Data-Driven Welding Expert System Structure Based on Internet of Things

Chao Chen, Na Lv and Shanben Chen

Abstract With the development of the information technology, the new techniques such as Internet of Things (IOT) and artificial intelligence are introduced into welding manufacturing. This paper introduces a new technique, data-driven welding expert system based on IOT. During welding process, the various sensor information including optical information, electrical information and sound information can be detected to assist welding monitoring. The application of IOT will make it easier to collect and integrate welding information. The data-driven welding expert system can learn and summarize the expert knowledge from these raw welding data without interacting with welding experts. In the end, the paper introduces a structure of data-driven welding expert system based on IOT and demonstrate its function.

Keywords Data-driven · Welding expert system · Multi-sensor information Internet of things

1 Introduction

It's obvious that, with the fast development of science technology, many new technologies have gradually influenced and changed industrial manufacturing. Nowadays, the fast development of industrial manufacture is based on the development of nine technologies [1], which are big data and analytics [2, 3], autonomous robots [4], simulation [5], horizontal and vertical system integration [6], the internet of things (IOT) [7–9], cybersecurity [10], the cloud, additive manufacturing [11] and augmented reality [12]. Because of the development of these emerging technologies, great changes have come into the welding manufacturing industry. This paper introduces a new technique, data-driven welding expert system based on

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IOT, which will be demonstrated in the follow three sections. Section 2 introduces the application of IOT in welding manufacture industry. Section 3 demonstrates the various welding information sensor techniques that includes electrical information, optical information and sound information. Section 4 introduces the application of expert system in welding manufacture and mainly elaborates the data-driven welding expert system based on IOT. Section 5 concludes the whole paper.

2 Welding Manufacture Based on IOT

With the technique development of Internet of Things (IOT), the production mode of the welding manufacturing industry has changed a lot. Through doing a series of researches about how IOT affects manufacturing industry, we learned that Shi Yong Wang use a brief framework of the smart factory based on IOT [13]. In the framework, the smart factory consists of four layers: physical resource layer, industrial network layer, cloud layer, and supervision and control terminal layer. As shown in Fig. 1, physical resource layer is based on smart device that can communicate with each other through industrial network. Various information systems, such as manufacturing execution system (MES) and enterprise resource planning (ERP), exist in the cloud that can acquire massive data from the physical resource layer and interact with people through the terminals. This actually forms a cyber-physical systems (CPS) where physical artifacts and informational entities are deeply integrated.

Zuehlke [14] uses a pyramid framework to demonstrate the architecture of intelligent factory based on IOT, from field devices (sensors/actuators) and programmable logic controllers (PLC) through process management and manufacturing execution systems (MES) to the enterprise level (ERP) software. As is shown in Fig. 2.

Kemppi's ArcQ [15] all-round welding quality management system is the first integrated system that systematically integrated the welding manufacture and IOT. Its implementation figure is as Fig. 3. ArcQ's management of welding quality is reflected in the following areas:

Fig. 1 A brief framework of the smart factory of IOT

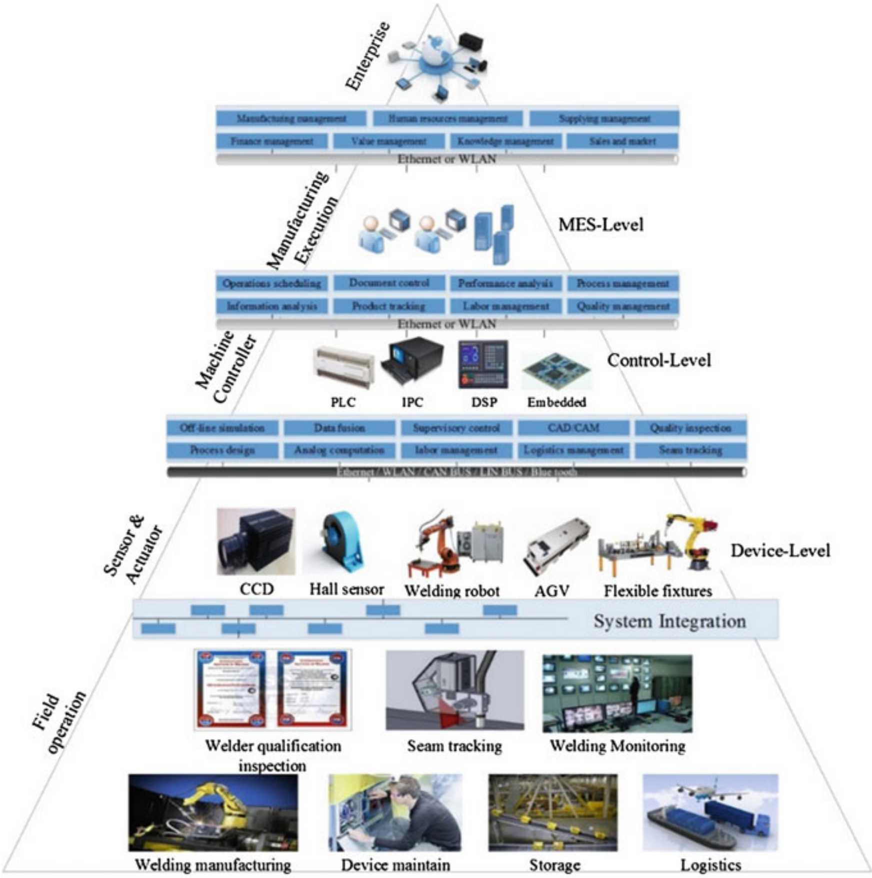


Fig. 2 A pyramid framework architecture of the intelligent factory base on IOT

1. A comprehensive and in-depth management to welding operators. ArcQ identify the qualification of welder at the beginning of welding to assure the welding is completed by correct, qualified and capable welder.
2. Based on WPS, keeping all welding operation following WPS standard. All ArcQ parameters come from WPS. All welding data will be compared to WPS demanding data.
3. Strict management to the use of welding materials. ArcQ demands that welding can start only after check welding stick, welding materials and process number. ISO3834 demands traceability to used materials.
4. Implementing all-time record and management to welding machine's pre-maintenance, use condition, use time. ArcQ can provide welding machine's all pre-use and after-use report to users and inspection department.

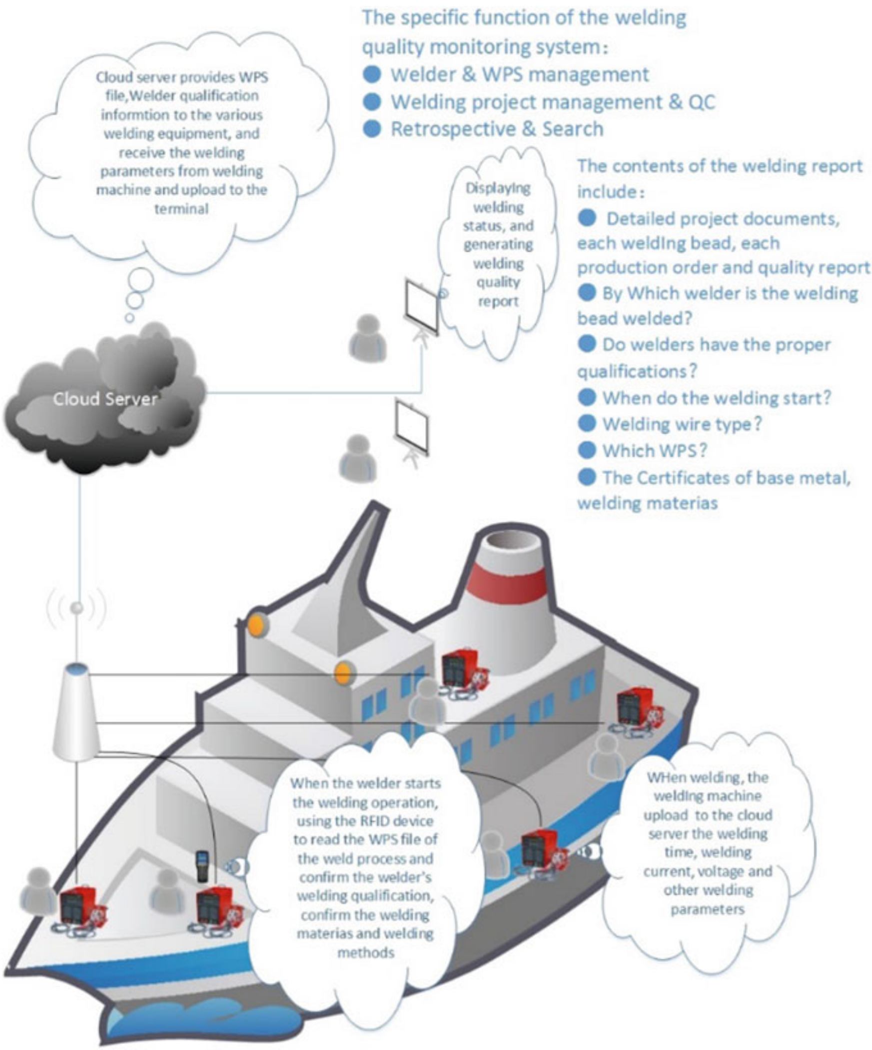


Fig. 3 ArcQ all—round welding quality management system

5. Full-process and full-time record and real-time delivery of all demanding welding parameters. Through above feedback, ArcQ can shorten time that problem is found and reduce the loss caused by problem. Not only can welding quality be improved, but also efficiency can be enhanced.
6. Only after dealing with all welding deviation, welding can proceed. When the welding deviation occurs, the system promptly alarm, ArcQ requires that the qualified operators must deal with the deviation, or the error record will remain unsettled state. ISO3834 has the same strict demand too.

7. Strict limit to operating authorization of welding operators, managers, technicists. Only by doing this, the dealing of welding deviation can be completed by correct operators, which conforms to ISO3834 demands.
8. Complement quality report. All WPS required parameters during welding can be recorded in units of 200 ms and can be permanent preservation.
9. Offering qualification management and performance appraisal for welding managers and human resources. Welding workpiece number, welding success rate, deviation number, deviation causes. These data can be used in manufacturing management and individual performance management.

3 Welding Information Sensing and Analyzing

Due to the development of IOT, the welding process data can be obtained and integrated more easily. There are a lot of researches about welding information sensing technique. In [16, 17], Shanben Chen presents a systematic overview on multi-information sensing technique of arc welding dynamic process. In [18], Zhifen Zhang demonstrates multisensory data fusion technique and its application to welding process monitoring. A series of welding information sensing technique are discussed as follows:

3.1 Electrical Information

As far as the electrical information is concerned, welding current and arc voltage is the parameters detected most commonly. As both of them have good ability of detecting the abnormal welding state such as excess or lack of welding gas, mismatched welding feed rate and so on [19]. Despite all this, it is still difficult to distinguish the specific factors that influence the normal welding state only by detecting and analyzing the welding current and arc voltage [20, 21].

3.2 Optical Information

The type of welding optical information includes the optical spectrum emission and vision information. The two types of optical information will be demonstrated from academic perspectives as follows.

Optical Spectrum Emission

Optical spectrum emission information has a lot of advantages. First, it contains abundant welding process information, which include spectral lines of the various particle in arc plasma and black-body radiation spectrum line of electrodes, molten metal and protective gases. Second, optical spectrum emission has a high sensitivity and accuracy. Besides, there is no direct influence on the welding system during acquired process of optical spectrum emission information. So the objectivity and accuracy of measured information can be guaranteed. There are two main method that extract the features. The one is extracting the plasma physical characteristic parameters such as arc temperature, electron density by analyzing wavelength and intensity of specific spectrum line. For instance, Mirapeix [22] measured electron temperature of corrosion resistant plate AISI-304 by using relative intensity temperature measurement of two spectral lines during welding process. The other is obtained geometric, morphological and statistical parameters such as peak value, spectral linewidth and intensity mean value through analyzing specific or many spectral line or section of spectral line. For example, Shea [23] realized a real-time Ar arc H concentration detection system by using the intensity comparison between 656.3 nm HI spectral line and 696.5 nm ArI spectral line. Sibillano [24] found that there is a strong relevance between weld seam surface oxidation layer caused by loss of Al and spectral area of Al(II) of 559.79, 625.04, 704.73 nm wave length and Mg(II) of 571.69, 766.9, 789.70 nm wave length, by analyzing active plasma arc spectral line during AA5083 aluminium alloy laser welding.

Vision Information

Welding visual information is mainly from the visible light information, which can directly reflect the dynamic change of welding pool and weld seam. It has abundant information which includes welding pool state, arc form, weld seam position, joint type and so on. The welding visual information can be divided into two categories according to the difference of objective light source. They are active mode and passive mode [25]. The visual sensor can be divided into the two dimensional plane mode and the three dimensional cubic mode according to image feature acquired by visual sensor system [26, 27]. In recent years, the research hotspot mainly focus on the weld seam shaping control [28], weld seam tracking [29], the initial welding position guiding [30] and welding defect detecting [31]. That extracts passive visual information mainly depends on the arc light and welding pool black-body radiation. Xu [32] developed a real-time seam tracking control technology base on passive vision system in robotic gas tungsten arc welding. The active visual information need the extra light source such as laser which is used to illuminate weld seam. And the geometrical information of weld seam and weld pool can be obtained by analyzing reflected laser stripes. Song [33] designed a set of welding pool visual detecting system combined by dot matrix laser and high electronic shutter camera. The clear dot matrix reflected image of welding pool can be obtained through this detecting system. In [34], ShanBen Chen establishes a welding robot system with single camera fixed on the weld torch end-effector for the robot to identify the dimensional position of typical weld seam by one-item and two-position method. It can be used to acquire weld seam dimensional position information in welding robot system.

3.3 Sound Information

The sound signal can be divided into AE(Acoustic emission) and AS(Audible sound). The acoustic emission signal [35, 36] is elastic stress wave signal taking place during the plastic deformation occurs inside of material. Its frequency can reach dozens of million Hz. Kannatey-Asibu [35] applied the acoustic emission sensor technology during the process of arc welding and laser welding to monitor the welding state. The audible sound signal can be transferred into voltage signal through vibrating membrane of the sound sensor. The processing method can be mainly divided into two categories: the one is extracting and analyzing feature in time domain, frequency domain and time-frequency domain; the other is extracting feature through building arc sound channel mathematical model by using LPC method. There is many researches about arc sound during the welding process. Arata et al. [37] tried to extract welding sound feature and explore the effect of welding parameters on welding sound. Lv [38] implemented a real-time monitoring system of welding path in pulse metal-inert gas robotic welding using a dual-microphone array.

3.4 Other Welding Information

Besides the above common welding information, there are many other types of welding information, such as temperature information, ultrasonic information and so on. They reflect dynamic welding process from different perspective, delivering welding quality information directly and indirectly. For example, Nagarajan [39] realized the real-time monitoring of welding dynamic process based on infrared sensing technique. In [40], the designed real-time ultrasonic testing device based on resistance spot welding can detect the broken welding spot and can reach 100% accuracy. However, duo to the complexity of welding process and limitation of sensing medium, every welding sensing technique has its own limitation.

4 Welding Expert System Structure

4.1 Traditional Welding Expert System Structure

The expert system is a computer software system that uses a knowledge repository that solves practical problems that can't be solved in a particular way in a particular domain. It is a branch of artificial intelligence application [41]. It is characterized by the ability that program expert knowledge of various fields. By relative inference method of the expert system program, the ordinary operators can input the initial data and question. Then the expert system can give the operator the relative

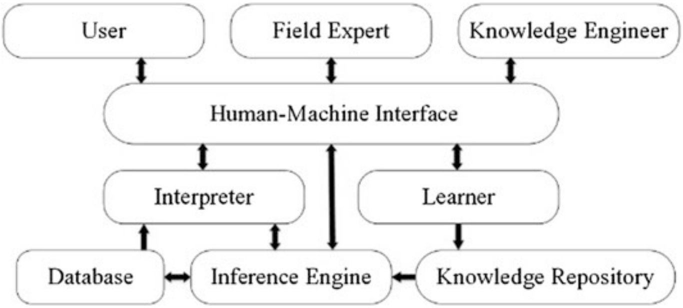


Fig. 4 Traditional welding expert system structure

conclusion of expert level. The traditional expert system structure is shown as Fig. 4. As the welding is a very complex process that need various decision information, which causes that many welding parameters cannot be confirmed through quantitative functional equation unless that giving the quantitative conclusion after qualitative judging welding condition. Nowadays, there are many examples that the expert system is applied to the welding field as shown in Table 1.

By analyzing the various welding expert system, we can find that the welding expert system can be divide into seven types according to the different function:

Table 1 Welding expert system example

Name	Type	Source	Country
Welder qualification	Welder qualification test	Danish Welding Institute	Denmark
Weldcrack expert	Defect diagnose	TWT	Britain
PREHEAT PLUS	Defect diagnose	Edison Welding Institute	America
Weld estimating	Cost estimation	Stone&Webster Engineering	America
Weld procedure selection	Welding process selection	Stone&Webster Engineering	America
Weld assist	Welding process design	Kuhne Cary and Printy	America
Weldex	Welding process design	Technical University of Berlin	Germany
SAW—Ship building environment	Welding process design	Queen University of Belfast	Britain
Weldgen	Welding process design	TW1	Britain
Weld symple	Welding structure CAD	CSM	America

welding process designing type [42], defect diagnosing or equipment failure diagnosing type [43, 44], real-time welding monitoring type [45], welding CAD designing type [46], welder qualification testing type [47], welding robot equipping type [48]. And the ultimate purpose of various welding expert is to control shape and property of welding products.

4.2 Data-Driven Welding Expert System Structure Based on IOT

Due to the powerful welding sensor technology during welding monitor process, on average, about 0.5 GB data will be generated per weld seam. As for the heavy industry and mass production industry, there will dozens of TB data will be generated every day. As the technique development of IOT, the data acquiring process will be easier and the method of data analysis will be more advanced.

As the welding data increases, the welding statistical feature will be more obvious and play a more important role in welding process analysis. However, it is obvious that the knowledge repository of the traditional welding expert system shown in Fig. 4 can't learn from these actual manufacture data and sensor data. It can only update its knowledge repository by interacting with welding expert and welding engineer. The Human-machine Interface module and Learning module of welding expert system can transfer the welding expert knowledge into the form that the computer can understand. The data-driven welding expert system can update its knowledge repository through analyzing and summarizing these welding data.

The Key Technique and Hot Topics

In Fig. 4, it is obvious that the core of traditional welding expert system is its knowledge repository and inference engine. The traditional knowledge repository is used to restore the knowledge offered by experts and engineers. And the knowledge presentation technology of expert system includes rules, semantic net, framework, script and language expressing knowledge such as KL-1, KRYPTON and concept map. In the data-driven welding expert system, the knowledge is created through analyzing welding manufacturing data. The data-driven expert system can: (1) extract effective data from manufacturing noise data; (2) transfer data into information; (3) transfer information into knowledge; (4) summarize the knowledge into the meta-knowledge. So it is one of the key technique to extract meta-knowledge from noise data.

Inference engine can obtain the conclusion aiming at the current problem according to the known information and condition input by users. There are two reasoning methods: forward reasoning and backward reasoning. The strategy of forward reasoning is to find out the rules that can match the input condition and to use the conflict elimination strategy to select one of these satisfied rules to change the contents of the original database. This is done repeatedly, until the database's facts are consistent with the goal, finding the answer, or stopping when there are no rules that match it. The strategy of backward reasoning is to proceed from the selected target and find the rule that the consequence can be achieved. If the premise of this rule matches the fact in the database, the problem is solved; otherwise, the precondition of this rule is regarded as new Sub-goals, and find new sub-goals can be applied to the rules, the implementation of reverse sequence premise, until the last rule of the premise can match the facts in the database, or until no rules can be applied, the system will be dialogue The form asks the user to answer and enter the necessary facts. The design of inference engine is another technique point of data-driven welding expert system.

The Structure Design of Data-driven Welding Expert System

The structure of data-driven welding expert system is shown in Figs. 5 and 6. Two kinds of expert system are exhibited such as welding process designing expert system and welding monitoring expert system. Distinguished from the traditional welding expert system, the data-driven welding expert system can update its Predicted System module (the Interpreter module in Fig. 4) by learning from welding manufacture data. In this structure, the Classification/Regression Model module substitutes the traditional inference engine that can only understand human expert knowledge.

The core of data-driven welding expert system knowledge repository is its data processing method that can analyze the raw welding data and induct the proper expert rules. The machine learning method plays an important role in data-driven welding expert system. Machine learning is a field of computer science that gives computers the ability to learn without being explicitly programmed [49]. Machine learning method can be classified into three categories according to their learning "signal" and "feedback". They are supervised machine learning, unsupervised machine learning, reinforcement machine learning. Supervised learning is the machine learning task of inferring a function from labeled training data [50]. The common approaches and algorithms include artificial neural network, decision tree

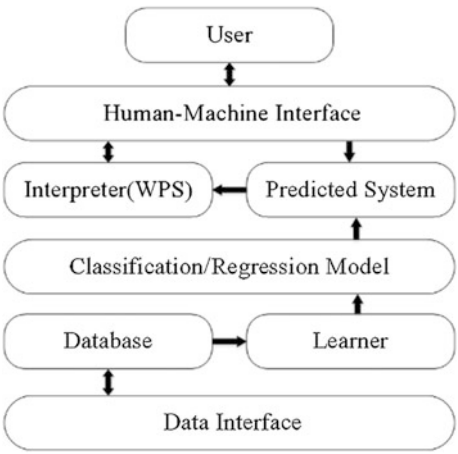
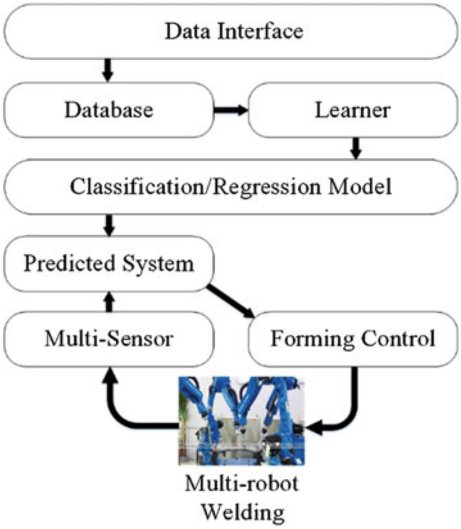


Fig. 5 Welding process designing expert system

Fig. 6 Welding monitoring expert system



learning, support vector machines, random forest and so on. Lv [51] applied a BP-Adaboost Model to predict welding penetration state during pulse GTAW process. Zhang [52] implement a multisensory-based real-time quality monitoring for Al alloy in arc welding by means of SVM-CV wrapper. Unsupervised machine learning is the machine learning task of inferring a function to describe hidden structure from "unlabeled" data (a classification or categorization is not included in the observations) [50]. The common approaches to unsupervised learning include K-means, mixture models, PCA, manifold learning, t-SNE and so on. Wu [53] used t-SNE and DBN model to monitor VPPAW penetration state based on fusion of visual and acoustic signals. Huang [54] used an improved K-medoids algorithm to select the arc spectral line of interest. Reinforcement learning (RL) is an area of machine learning inspired by behaviorist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward.

There are many researches about data-driven welding expert system. Wang [55] designed a GTAW procedure expert system based on neural network. The welding expert system can present the welding procedure specification (WPS). And its database design was based on the C/S mode. The neural network model was established to implement the welding procedure design. The welding expert system can update its function accuracy by expanding its welding case in database. Zhan [56] designed an intelligent welding procedure qualification system for Q345R SMAW. The system consisted of three sub-system, welding procedure design expert system, welding procedure document manage system and prediction system with artificial neural networks. The welding procedure design expert system can generate WPS document according to the user's initial input condition. Then the WPS document was input into the prediction system and the welding procedure qualification report (WPQR) document will generate by calculation of artificial neural network. If the WPQR is not qualified, the system will demand redesigning the WPS until the corresponding WPQR can meet the requirement.

The Application of IOT in Data-driven Welding Expert System

This paper provides a structure of data-driven welding expert system based on IOT which is shown in Fig. 7. The welding expert system is based on B/S mode. The user can access the WEB server through the browser and submit the initial welding demands. The welding procedure design expert system on the WEB server will feedback the proper WPS document. The user can present the WPS document to the field device. When the welding process starts, the welding information can be detected by multi-sensor. The welding information including welding current, arc voltage, welding pool image and weld seam image will be sent into the predicted system. Then the predicted system will give out welding qualification report to the Forming Control module. The Forming Control module will compare the calculated welding qualification with the demands of WPS. By real-time rectifying the deviation between the calculated welding qualification and WPS demands, the welding expert system can obtain the aim of controlling welding formation and property. More than that, the welding expert system can self-learning by updating its database according to actual welding case. The bigger data size the database has, the more accurate the expert system will be.

And the display interface is shown in Fig. 8. On the browser, we can manage relevant welding operators and welding material. The WPS document can be generate according to input weld condition by users and can be appointed to the corresponding welding project. The welding process information and WPQR document of corresponding weld project will be send back and displayed on the browser. These data will be restored in the database and serve as the weld raw data to update the data-driven knowledge repository of welding expert system.

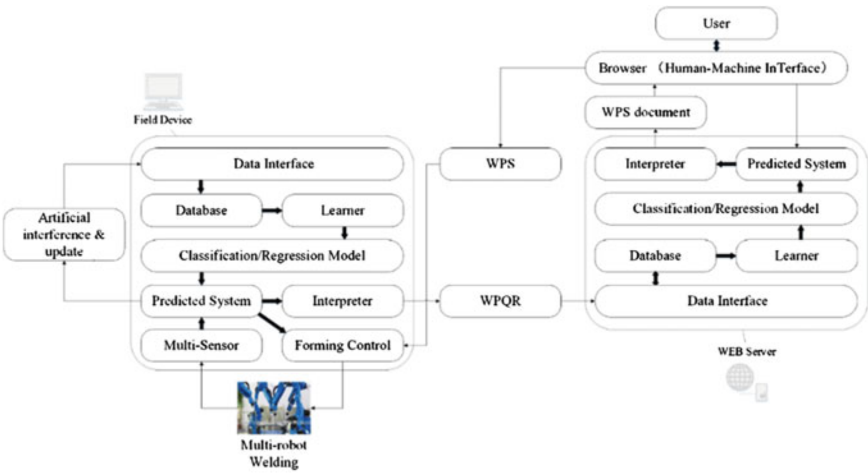


Fig. 7 The structure of data-driven welding expert system based on IOT

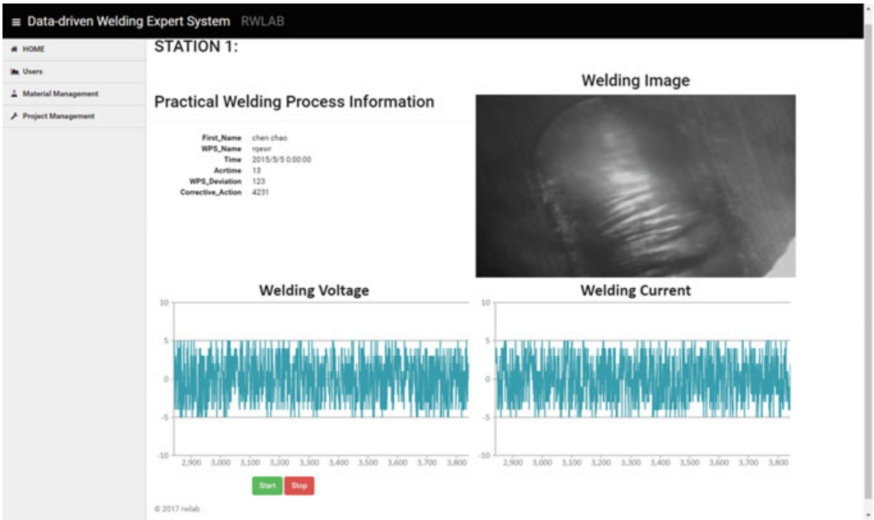


Fig. 8 The display interface of data-driven welding expert system based on IOT

5 Conclusion

With the development of the weld technique, there comes a lot of technique innovation in the welding manufacture industry. The strong sensor technique makes it more convenient to get welding process information including welding current, arc voltage, welding sound and optical information. The innovation of IOT accelerates the process of data collection and integration. As data scale increases, the statistical features of welding data can't meet the requirement of welding manufacture. The artificial intelligence plays a more important role in welding manufacture industry as it can learn from welding data and provide more information and function. As a fatal branch of artificial intelligence, the expert system can assist welding manufacture effectively. The main goal of welding expert system is to control welding formation and property. However, the traditional welding expert system can't update its knowledge repository unless depending on the interaction of filed expert and welding engineer. So the data-driven welding expert system will be a trend in future because it can learn from the raw welding case and summarize its expert knowledge to update its knowledge repository. So the paper constructs a structure of data-driven welding expert system based on IOT.

The core problem of data-driven welding expert system is its establishment of knowledge repository and designation of inference engine. In the future work, we need to combine the expert system and data-driven method such as machine learning effectively. The establishment premise of specific self-learning knowledge repository is to make data-driven method extract the expert rules from welding noise data.

And the matched inference machine mechanism need to be designed to calculate out the proper conclusion through using the expert rules in knowledge repository.

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