welding as well as analyzing the relationship between the data and product quality data by using algorithms such as decision trees, neural networks, support vector machines, clustering. The parameters affected by quality fluctuations are controlled in a targeted manner as shown in Figure 11.

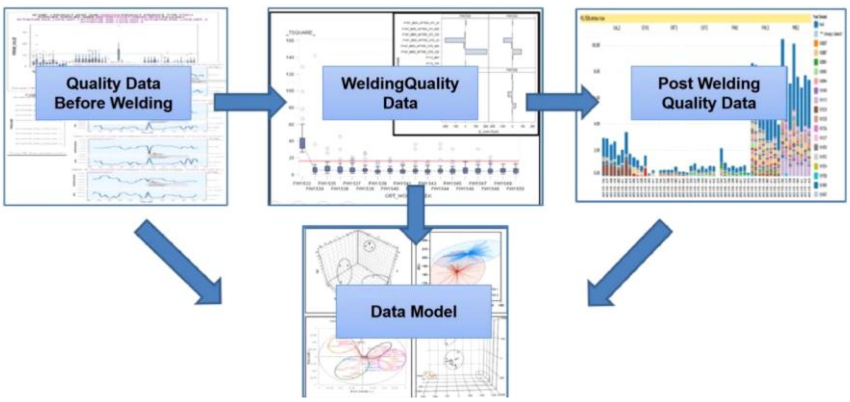

Figure 11: Design framework of quality data model

3) Design for Quality Defects

With the help of the quality defect model design, it is analyzed the key that affects the quality of laser welding lies in the height of welding leg and the angle of welding seam after welding. After the database design which is based on the model parameters is completed, the realization is considered by maintaining the threshold information after welding and based on the base metal, butt joint. The post-welding threshold is allocated according to the method and other information to realize the association between the threshold and the material data. With the help of knowledge base for post-welding quality data and model-based quality prediction analysis, threshold information is used as a key factor in defect model identification. Figure 12 and Figure 13 show the threshold definition/ assignment implementation.

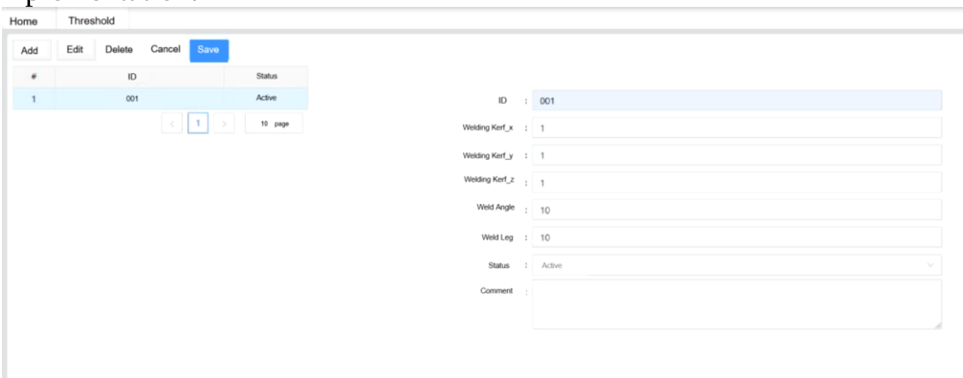

Figure 12: Threshold definition implementation

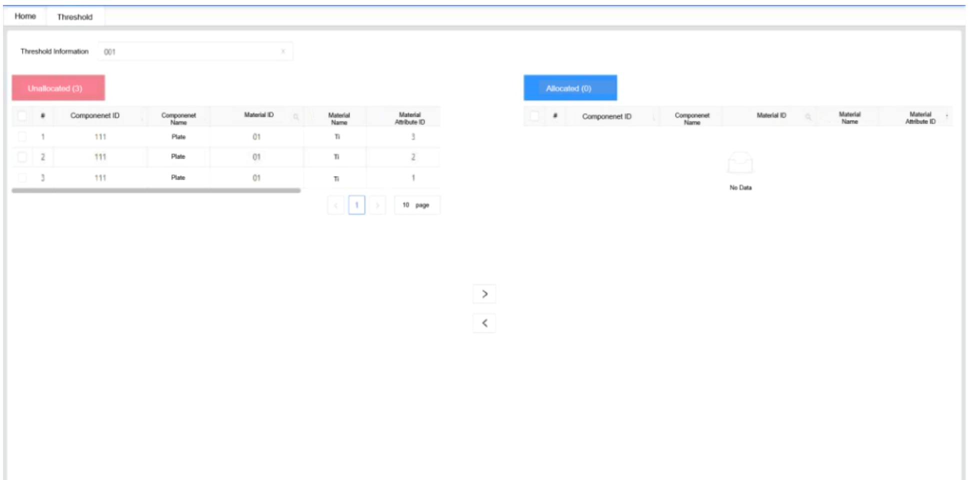

Figure 13: Threshold assignment implementation

4) Implementation Design for Process Quality Data Management

The quality data model can be used to distinguish the quality knowledge base of laser welding for the three stages of pre-welding, welding, and post-welding. The database design is carried out with the help of the data collection of equipment in the whole process and stage of laser welding. The quality data is pushed according to the dimensions of base material and process. A complete quality data pool based on the model provides effective and reliable data support for quality analysis and decision-making. Figure 14 shows the development interface of quality database for pre-welding.

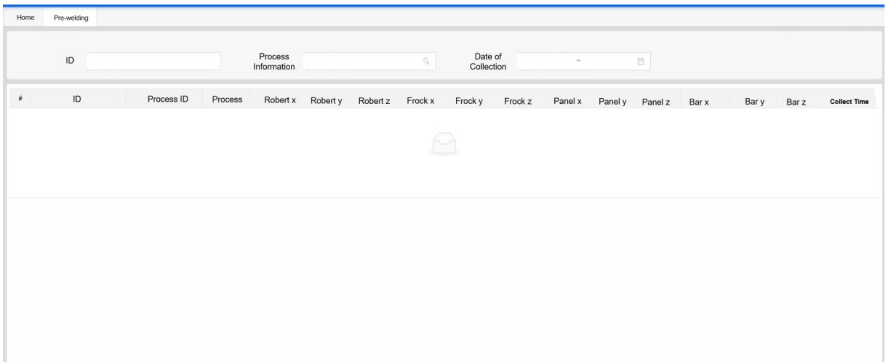

Figure 14: Quality database for pre-welding

5) Implementation Design for Quality Decision-making

To make full use of the welding process quality data pool under the current quality model, and integrate the quality defect model for intelligent decision-making of quality problems, the quality problem record is formed by analyzing the post-welding quality data, as well as the process reverse optimization can be initiated based on the record, and the new base metal will automatically match the optimization process when the new base metal is welded in the same form again.

When the quality data is pushed before, during and after welding, the system will firstly match each link of laser welding to see if there is valid knowledge data in the corresponding quality database. With the help of the valid quality knowledge data, reliable quality analysis and judgment can be made to provide timely guidance. Operators can carry out effective follow-up operations to achieve structured and unified management and effective and rational use of quality data throughout the entire process.

4.2. Programming Languages

The data processing part is developed using Java, Python and Go languages, the database is developed by oracle platform, the background engineering simulation and calculation part is developed by MATLAB. Data collection will use python/C++/QT/C# language to collect related data by establishing hardware interface with PLC language. The results of this project can be used in conjunction with relevant intelligent production lines, it also can make perfect use of all valid data, and mine interesting data for users.

4.3. Experimental Test and Output

The main methods of software testing are "black box testing" and "white box testing".

Black box testing is the main testing technique, and the internal code of the program being tested is not displayed to the testers. Testers are primarily concerned with whether the program inputs and outputs are correct. Testers do not need to review and test the code.

White box testing is a software testing technique known as out-of-the-box testing, whereby testers gain a clear understanding of the inner workings of the project being tested. In the white box testing process, the compiled test code is usually used to complete the test. Testing is accurate only if the tester knows what the program is supposed to do. The tester can clearly observe the goals of the program and whether it achieves them. However, white box testing cannot account for errors caused by omissions, and all visible code must also be readable.

The software testing process usually needs to complete white box testing and black box testing. In this study, the output laser welding quality system has passed the black and white box tests.

5. Conclusions

In this paper, we establish a laser welding quality model that fully considers the quality concerns of robotic laser welding at each stage of the welding: pre-welding, welding, and post-welding. Summarizing these findings is valuable for future research, we clarify a method to achieve close binding of process and quality based on the refinement of quality data for each stage of welding model design-process quality data which is the fusion of base material information and welding parameters. The model has focused on pre-welding position, laser parameters during welding, post-welding foot/weld seam and other information, and ultimately to rely on the abstract refinement of the quality model to open up the effective interaction with process data.

This study is also based on the quality data collection and laser welding data model of each link for the multi-faceted system, the external release of the standard quality data synchronization RESTful API interface, the interface uses HTTP transmission protocol to achieve a multi-technology stack based on C/C++, Python, QT, C#, Java and other interface calls. The quality data has been pushed for robot equipment parameters and HD camera visual recognition data before, during and after welding respectively. Furthermore, a seamless integration between the data collection equipment and the process quality data pool has been opened up. The quality analysis decision-driven process-oriented tuning has been completed. In the laser welding, quality data model is completed and all aspects of quality data collection can be properly invoked under the premise of quality data synchronization interface that is based on post-welding quality data analysis, as well as matches quality knowledge base comparison and outputs the quality problems. Laser welding process parameters can be effectively tuned based on quality issues, while pushing the new process to the process knowledge base, using post-welding quality decisions to drive process optimization, and making full use of process quality data to achieve continuous improvement of process design. However, this study only captures the key quality characteristic factors for the abstraction and simplification of the quality model due to the complexity of laser welding quality data, the multi-dimensional nature of the welding process parameters and the limitations of the existing process, process quality data inventory. After analyzing, the current data of other dimensions do not have the conditions for model building.

To distinguish the stages of the laser welding process, robot, tooling, wall plate, bar position information before welding are focused on; the abstraction of several key process features affecting laser welding parameters: weld point, welding speed, laser power, trajectory information have been focused during welding; several key points affecting the evaluation of welding quality after welding, such as weld position, weld angle have been summarized.

With the continuous accumulation of process quality data, the system can be used to dock the data collection, carry out decision-making and process optimization, as well as verify the reliability of the existing model. If the optimization results do not converge with the model, the data analysis results, welding process characteristic values, quality features and computing model can be used to simulate the optimized process quality data model. In this way, the reliability of the quality analysis results can be continuously improved.

Acknowledgement

Thanks are due to Jiang Zhang for assistance with the experiments and to Jing Yang for the valuable discussion. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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