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Review

Overview of recent advances of process analysis and quality control in resistance spot welding

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ABSTRACT

Resistance spot welding (RSW) is frequently employed in current industrial occasions. However, the process is multi-field coupled and highly nonlinear, and full of uncertainties and disturbances. This paper presents recent primary advances and progress in process analysis and quality control of the RSW operations. Online welding process analysis, and relative online quality estimation for the welding products, are very important because they can help to save energy and improve the efficiency during actual production. It should deeply interpret the process characteristics, and then reasonable relations between selected monitoring process variables, such as dynamic resistance or electrode displacement, and quality criteria, such as nugget size or tensile-shear strength, can be established. Apart from online process analysis using mathematical tools, using different kinds of auxiliary measuring signals from external sensors and intrinsic process variables to monitor the process and obtain the quality information of the weld is presented and discussed. Then various process control works are reviewed. Besides the various parameters optimization methods, kinds of controllers, including feedback controllers, intelligent controllers and comprehensive controllers which combined the online quality estimation and control strategy application together, for obtaining welds with satisfactory quality, are respectively discussed. It can be seen that the establishment of general models to online process analysis, quality estimation and real time control system design for obtaining welds with satisfactory quality still remains a big challenge in reality. This work can provide references and enlightens for current academic researches or actual production in RSW relative area.

Contents

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1. Introduction

Resistance spot welding (RSW) is extensively employed in joining sheet metal components, such as in the manufacturing of automobiles, trucks trailers, buses, recreational vehicles, office furniture and appliances, railway vehicles, airplane structures, aeronautical and space applications and many other products [1–5]. Especially in the automobile industry, over 90% of assembly work in a car body is completed by RSW [6]. The automotive structural assemblies use groups of spot welds to transfer load through the structure during a crash. Typically, a modern vehicle includes 2000–5000 spot welds [7]. These are the main reasons that the RSW is employed extensively currently. The main advantage of the RSW is that the process can be automated and robotized in high volume for high production rate operations. However, RSW process involves interactions between electromagnetic, thermal, mechanical, fluid flow and metallurgical phenomena across faying interfaces and so that is very complicated [8]. The process is difficult to properly control because the final weld quality is determined by interaction between various operational parameters and mechanical/electrical characteristics of the machine and equipment involved. In general, a modern automotive production line of high volume models produces approximately 7 million welds per day [9]. Hence, to ensure the integrity of the welded structure and improve the efficiency of the welding production, the recent advances of some important aspects during the RSW process, including online process analysis and monitoring, online non-destructive weld quality estimation and control system design to guarantee the high quality, are considered in this paper.

During the traditional RSW working process, two or more parent metal sheets are pressed together by electrode force, which is usually controlled by air pressure in the pneumatic cylinder, or servo actuator. After the parent metal sheets are fixed, external electrical energy is delivered into the welding system and the welding current goes through the parent metal sheets, then heat energy is initially generated at the interface of the metal energy due to contaminations and surface asperities, so that the interface has the largest resistances at the beginning of the process [10,11]. The amount of energy delivering into the welding system follows the commonly used energy generation equation:

$$Q = \int_{t_1}^{t_2} I^2(t)R(t)dt, \tag{1}$$

where Q denotes the energy delivered into the welding system in Joule, t_1 and t_2 respectively denote the beginning and terminating time of the welding action, $I(t)$ is the welding current, $R(t)$ is the total resistance between two electrodes, in general cases, the resistance of the welding load dominates the total resistance [12,13]. The heat energy makes the temperature of the parent metal increase and some solid metal melts, and then the liquid metal appears initially from the interface of the parent metal sheets. As more and more amount of energy delivered into the welding system, more solid is melted to form the liquid nugget. It can be seen that the RSW process is a metal absorbing energy followed by melting and solidification. The amount of heat depends on the applied welding current $I(t)$, the material of the parent metal, which determines the resistance $R(t)$, and the welding time t. As the temperature changing during the process, phase transition occurs in the parent metals. Hence, the resistance $R(t)$ is a varying parameter, and called dynamic resistance, which can approximately denote the resistance of the welding load because the effects of other components can be ignored generally. When the amount

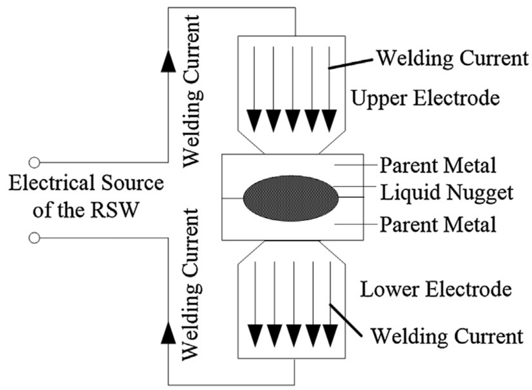

Fig. 1. Schematic of the RSW process.

the liquid nugget achieves a predetermined level, the external electrical energy delivery terminates, then the liquid nugget solidifies and the original separated parent metal sheets are joined together. Fig. 1 shows the schematic of the process.

In Fig. 1, the welding current is generated from a special electrical source of the RSW system. Actually, because the welding loads are sheet metal, their resistances have very small values, and the value of welding current is so large. During the process, the maximum value of the welding current depends on the capacity of the electrical system and the load resistance.

In addition to the above conventional RSW process, to meet the requirement of making welds on the auto-body floor, or welds that are located in closed-section parts that ordinary RSW gun cannot access, or some other new structures which the conventional RSW is not applicable, single-sided RSW has been developed to conduct the work [14,15]. Especially, it is frequently used in integrating the hydroformed tubes without flanges into vehicle body structures [16]. Using this RSW scheme, spot welds can be made using only single-sided access with or without a backing plate. Actual application of this modified process exhibits many special characteristics. Previous works have explored its characteristics using numerical simulations [16], actual experiments [17] or designed adaptive control algorithm [18]. As the single-sided RSW machine is approximately the same as the conventional RSW machine, it will not be separately discussed in following sections.

Moreover, the RSW process can be divided into small scale RSW and large scale RSW processes, according to different thickness of the metal sheets. The thickness in the small scale RSW is usually less than 0.2–0.5 mm, while the large scale RSW welds sheets of thickness greater than 0.6–0.8 mm. The small scale RSW was commonly used in the electronic components and devices. Currently, there is fewer literature dealing with small scale RSW than that of large scale RSW [19,20]. Because of different contact areas between the RSW processes, the small scale RSW has some different characteristics when compared to the traditional large scale RSW. For example, the magnitudes of electrode force, current density, heating rate and peak temperatures between the two kinds of RSW may be different [20–22]. However, because the two processes follow the same fundamental mechanism, basic operations, measurement and control process, cooling way of the electrodes, and other relative aspects, no further distinction will be discussed in this paper regarding large scale RSW and small scale RSW.

In general, there are two kinds of electrical source of RSW: single-phase AC power source and three-phase medium frequency DC power source both commonly applied in industry. Both of two sources are prevalently employed in reality. As they have different energy transmitting modes and can generate different effects during the process [23–25], they are used in different occasions [26]. However, no matter which power source is used to determine how much energy is delivered into the welding system, only one control parameter can be used during the process. This parameter is the firing angle of Silicon-Controlled-Rectifier (SCR) for single-phase AC power source and the duty cycle of Pulse-Width-Modulation (PWM) wave for three-phase medium frequency DC power source. Then the energy is delivered into the welding system through a step-down welding transformer in both of two types. In other word, it is a single input and single out (SISO) system. In addition, since the control actions in both types of power sources are conducted in the primary coil of the welding transformer, but the processes of metal melting and liquid nugget formation and growth occur in the secondary coil of the welding transformer, it is difficult to adjust the control action in real time according to the information of liquid nugget formation and growth. Because of the existence of the step-down welding transformer, it is a low-voltage-high-current circuit in the secondary coil, any tiny change in the secondary coil can induce a big fluctuation in the primary coil [27]. Moreover, there are a lot of uncertainties and disturbances, such as surface roughness or contaminations [28], poor fit-up condition [29], electrode wear [30,31], axial or angular misalignment [32,33], and so on. Even for the parent metal sheets from the same batch, the quality of the welds, such as tensile-shear strength or nugget size, may have large variations when the same welding schedule is conducted.

To overcome the drawbacks of uncertainties and variation of the weld quality and obtain the welds with high quality, the characteristics of RSW process should be thoroughly interpreted. Then corresponding measures can be taken to assure the stability of the process and consistency of welds quality. Many previous works considered the problems. A lot of scholars wanted to establish models to simulate the process, and then to explore the features and regular patterns. In addition, some auxiliary measuring signals from various external sensors, such as digital camera, acoustic microscopy or infrared camera, can also be introduced to monitor the process and relate the input variable and welding products. Also, some process variables were used to describe the process, in other works, they can be used to be sensors by means of mathematical tools. Moreover, based on the different concerns, some scholars took efforts to optimize the control variables or design various corresponding controllers so as to improve the weld quality during the process.

In this paper, some recent contributions and primary advances of process analysis and quality control in RSW operation will be reviewed. Section 2 will consider the online process analysis and online quality monitoring and estimation, which includes the process analysis using mathematical tools, and the online quality estimation using different auxiliary measuring signals from external sensors or intrinsic process variables obtained during the welding process. Section 3 will deal with the process control. The section includes the parameter and control process optimization of the RSW, and different kinds of controllers were presented to obtain the welds with satisfactory quality. The last section of this paper will be the concluding remarks and suggestions for the future works.

2. Online process analysis and quality estimation of the system

The product of the RSW operation is the welds, and during the process solid metal sheets melt with the formation and growth of a liquid nugget. Following of the withdrawal of the external energy, the liquid nugget solidifies and then the original separated metal sheets are joined together. During the process, the melting phenomenon is completely enclosed between the parent metal sheets, as a result, observation and measurement are strictly constrained. However, using proper methods to online observe the process and explore the variation of the metal sheets is very important in reality, because it can not only guarantee obtaining welds with satisfactory quality, but also avoid expulsion occurring, which is because the amount of liquid nugget is so large and the surrounding solid metal cannot hold it under the squeezing by the electrode force, the liquid nugget spills. Hence, for the one and only purpose of assuring the quality of the weld, the principle goal of RSW research has been to examine and control the process [34]. Traditionally, the tensile-shear strength of the weld can sufficiently present the joining quality. It is the most common quality estimation criterion in the previous works. However, measuring the tensile-shear strength is destructive and time-consuming and costly, and the method can only be done on a sample basis. In many works, nugget size, especially the nugget diameter, is also used as a quality estimator in realty, because it is closely proportional to the tensile-shear strength [32,35,36], and nugget diameter is specified in the handbook published by Resistance Welder Manufacturers' Association as an indicator of weld quality. Hence, a correlation between nugget size or nugget diameter and heat energy delivered into the welding system should be sought. The goal of online process analysis and quality estimation is to explore the correlation and seek the effects of input variables on the quality of the welding products. To achieve this goal, different tools and methods were employed.

To sufficiently understand the process and obtain the information of the weld, the review for previous works will focus on three aspects: 1. using mathematical tools to establish models to simulate the process; 2. using auxiliary measuring signals from external sensors to investigate the welding process; 3. using intrinsic process variables to monitor the process.

2.1. System modeling using mathematical tools

The modeling of welding process relates to the materials characteristics and internal changes of the parent metal sheets. Due to the high nonlinearity of the process, using analytical method is very difficult. There was a very small number of works about using mathematical or physical analytical tool to analyze the resistance spot welding. One contribution [37], which was about expulsion exploration and prediction, established the analytical model to analyze how the expulsions occurred. According to the force equilibrium equations and relative analyses, the effective electrode force was considered the most important element to induce the expulsion. It can be observed that the analytical method is difficult to be employed to establish effective multi-field coupled models for RSW system and earn comprehensive achievements actually.

Finite element method (FEM) has frequently been employed to analyze the complex process, because it has more advantages in solving problems with large deformations and can be used for many kinds of engineering problems, especially with complex geometry and material combinations [38]. In addition, the results obtained from the FEM modeling could be useful

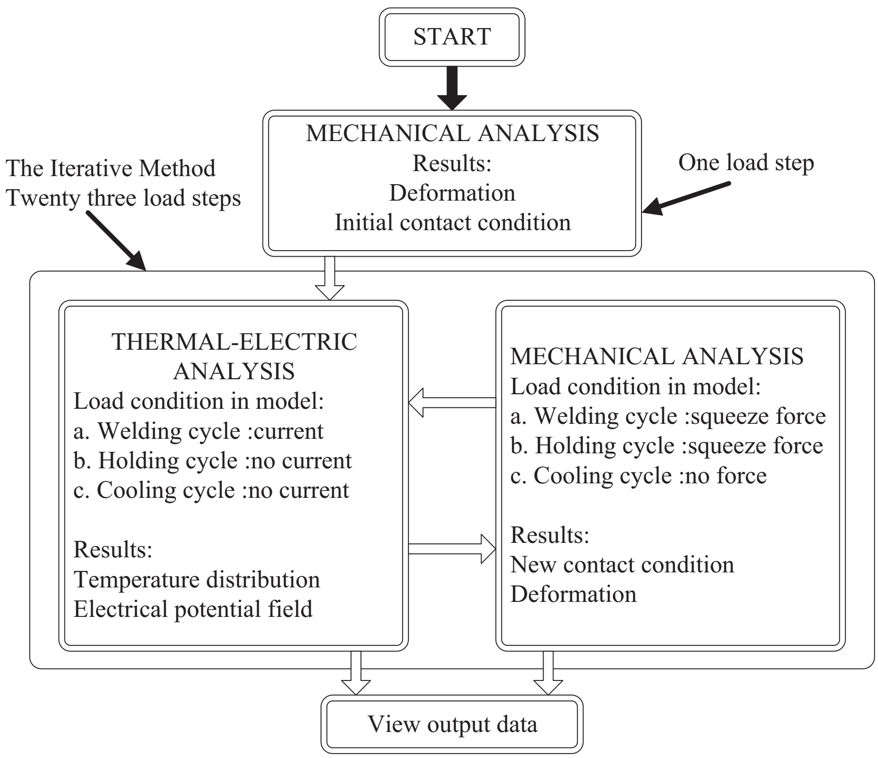

Fig. 2. Flow chart of the FEM program [40].

for clarification of the complicated nature of the interrelated electric, thermal, mechanical and physicochemical welding process, and be expected to facilitate proper control and improvement of the welding system [39].

Recently, a lot of works employed FEM to simulate the RSW process. The following reviewing contributions focused on various contributions using FEM calculating and analysis method. Generally, the RSW process can be considered as an electrical-thermal-mechanical coupled process, hence, the most significant work using FEM to analyze the RSW process is establishing appropriate models and then combining them so as to simulate the special process, based on the characteristics of RSW process. Due to the symmetric nature of the electrode and the parent metal sheets, a half or a quarter of the physical model was usually used to simplify the calculation. In order to quantitatively understand the effects of the different parameters, such as current density, welding time, sheet thickness and material, geometry or other conditions of electrodes, electrode force and current shunting, contact resistance and the nugget size at different cycles, Eisazadeh et al. [40] employed a commercial finite element code ANSYS to model the couplings between electrical and thermal phenomena and between the thermal and mechanical phenomena. The power source used single-phase AC type. The flow chart is shown in Fig. 2 [40].

Based on Fig. 2, the subroutine defines the squeezing cycle as a single load step and divides the welding time into 23 load steps. The APDL language was used to compute the nodal temperature distribution and updating of deformed geometrical information. The model was a half of the actual physical model for two dimensional (2D) analysis. To verify the reliability of the model, actual experiment, which used the same conditions with the FEM model, was conducted. Through measuring the actual nugget size, the result showed that a good agreement between calculated results and measured data for the nugget size. For example, the thicknesses of the molten zone were respectively 2.12 mm and 2.23 mm for the calculated and measured results. Also, the model can predict the temperature distribution and nugget size in the joint, and help to achieve an optimum parameters setting. This work can predict the temperature distribution and spot nugget size in different cycles, through adjusting the parameters, optimum setting of the welding parameters for the desired quality can be obtained. Hence, it has a significant active meaning for the academic research and actual production.

In addition, to investigate the heat and mass transport laws in the weld nugget, and then to reveal their evolution during the welding process, Li et al. [6] proposed a multi-physics coupled model to simulate the RSW process using a single-phase AC power source. According to the axisymmetric characteristics of the RSW operation, a simplified model in this work employed a 1/2 axisymmetric sub-model to analyze the electric characteristic, a 1/4 axisymmetric sub-model to do fluid dynamics analysis, and a 1/4 3D wedge-shaped sub-model to accomplish the magnetic field analysis. Then an incrementally coupled procedure was used in this work. The sequence was electrical analysis, 3D magnetic analysis and the fluid dynamic analysis, and at the holding phase, only the only the fluid dynamic analysis was employed. The model comprehensively considered the coupling of electric, magnetic, thermal and flow fields, and used the temperature-dependent physical properties and phase transformation to examine the RSW process. The commercial software ANSYS was employed. Combined calculations and relative analyses, the work obtained the relation between liquid metal moving features under the effect of magnetic field, and the heat transport pattern in different phases. The drawback was that because the induced magnetic field could not be removed from the real weld nugget formation process, the experimental methods did not have the capability to explore the difference of the welds with and without the induced magnetic field. Also, in their other contribution [41] which employed approximately the same simplified method, a magnetic fluid dynamic model was proposed to investigate the fluid flow and heat transfer behaviors in the liquid nugget. The model included a 2D asymmetrical electric-thermal-flow

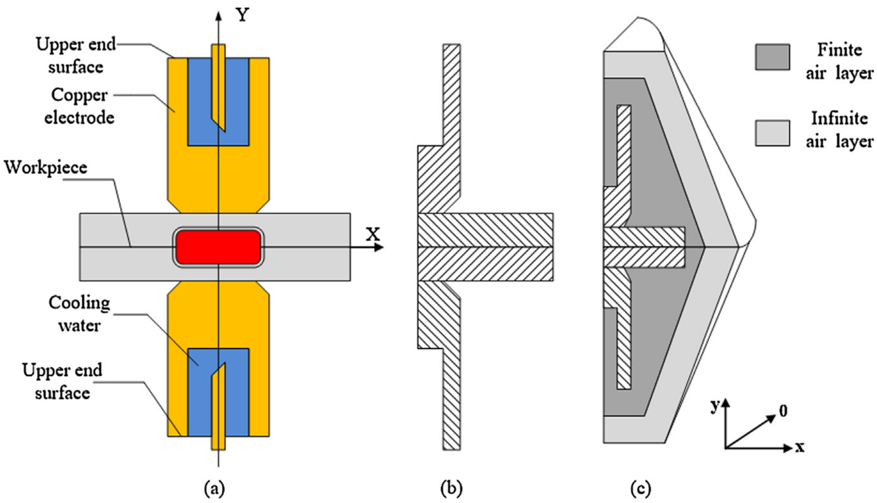

Fig. 3. Metaphysics coupled model used in the work. (a) Schematic view of a RSW process, (b) 1/2 asymmetrical electric-thermal-flow model, (c) 3D wedge-shaped magnetic field model [41].

sub-model and a three dimensional (3D) wedge-shaped magnetic field sub-model, and comprehensively considered electric field, magnetic field, thermal field and fluid flow. The model can be shown in Fig. 3 [41].

The model was a little more complex than that of the preceding work [6]. Through corresponding calculation, some significant achievements had been gained, and the work showed that the effectiveness of Finite element model in simulating the magnetic fluid dynamic behavior in RSW process and predict the nugget growth. The members in the same group also provided a numerical analysis for single-sided RSW process used in sheet-to-tube joining [16], according to the simulation using ANSYS, they concluded that the electrode force was crucial to the formation and shape of the nugget, under the special conditions of the work, and modifying the electrode force during the process was a valid method for obtaining acceptable nugget, with less welding control cycle and energy delivery. The work provided a guided method for optimizing the parameters and improving the quality of the ring nugget for this special application.

Moreover, there were many relative works employing FEM models to do relative analyses, Chigurupati et al. [42] developed a coupled model, which included the thermal, mechanical, electrical and metallurgical sub-models, and used DEFORM™ to execute the simulation, and obtained that some critical process design variables, such as applied current, pressure, the welding time and hold time, had strong imparts on the quality of the final product. Vural's work [43] also employed a combined thermal-electrical-mechanical simulation system to study the formation of the welding nugget and the effect of welding process parameter on nugget shape and size. To explore phase transfer process and variation characteristics of weld pool of RSW for aluminum, Khan et al. [44] proposed a three-dimensional thermal model, and then obtained the effects of some welding parameters, such as welding current, faying surface electrical contact resistance, and electrode-workpiece thermal contact conductance, on the nugget and heat-affected-zone (HAZ) geometry. Also, the phase change morphology, including melting and solidification rates and weld pool dynamics, and the relations between nugget growth and the welding current and faying surface electrical contact resistance, were obtained. Nodeh et al. [45] employed an electro-thermo-mechanical model to predict electrical potential, temperature, residual stress distribution and their effects on the heat transfer and nugget formation during the different stage of the RSW process, and then the result of the model was compared with the actual measured residual stresses and observed a good agreement. The simulation results showed that the maximum tensile residual stresses were located at the weld center while they were reduced towards the nugget edge. In addition, Wei et al. [46] employed a model to investigate the phase change effects on transport processes in RSW, the work accounted for electromagnetic force, heat generations at the electrode-workpiece interface and faying surface between workpieces, and dynamic electrical resistance taking the sum of temperature-dependent bulk resistance of the workpieces and contact resistances at the faying surface and electrode-workpiece interface. The characteristics of phase change in the course of heating, melting, cooling and freezing were realistically and extensively studied by model computation, and the heat transfer rate, nugget growth in different directions, thermal conductivity between different phases, melting and solidification rates and specific heat ratio in phase change were also considered. In their other work [47], an approximate model and numerical procedures were employed to explore the workpiece property effects on nugget microstructure. The work focused on the nugget microstructure by studying the temperature gradient and solidification rate, and then some important conclusions which were relative to nugget initiation, heat fluxes, solidification rate in all of directions, morphology parameters, cooling rate were drawn.

Moreover, in addition to employ ANSYS and DEFORM™ to execute the numerical simulation, other software tools are also used. To analyze and improve the structure design, some special elements in commercial Computer Aided Design (CAE) software tools, such as CWELD [48], ACM2 [49] and CHEXA elements [50] were employed. However, they can only be used in structure analysis instead of multi-field process analysis. As for process analysis, based on the principle of FEM, some professional software tools, such as SYSWELD [51] and SORPAS® [52,53], which integrated some welding operation relative functions, were also frequently used in reality. These integrated tools contained various electrode models, materials characteristics of some commonly employed workpieces, special welding schedules and some other relative tools. The meshing and quality evaluation tools may be included or excluded in the tools. Using these tools is more convenient because the designers did not spend time on the basic model establishment. However, they followed the principle of FEM, and should obtain the same results if the same model can be established by other software tools.

In this section, some typical previous works have been reviewed. It can be found that all of models used AC power source, which might be that the RSW process with single-phase AC power source was commonly explored by scholars and engineers previously. Because the medium frequency DC power source has a much steadier electrical delivery than of AC power source, the contributions obtained by using AC power source can be easily used in that using medium frequency DC power source [27]. In addition, because of the cylindrical symmetry of RSW system, 2D model was used widely in majority of previous works only except [6,41,44], which used 3D models, due to the works [6,41] were to explore the characteristics of magnetic field, while the work [44] focused on the vibration of molten pool. It meant that in general cases, 2D model can denote majority of variation characteristics of the RSW process. Also, majority of numerical simulation employed 1/2, even 1/4 models to simplify the calculations because of its axisymmetric feature. Many preceding works employed thermal-electrical-mechanical coupled models. Some works used fluid models to explore the special characteristics [6,41]. By means of various numerical models, many important characteristics, such as temperature distribution, nugget size (width and thickness), fluid flow or heat transfer behavior, effects of some important parameters on weld quality, and so on. It can be found that the models had many common features, and followed the fixed rules.

In summary, according to review the previous works, FEM is a strong modeling tool to simulate the welding process and a lot of remarkable achievements have been obtained in recent years. Many scholars used it to explore the characteristics of

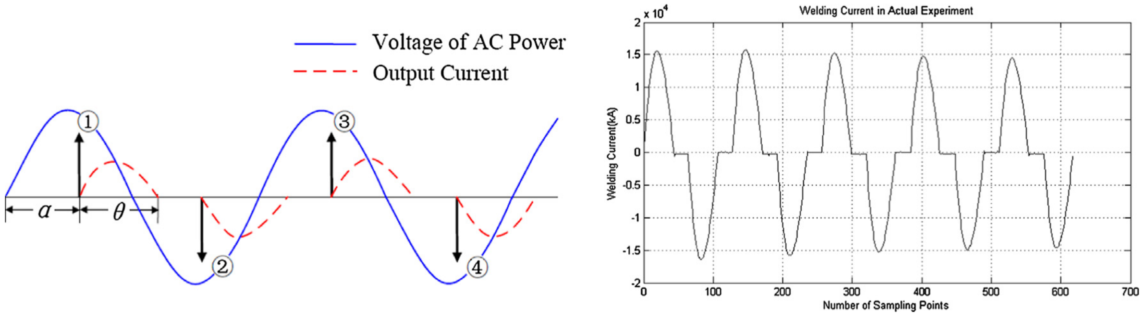

Fig. 4. (a) Waveforms of the mains voltage and welding current [28], (b) An actual measured welding current.

RSW process, and gained a lot of remarking achievements. Due to the complexity of the RSW process, integrated simulation required multi-field coupled calculations, and by means of these tools, many characteristics can be obtained, though some assumptions were made. However, the methods had some shortcomings in reality. Majority of contributions only focused on characteristics research of welding process and the effects of different parameters on the nugget formation and quality. Through examining the published contributions concerning FEM simulations, they have many assumptions, such as for the RSW process with single-phase AC power source, majority of simulations used the successive sinusoidal welding currents or root-mean-square (RMS) current as the electric input. In fact, the actual welding current is not true successive sinusoidal pattern and there is an idle, when there no welding current passes through the parent metal sheets, between two adjacent welding cycles [54], as shown in Fig. 4.

Fig. 4(a) shows the waveform of mains voltage and welding current during four successive control cycle or the RSW process with single-phase AC power source. In this figure, α denotes the firing angle of the SCR, θ denotes the conduction angle, which is also the duration when the welding current passes the parent metal sheets. The electrode voltage and the welding current have the same phase because the load only has the impedance. Fig. 4(b) is a welding current waveform collected from an actual welding experiments. The figure clearly shows that though the voltage waveform of the AC power is sinusoidal, the waveforms of actual electrode voltage and welding current are not sinusoidal and not successive actually. In addition, though the works provided the governing equations according to physical characteristics, the equations cannot sufficiently describe the phase change effect, which is very important during the welding process. Also, some important characteristics parameters, such as thermal conductivity, specific heat, density and thermal diffusively as functions of temperature and required in order to compute the temperature destitution, are not precisely provided for simulation in realty [1]. Based on these deficiencies, though the previous contributions obtained some prominent findings by means of FEM or other mathematical models after ingenious designs and obtained good agreements between simulation and experimental results, and the achievements were useful to study the principle and mechanism of the welding process, the numerical simulation procedures cannot be consistent with the actual welding process. Due to the actual welding process includes many disturbances and unexpected phenomena, such as mechanical or metallurgical uncertainties, or uncertainties in the surfaces of parent metal, even from the same batch, and so on, it can be concluded that the simulations in current works can only be an auxiliary mathematical analysis tool and is insufficient to use it to instruct the actual control operation and non-destructive tests (NDT) or relative designs. In other words, these tools cannot effectively be employed in occasions of quality inspection and control process design, and is expected to be improved in the future works.

2.2. Auxiliary measuring signals from external sensors

Recently, a lot of external auxiliary sensors were employed to online monitor the welding process and collect chosen data to do further analysis, such as NDT. Direct measurement of tensile-shear strength and nugget size may cost more and have low efficiency, so that other methods which may be more efficient are required for time and cost saving [55,56]. In general, sensor monitoring is closely relative to the NDT and employed more in industrial production or academic research occasions. Some works focused on the online process monitoring or detection, while other works considered the post-weld test. However, the contents in this part only consider the external sensors which worked independently and mounted externally, and the signals focused on the auxiliary measuring signals, instead of intrinsic process variables, such as welding current and electrode voltage, though they are also collected by means of corresponding sensors. The intrinsic process variables will be mentioned in the next part.

The nugget formation and growth process relates to the metal melting and phase change. During the majority of RSW process, a mixture of solid metal and liquid nugget exists between upper and lower electrodes, and the liquid nugget is usually confined with the two solid parts and not exposed, only except when expulsion occurring, which should be avoided during the process. This characteristic was appealing for researchers and engineers to employ different external sensors to monitor the process. Cho et al. [57] used a digital high speed camera, a specially designed electrode tip and illumination system to visually monitor and observe the process of nugget formation, and then the results were compared with the dynamic resistance monitoring. The work can only obtain an approximate results and give clues to research the process. An approximate similar work, which was conducted by Tan et al. [58], focused on the small scale RSW operation, and the workpieces were Ni sheets. This work employed the scanning electron microscope (SEM) offline collected the photo of the weld in the different welding time, and then corresponded to the dynamic resistance profiles in different stages. The work also showed that the beginning time of solid metal melting and the time when the maximum nugget formed of small scale RSW of Ni were different from those during large scale RSW of mild steel, due to the difference in electrode force and the resistivity of the parent metal. Due to there was a large resistivity difference between solid Ni and liquid Ni at the melting temperature, the solid to liquid phase change of Ni would subsequently increase the dynamic resistance during the nugget formation. Though the work did not directly consider the welding process, the various photos can be combined to approximately demonstrate the welding process. These works can examine the nugget formation mechanism and its relation to the process parameters.

Apart from using camera or special microscope, other more direct sensors were also employed to investigate the nugget formation and growth process. Karloff et al.'s work [59] presented an effective method of using acoustic reflections to monitor the signature of a spot weld. In the work, a series of A-scans through the cross-section of the weld during the welding process, which contained many reflections resulting from the various interfaces of the layered weld structure, were captured. Fig. 5 [59] shows the schematic of the work.

After plotted in gray scale and each *A*-scan was placed beside the next, the resulting *B*-scan image was formed and the different parts between two electrodes can be clearly identified by means of acoustic reflection technology. The figures in the work underwent special processing, such as identifying and removing interference, image enhancement of shifting reflection, and so on. Finally, the solid-liquid metal interface can be accurately identified and located, and the depth of liquid nugget penetration into the steel plates can be quiet accurately determined. The work can permit the accurate measurement of the thickness of the weld and help to improve the quality control. Another work, which also used the similar sensor technology, was conducted by Chertov et al. [60], to make offline quality evaluation. The work used the scanning acoustic microscopy (SAM) for the purpose of weld quality verification. In the work, a collimated ultrasonic beam was used to inspect the object, and the plane waves that are generated by a piezoelectric crystal were focused by a special acoustic lens. The specimen should be aligned along the plane perpendicular to the lens axis, and water was utilized as a couplant to allow the acoustic waves to travel from the transducer to the specimen and back. A schematic of the investigation of a spot weld is shown in Fig. 6 [60].

In Fig. 6, when the lens moved along the specimen, it emitted and received the waves at different positions above the weld. The position *A* and *C* denoted the boundaries of the weld joint, or no-weld regions, and the position *B* denoted the region of liquid nugget. Then the reflection may present different curves. After using microscopy examined the figures and corresponding analyses, the nugget size and shape, can be investigated, and the cracks, voids, or other discontinuities affecting the integrity of the weld, can also be discovered. It can be concluded that the SAM technology can not only be used in online process monitoring, but also in offline weld quality estimation. Similarly, Liu et al. [61] employed the ultrasonic echo signals to detect four types of stainless steel RSW specimens, which were failed weld, stick weld, defective weld with gas pore and good weld, and analyzed the characteristics respectively in time domain, frequency domain and time-frequency domain. Then the characteristics signals were automatically recognized and classified by back propagation (BP) neural network, and the accuracy of the classification and identification of defects reaches more than 96%. Hence, it is an effective method to serve the offline quality evaluation. Furthermore, other types of sound signals, such as acoustic emission and sonic emission signals, can also be used to estimate the weld strength, detect the expulsion appearing, and predict the electrode wearing in reported previous work [62], through establishing curve fitting relations between collected data of the signals and the measuring physical targets.

Also, the infrared (IR) thermography was used for the NDT for the spot weld. Chen et al. [63,64] developed a NDT system based on infrared thermography to evaluate the quality and integrity of the welds in automotive assembly structures. The

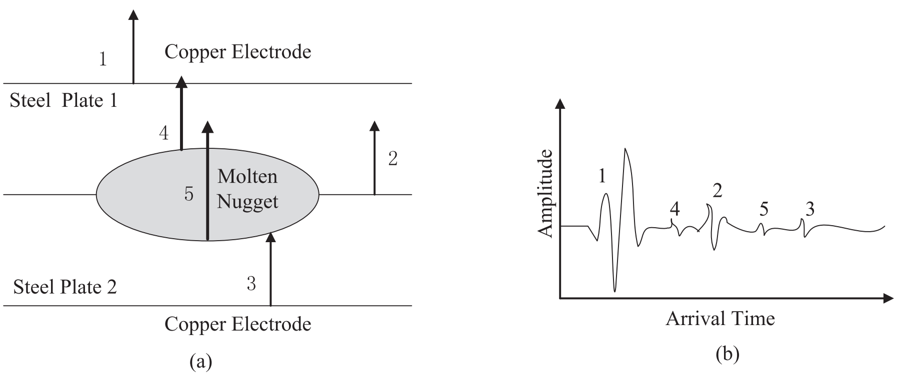

Fig. 5. (a) Source of reflected pulses in a weld, (b) Expected A-Scan through the cross section of the weld.

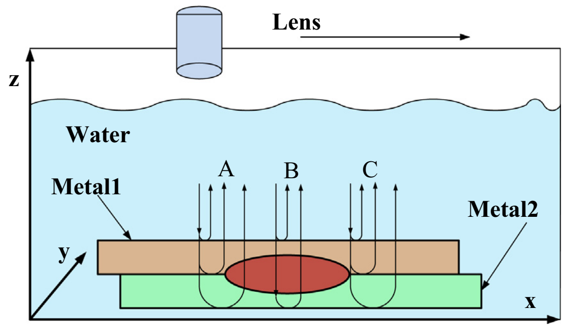

Fig. 6. Schematic of using SAM to inspect a spot weld specimen.

system can be used in both of real time inspection and post-weld inspection. It included an IR camera, a computer for image acquisition and analysis, an induction heating device (for post-weld inspection), and a pre-established weld quality database. The system required a special data processing algorithm to support the work. The schematic of the real-time and post-weld inspections is shown in Fig. 7 [63].

For the real-time inspection in Fig. 7(a), because the welding heat was related to the welding quality, the IR camera monitored the heat flow generated from the welding process. According to the schematic and the image in the work, the IR camera did not need line of sight to observe the nugget and the original image was collected from a lateral view. Then the corresponding IR image analysis algorithm can automatically and intelligently identify the real time "thermal signatures" extracted from the images collected by the IR camera, and then compared with the data in the database and determined the quality of weld instantaneously. On the other hand, for the post-weld inspection in Fig. 7(b), an additional induction heating unit was required to locally heat the as-welded region, and the IR camera was positioned on the other side of the weld to monitor the transmitted heat flow, which was different from that in the real-time inspection. Then through comparing the processed post-weld "thermal signatures" to the quality database, the nugget information, including the diameter, shape and thickness, can be quantitatively obtained. According to the results published in the work, the methods can obtain the contour of the nugget, and the distance should refer to whether the IR camera can detect the heat in reality. Also, the work presented the database establishing process, which included the offline destructive experiment and comparison between weld attributes and thermal signatures. The final experimental results showed that the accuracy of both real-time and post-weld inspection can achieve at ±0.5 mm, and the post-weld IR NDT can measure the nugget thickness with accuracy at ±0.1 mm, also, the nugget shape can be positively identified. In addition, in their previous other work [65], the correlation between weld quality and thermal signature of each weld can be established, and a finite element analysis was developed to simulate the heat flow during inspection. The thermal model can provide insight into the effect of the nugget size and indentation depth on the peak temperature and heating rate. Hence, the method had sufficient theoretical support and the application followed the thermal analysis. Moreover, other recent popularly employed sensor, which was lead zirconate titanate (PZT) transducer, was also used in NDT of post-weld of RSW production [66,67]. It used the principle of the

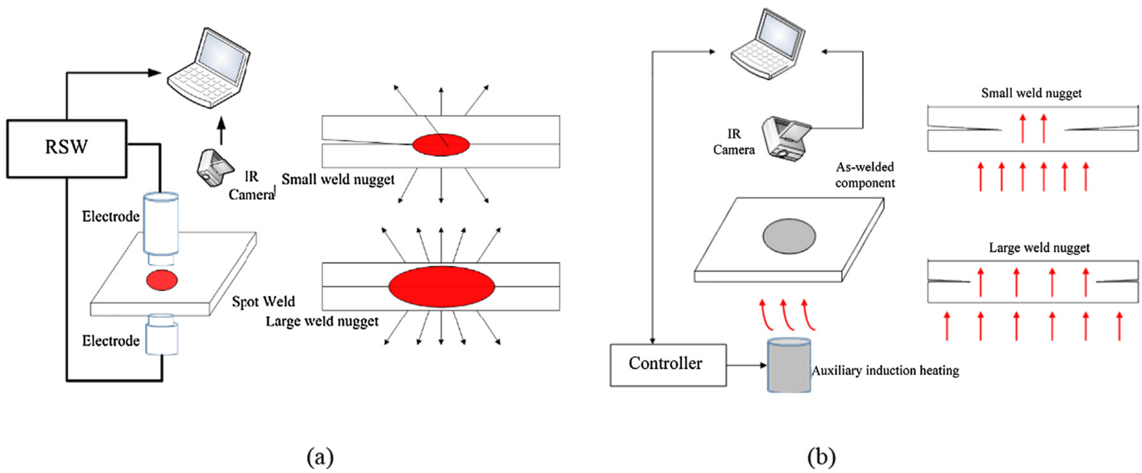

Fig. 7. Schematic of IR based weld NDT system: (a) real time system inspection, (b) post-weld inspection.

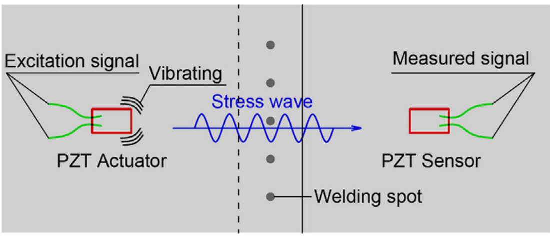

Fig. 8. Schematic principle of PZT-based quality estimation system [66].

failure of the spot welded joints and opening between the faying faces at the joints reduced the amplitude of the stress wave received by the PZT sensor. Fig. 8 [66] shows the schematic figure of the principle.

Using the principle, if the PZT sensor received an abnormal stress wave, it meant that the spot welded joints had bad quality, or the existence of opening deteriorated the contact quality. By means of FEM calculation, sensing system and digital image correlation system, the effect of PZT-based NDT method had been effectively validated.

In addition to above technologies to use auxiliary measuring signals from external sensors, magnetic signals were also employed to analyze the welding process and estimate the welding quality. Harada et al. [68] developed a RSW quality evaluation system using eddy current test (ECT). The measurement results from ECT can analyze the variation of internal structure of the spot welds, by means of the relations between frequency of current in induction coil, magnetic field strength and nugget formation process. Then through actual tensile-shear test of the workpieces, a good correlation between measured magnetic field strength and the tensile-shear load was found. Hence, the work indicates that the ECT can visualize the internal structure of the weld and do non-destructive test for the weld. Also, Tsukada et al. [69] employed the magnetic flux leakage to correlate the tensile-shear strength, which also showed that this magnetic signal can be expected to be a method for online monitoring of the spot welds. Moreover, Tsukada et al. [70] combined techniques of magnetic flux penetration and ECT for weld estimation and nondestructive test. In this work, the magnetic flux penetration through both upper and low surfaces of the workpiece was measured at low frequency, and the correlation between the shear strength of the workpiece and a calculated criterion which was derived from measured magnetic field intensity can be established. On the other hand, the ECT was performed at each surface with multiple frequencies, and the nugget depth profile can be obtained by means of the measured magnetic intensity map, according to analyze the features of the magnetic intensity map, the observed cross-sectional microscopy and the characteristics of nugget formation. Hence, this combined technique was expected to be an effective method for online monitoring the welding process and do NDT for the RSW products. Above three works have the same corresponding author. Other reported work by Vértesy et al. [71] employed the magnetic hysteresis measurement method for inspection of RSW and do NDT. Though a good correlation between the result of destructive characterization and nondestructive magnetic descriptors was found, it also found that the signal was very weakly sensitive and still can be considered as a future possible practical application.

In summary, though there are many auxiliary measuring signals from external sensors employed to monitor the welding process or NDT, the signals can only include some limited information, and the majority of the applications were post-weld inspection or offline NDT, only few can be used in real time occasions. There are some drawbacks and limitations in their applications. The first is that proper setting the sensors is difficult, for instance, using ultrasound transmission, the sensors must be mounted on the metal sheets, which increases the cost and the complexity of the necessary equipment so as to limit the mass usage, and frequently mounting the sensors for each metal sheet is so time consuming. The second is that the quality of the signals transmission is affected by the welding environment. There are a lot of noises existing in production, which may seriously affect the accuracy of the signals, especially for sonic and sound signals, and the stress wave used in the PZT-based NDT method. In addition, the dirt and fumes produced during the welding process may corrupt the infrared signals, because it requires constant surface emission. Though some types of magnetic signals have been used in process analysis and NDT for the welds, the experimental platform was so complicate that various errors may be included, the measuring and analysis process included some uncertain elements, and the previous corresponding works only contained limited effective validating results. Furthermore, all of these signals should be transformed into the weld information, in other words, the results are indirect, which needs corresponding transformation algorithm and modeling to transform them. The design of the algorithm and establishment of the model need many offline experimental data and experiences, which may exist the limitation and not be able to apply in general cases, because the data and experiences may not be sufficiently general and comprehensive. After reviewing some relative contributions, it can be concluded that though they can be effective tools in some particular occasions and obtain useful information, their usages are limited in general occasions. Most of the applications can only be in laboratory and not able to be employed in mass industrial occasions. Some further improvements are required to be taken in order to make the auxiliary measuring signals from external sensors effectively utilize in actual production.

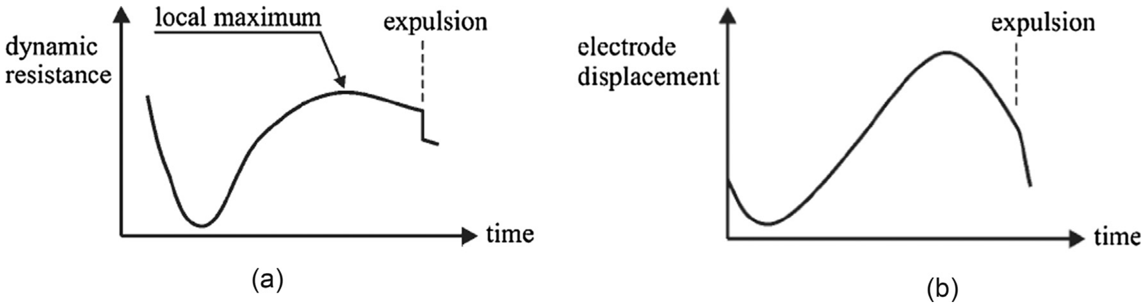

Fig. 9. Theoretical description of the signals, (a) Dynamic resistance; (b) Electrode displacement [74].

2.3. Using intrinsic process variables to monitor the process

During the RSW process, many process variables can be obtained in real time, and then can be used for process analysis, online quality monitoring and evaluation, as well as the online process and quality controls. Though they are also collected by means of corresponding sensors, they directly reflect the internal variation of the RSW system and are different from the signals mentioned in the preceding part.

In practice, dynamic resistance and electrode displacement are two of the most commonly used signals to research the welding process, online evaluate or control the welding quality, because they can indirectly describe the internal characteristics variations of the parent metal sheets and provide significant data for evaluating nugget quality [72]. The internal characteristics variations include corresponding variation resulting from phase change, such as electrical resistivity, thermal conductivity, specific heat, density or thermal diffusivity [73], and morphology variation. Fig. 9 [74] shows the theoretical description of these two distinct and remarkable signals.

Fig. 9 shows the typical pattern of low carbon steel. Other special parent metal sheets, such as aluminum, may show different patterns. However, the low carbon steels have more stable physical characteristics and the curves can show a clearer and evident feature. According to the theoretical descriptions of these two signals, they obey the district laws during the RSW process. For the dynamic resistance, the initial value is very high because the resistance of various asperities, such as contaminants or oxides, between parent metal sheets, which is the contact resistance, is very high at this stage. Then as the electrode force squeezes the metal sheets, the asperities collapse and contact resistance sharply declines, which induces the resistance fiercely drop. As is energy delivering into the system, the temperature of the solid metal increases, which makes the resistance of metal sheets increase. As the temperature increases, solid metal melts and liquid nugget forms, and the distance between two electrodes decreases resulting from the electrode force, then the total dynamic resistance decrease. If the amount of liquid nugget is so large and the surrounding solid metal cannot hold it under the squeezing by the electrode force, the liquid nugget may spill, and expulsion occurs. On the other hand, for the electrode displacement, which is also the electrode indentation, the initial drop also results from electrode force bringing the metal sheets into closely contact and asperities collapse. Due to thermal expansion, the curve rises and then reaches its maximum value, then the curve drops because of the softening of the metal sheets. Also, expulsion can make the curve drop significantly. It can be seen that the two signals respectively have their unique characteristics during the process, which is the reason that they can be used to reflect the internal variation of the parent metal sheets. Apart from the theoretical analyses, the experimental observation results also support the applications of the signals during the process [5,75,76].

For dynamic resistance, different stages of nugget formation and growth process show different characteristics, which is useful to online estimate the nugget growth and weld quality [77]. There are two methods used commonly to obtain its values when single-phase AC RSW machine is used, the first is that using RMS value of electrode voltage divided by the RMS value of welding current, the second is that using the peak value of electrode voltage divided by the welding current for each control cycle. The first method required a lot of online data collecting and calculation, but the value has high accuracy and is insensitive to the various noises, while the second method requires less calculation, however, only two collected data, which is electrode voltage and welding current in the peak during each control cycle, was used to obtain each value of dynamic resistance, so the reliability and accuracy of the result are easy to be assured. Traditional measurements obtained the value in the secondary coil of the welding system. Cho et al. [78–80] thought that the traditional method may induce a lot of noises during the process, and proposed a method which obtained the value in the primary coil of the system. After obtained the dynamic resistance, the work [78] established a neural network for quality estimation. The input of the network selected some points from the dynamic resistance curve, such as beta peak location L_{btp}, which was related to the nugget growth and mechanical collapse, the speed of increase of the dynamic resistance R_{slope}, which was related to the nugget growth rate, the maximum dynamic resistance R_{max} which was used to examine whether the heating is adequate for nugget generation, and the standard deviation of the dynamic resistance R_{std} which was used in order to examine the resistance variations. The output of the network was the ultimate strength, which was obtained through the offline tensile-shear strength test. Two hidden layers, each containing ten nodes, linked the input and output. The effectiveness of the method was testified by

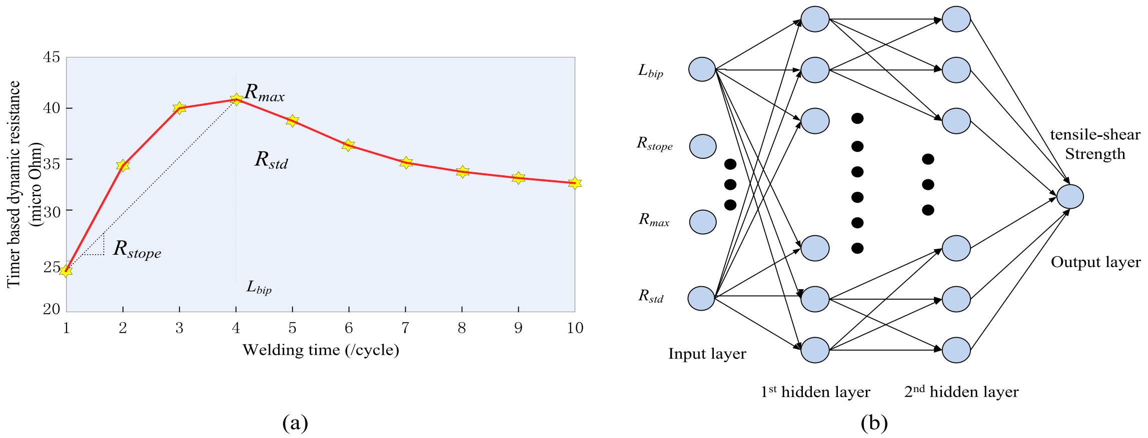

Fig. 10. (a) The primary dynamic resistance pattern and feature extraction, (b) The neural network architecture.

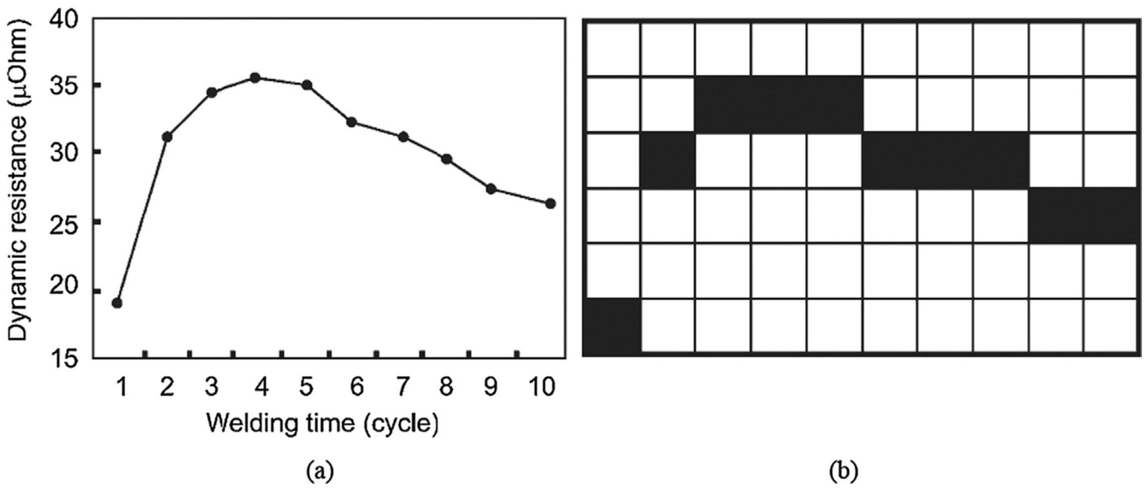

Fig. 11. (a) Original dynamic resistance pattern, (b) Graphical dynamic resistance pattern [74].

the actual calculations and measurements. Fig. 10 [78] shows the primary dynamic resistance pattern and feature extraction, as well as the neutral network architecture.

The work [79] also used the same dynamic resistances calculation method, and then employed regression model through multiple linear and nonlinear regression analyses to estimate weld quality. In the model, the tensile-shear strength and the nugget diameter were selected as dependent variables, and ten estimation factors were used to determine the regression equation. Following the regression analysis, a multilayer neural network can be used to estimate weld quality, and the final experimental results showed that the neutral network had a high performance. The work [74,80] employed a Hopfield neural network, which was comprised of single-layer feedback networks with symmetric weights. The dynamic resistance values were collected, and then were normalized between 0 and 1 before the values were converted into a two dimensional pattern vector. Then the normalized dynamic resistance is mapped into a 6×10 element bipolarized vector, and then used black and white squares to denote the pattern. The original and graphical pattern of dynamic resistance is shown in Fig. 11 [74].

The Hopfield neural network stored five prototypes which were described by graphical dynamic resistance pattern, one prototypes denoted one class. Each class denoted a range of weld strength. In the work, the parent metal was low carbon cold rolled steel. For example, the weld strengths of class I were 1.17–1.25 kN, which was much lower than the strength criteria of 2.89 kN; while the weld strength of class III–V were 3.15–3.70 kN, showing adequate strength for any circumstances. Then for any new collected graphical dynamic resistance pattern, applied them to the AI pattern recognition method to classify into corresponding class. Using the classified pattern, real-time estimation of the weld quality was made possible. Also, El-Banna et al. [81] employed an algorithmic framework based on a linear vector quantization (LVQ) neutral network for online estimating the button size class based on a small number of dynamic resistance patterns for cold, normal and expulsion welds. In the work, they used Constant Current Control (CCC) method for medium frequency DC RSW machine, and a self-proposed constant heat control (CHC) method for single-phase AC RSW machine. Two metal stacks were used: 2.00 mm

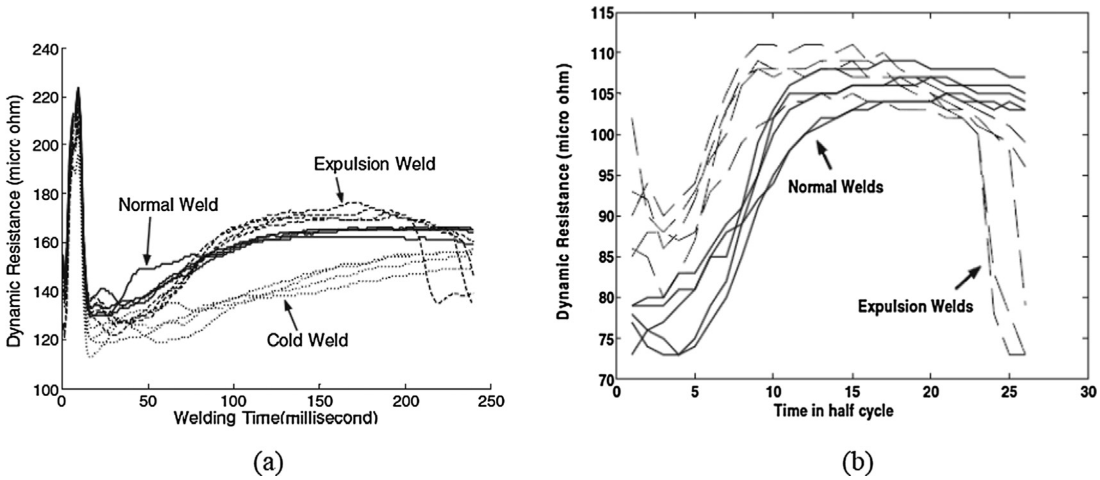

Fig. 12. Sample dynamic resistance profiles for cold, expulsion, and normal welds for (a) A CCC using Medium Frequency DC, (b) An AC constant heat controller [81].

gauge hot tip galvanized high strength low alloys (HSLA) steel, and 0.85 mm gauge electro-galvanized HSLA steel. Then for each type of RSW machine, corresponding results can be shown in Fig. 12 [81].

It can be seen from Fig. 12 that for two types of RSW machines with different controllers, the neural network can classify the welds into three catalogues: normal weld, cold weld and expulsion weld. However, the profiles were not easily distinguishable in reality. The dynamic resistance profiles of cold welds tend to be lower than the other profiles, while the profiles of expulsion weld tend to have a sharp drop, especially towards to the end. Then the LVQ neural network was used to assist the classification. The inputs of the neural network were some easily accessible dynamic resistance profiles, such as maximum, minimum, mean value, standard derivation of the collected data, slopes in different regions, RMS values, and so on. The work showed using limited collected data can obtain promising classification results. Also, the effects when reducing feature sets were employed were also reported. Combined the control strategy using RSW machines with different types of power sources, the contributions in this work can provide reference in many aspects in RSW. In addition, Zhu et al. [82] used a multi-pulse method to eliminate the contact resistances between two electrodes and workpieces and the errors of resistance caused by temperature rising, and then the models of relation between brazing rate (the ratio of the effective welding area and the area of welding gap) and the resistance, as well as the relation between brazing rate and the tensile-shear strength can be established from a lot of experimental data. With two equations which described the two relations, the welding quality could be estimated by brazing rate and tensile-shear strength based on calculated dynamic resistance. Through comparing experiments between calculated and measured values, it was believed that the method was reliable. An approximate work was conducted by Luo et al. [83]. The work showed that there was a high linear relationship between

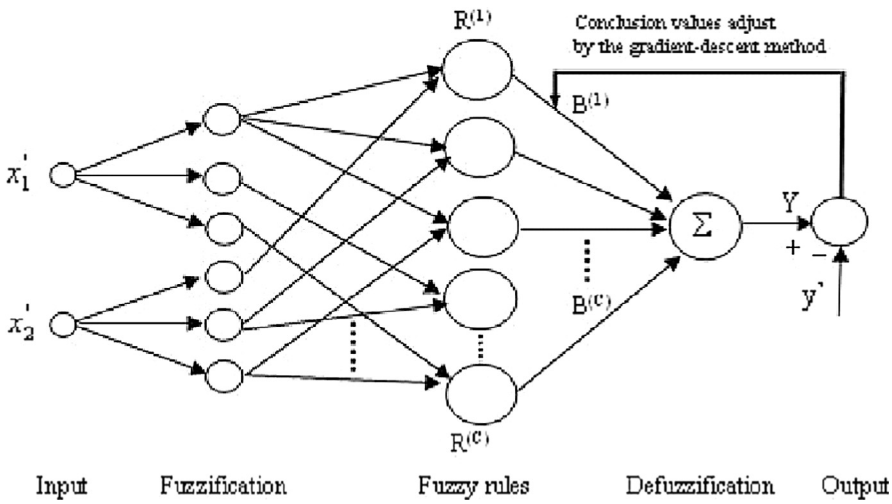

Fig. 13. The neuro-fuzzy scheme [86].

energy for nugget growth and mean dynamic resistance, and more prominent polynomial relationship between energy for nugget growth and dynamic resistance heat. The dynamic resistance heat was an important evaluating indicator of the nugget growth. Then corresponding curve fitting equations between dynamic resistance heat and nugget diameter, and tensile-shear strength were established, to achieve NDT of nugget quality features. Also, as a mathematical model for classification, random forest (RF), was also used in weld quality classification based on dynamic resistance features and other welding parameters. Xing et al. [84] collected some features from dynamic resistance profiles, such as value in the first decline point R_α, value in the peak R_β, value in the end R_γ, relative velocities for asperities or contaminates breakdown υ_1, local melting and initiation of nugget formation υ_2, and nugget growth υ_3, and maximum absolute gradient in stage of nugget growth ∇_{max}, standard deviation σ, together with some other operational variables, a weld quality classification model based on RF was obtained. The result showed that the methodology can improve the accuracy of the quality classification, which can achieve 98.8%. The work also obtained that the four parameters of dynamic resistance profiles, which were υ_2, υ_3, R_γ and ∇_{max}, and the welding current, were the most important variables for quality classification. Also, for small scale RSW, Wan et al. [85] employed some special features from dynamic resistance signals as the input of the neural network, and the nugget size as the output, then a reliable welding quality system can be achieved. It meant that the dynamic resistance can be also used in small scale RSW.

On the other hand, electrode displacement was also used in many previous works. Zhang et al. [86] employed the electrode displacement and electrode velocity as the inputs, and the nugget diameter as the sole output, established a neuro-fuzzy inference system to online monitor the weld quality of RSW operation, the neuro-fuzzy scheme was shown in Fig. 13 [86].

The two inputs were codified into linguistic values by the set of Gaussian member functions, and the respective activation degree to each rule can be calculated. Lastly, the inference mechanism weights each conclusion values, and the error between the inferred output value and the respective desired value was used by the gradient-descent method to adjust each rule conclusion. The final experiments showed that the 88% specimens were successfully inferred, and the errors was within 1.5%, which meant that the artificial intelligent can improve the welding academic research and actual production. Also, Lai et al. [87] and Zhang et al. [88] used online measurement electrode indentation from servo encoder to accurately distinguish welds which cannot meet the requirements of strength and diagnose welding failures. The works validated the electrode indentation was separately relative to the welding quality, and can serve to the non-destructive quality test in the actual production line. Zhang et al. [89] mapped the collected electrode displacement signals into a 15×25 element bipolarized matrix by means of fuzzy theory. In the work, low carbon cool rolled steel place with 0.7 mm thickness was employed. For 25 sample points, each value used the mean value and was processed by rigorous procedures, so as to assure the bipolarized matrix can denote a standard and normalized electrode displacement pattern. Fig. 14 [89] shows the mean value of electrode displacement and corresponding pattern.

Then the genetic K-means algorithm (GKA), which was an iterative algorithm to find a partition that minimizes the square-error (SE) between the assigned pattern and selected reference pattern, was utilized to realize the clustering analysis and quality estimation of the welded spots. The final clustering analysis results validated that the electrode displacement pattern matrix can provide adequate quality information of welded spots for machine learning and complicated programming works could be avoided. Also, the same group developed another method which employed radar chart to analyze the electrode displacement through noises reduction, then utilized the geometric features of the closed polygon to achieve the welding quality evaluation [90]. In the work, decision tree was employed to classify the welded spots, even under some abnormal welding conditions, the diagnostic procedures for welding quality was visible and intuitive and easily understood and interpreted. A similar work was conducted by Gong et al. [91]. The work collected the electrode displacement and then used the Bayesian Belief Network (BBN) to provide a quantitative model for weld quality classification. Shear strength was used to classify the welds. Apart from providing a new weld quality classification method, the model can predict the expulsion limits for the materials studied, and the work also provided a generic probabilistic methodology to analyze other weld-

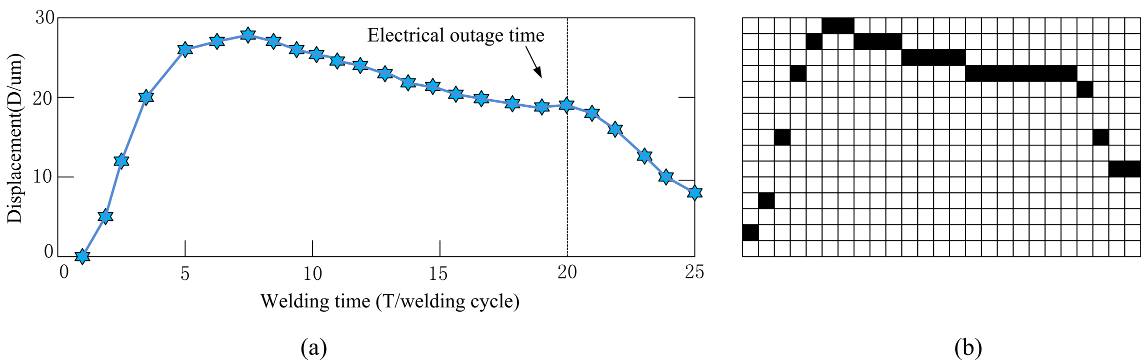

Fig. 14. (a) Mean electrode displacement waveform of each welding cycle; (b) Electrode displacement pattern.

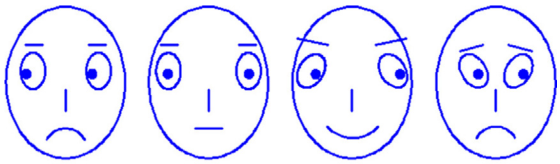

Fig. 15. Chernoff faces template corresponding the different welding quality catalogues [92].

ing parameters in various materials systems. In addition, a visual and interesting approach was developed by Zhang et al. [92] using electrode displacement to assess the welding quality in non-destructive method. The work extracted the multi-dimensional features from the electrode displacement signals. Then the features can be viewed as the facial variables to draw the Chernoff faces, which required 17 variables, according to the rules of this type of drawing. The quality criterion was tensile-shear strength, and can be classified into four catalogues: poor, good, excellent and expulsion. The corresponding Chernoff faces were shown in Fig. 15 [92].

It can be observed that the results were visual and intuitive. The range of the drawing can be freely adjusted. Also, the work can detect the shunting effect during the process. This work was a good alternative in the welding quality estimation. Then, the group extended the contribution. In their recent published work [93], the original Chernoff face image was converted into binary pattern matrix, which was approximate to the Fig. 14(b), and then the features matrices can be corresponded to five welding quality levels and trained a Hopfield associative memory neural network. The five levels were poor, qualified, good, excellent, and expulsion welds. Final test results showed the proposed classifier can present good performance as expected. All of these previous contributions denoted that combining the commonly-employed mathematical tools and electrode displacement, the weld quality can be detected or analyzed after relative efforts.

In addition to separately employ dynamic resistance and electrode displacement, other intrinsic process variables, such as electrode force, or two or more intrinsic variables were also employed to obtain more convinced results. As one of the most control parameters during the process, electrode force can affect the welding quality in a lot of aspects and was considered by some previous works. For example, Park et al. [94] employed the electrode force pattern to do quality estimation. The used quality criterion in the work were the tensile-shear strength and electrode indentation. They conducted experiments under different welding conditions under different process parameters such as welding currents and electrode forces, then the relations between force patterns and qualities could be determined. The experimental data was collected to train the proposed neural network to evaluate welding qualities through the classification into standard patterns. In the work, LVQ and BP neural networks were employed and presented good performance in the classification work. It is concluded that the welding quality evaluation by means of electrode force patterns could be employed with satisfactory accuracy. Also, as one main process variable during the process, welding power signal was employed to online evaluate the weld quality. Zhang et al. [95] developed a method to acquire dynamic reactance signal, and then found that the morphological feature of the reactance signal was closely related to the welding current and significantly influenced by some abnormal welding conditions. The features can be extracted from the reactance signals, and then the weld nugget strength and diameter prediction models based on the radial basis function (RBF) neural network were established using them. The effectiveness of the methods was supported by the experimental results. Ju [96] used the five variables to establish the quality estimation model, which were peak power, peak time, GI coating (uncoated or GI coated, where GI stood for pure zinc), electrode force and power drop. The model was established by multinomial logistic regression. After examining the significance of the parameters, only three variables, which were peak power, GI coating and power drop, were used to establish the weld quality prediction model. The experimental results showed that the overall accuracy can achieve 95% or higher. In the meanwhile, the expulsion can also be detected by means of the signal of power drop. The work believed that welding power signal was better than dynamic resistance because the signal is controllable and the amount of energy delivery can be directly expressed, and it is not affected by the electrode force or other elements during the process. Moreover, electrode voltage can also be used to establish a neural network for online quality estimation. Compared to the large scale RSW, the electrode displacement is more difficult to measure because the magnitude is very small, on the other hand, the force signals are relatively large and the measured noise was less susceptible [22]. Hence, force signal was commonly employed in corresponding operation in small scale RSW. Zhao et al. [21] employed a small scale RSW equipment with three-phase medium frequency DC RSW operation, and conducted constant current control mode. The work used four factors extracted from the electrode voltage curve, and then established a model using neural network to correlate the factors and nugget diameter. The maximum average forecast error of the trained network was about 0.15 mm for nugget diameter in the experimental verification, which showed that the voltage curve was also reliable in online quality estimation and monitoring.

Also, some intrinsic parameters can be together employed to achieve the goal of online quality measurement and evaluation. Li et al. [97] used a single-phase AC RSW machine and simultaneously employed some parameters, such as electrode force, electrode displacement, dynamic resistance, welding current using RMS values, initial force and welding time, to make up a multi-layered feed-forward neural network to establish a model. The parameters were collected from 170 samples under various conditions, such as 3.0–4.0 kN electrode force, 6.9–13.4 kA welding current, 3–36 welding cycles (times) and 6.4–7.2 mm contact diameter, and dynamic resistance during each control cycle calculated from tip voltage and welding current at the current peak. The final results showed that the estimation errors of nugget diameter were less than 10%. In addition, Chen et al. [98] proposed an information acquisition and evaluation method based on online monitoring of the weld quality for titanium alloys. The parameters included the welding current, electrode voltage, electrode pressure and electrode displacement signals. Based on the signals characteristics from online observations and analyses, the system can detect the defects including splash and incomplete fusion of the welded spots. In addition, they analyzed the relation between pressure waveform data and the splashed welded spot, and the relation between dynamic resistance variation and incomplete fusion phenomenon. The relations between different parameter variations and the defects can provide clues for online quality assessment. However, only simple and rough judgments can be obtained in the work. An approximate work was conducted by Deng et al. [99]. The work used three variables, which were welding current, electrode force and electrode displacement, to establish an evaluating model of nugget size using fuzzy mathematics. The model can help the welders explore why the nugget size was substandard. In addition, Wan et al. [100] used two types of neural networks to online predict the weld quality of small scale RSW process. The first type used the electrode force, welding current, welding time and four features extracted from electrode voltage and dynamic resistance as the inputs, and the value of failure load as the only one output to establish a BP neural network. However, the structure was so complex and the quality can only be determined after obtaining the specific failure load magnitude. Then the second type used the electrode voltage signals as the inputs and the different levels of the failure load as the outputs, and the probabilistic neural network (PNN) to establish a model. Both of the two neutral networks presented high accuracy in the experiments. They had conclusion that the first neural network model was more suitable for specific estimation of failure load magnitude, while the second model was more appropriate to be used in quality classification. Hence, combination of two models may provide a better solution of online quality estimation. It is a typical work for online quality estimation for small scale RSW.

In addition, recently some frontier analyses based on the machine learning and pattern recognition have been used in RSW related areas, especially in the quality estimation or classification using various intrinsic process variables, due to the RSW system is an obvious multi-input-single-output (MISO) system which meets the requirements of those tools. Apart from various neural network tools, decision tree and RF, other methods, such as elastic nets, support vector machines (SVM) and boosting techniques, were also be employed. Martín et al. [101] used the welding current, welding time and electrode force as the inputs, while the tensile shear load bearing capacity (TSLBC) as the output, and the regression calculation technique utilized the quadratic regress expansion with elastic net regularization. The result showed that it can be used as an amensable tool to serve the RSW related researches. Also, to estimate various classification methods, Pereda et al. [102] compared several classifiers including pruned tree, boosting, RF, SVM radial, SVM linear, logistic regression, and so on. The input variables for training the models were welding current, welding time, electrode material, treatment (applied to electrode material), and electrode force, which was only a constant variable. The output was the classification of the nugget. According to the comparison and corresponding analyses, it could be concluded that there is no a dominant classifier for every possible pair specificity/sensitivity. A method or tool can perform better than others depending on the industrial context that determines the difference cost of a prediction error. In this work, the SVM using radial kernel, boosting, random forest techniques can obtain the best performance.

Expulsion is a negative phenomenon which can seriously affect the weld quality during the welding process and a lot of previous works concerned it. This phenomenon occurs at the internal of the workpieces and many process signals have correspondingly significant changes, hence, intrinsic signals were always employed to online detect it. To online detect the expulsion, Podržaj et al. [103] collected the dynamic resistance, filtered values of electrode force, amplitude of the electrode force variation and electrode displacement, and then employed the LVQ neural network to detect the expulsion for the cases of different mild steels and zinc-coated steels being welded. Then the work concluded that the LVQ network could detect the expulsion with the highest possible accuracy when only the welding force variation signal detected by a piezoelectric sensor, was employed. The work also pointed out the electrode force signal was the most important indicator of the expulsion occurrence, when compared to other signals. Also, the same group also studied the expulsion by means of examining the welding current shape [104], and concluded that higher peak values of the welding current were much more likely to induce expulsion under the condition that the welding currents had the same RMS values. The similar conclusion can also be appropriate in small scale RSW research [105], the work showed that though monitoring one or more of the variables can give an indication of whether the expulsion occurs, the force signal appears to be the most sensitive when compared to the voltage and displacement signals under this circumstance. Moreover, Zhang et al. [106] proposed various models to explore the mechanism of expulsion occurring. The models were established based on experimental data, and the expulsion probabilities were presented as a function of electrode force, welding current and welding time. Through statistical analyses, the expulsion limits under different parameters conditions can be obtained. It concluded that the most influential parameters in determining expulsion was welding current for the steel and aluminum alloys, and following is the electrode force, the least influential parameter is the welding time. Apart from the experimental observation, Senkara et al. [37] explored the mechanism of expulsion occurring, and pointed out that it could be described by the interaction between forces from the liquid nugget and its surrounding solid containment. The effective electrode force, which was usually a portion of the total applied/nominal electrode force, was used to evaluate the expulsion, and the value could be calculated in the work. Also, the work provided a guideline for the electrode force selection. It can be seen that for expulsion, the current researches were not just about online detecting them using numerical models, but also the mechanism explorations were conducted by some scholars.

Apart from employing auxiliary measuring signals from external sensors or intrinsic process variables to do online process analysis and quality estimation, some scholars employed multi-sensor, which combined the both of two types of signals together to obtain more abundant information. Chien et al. [107] presented an investigation of various sensors system for RSW, and the signals were analyzed and correlated with nugget formation and growth. The system included a fiber-optic displacement sensor, an acoustic emission sensor, a force transducer, and the current and voltage measurement, which were simultaneously monitor the welding process. Then the signals were analyzed to correlate to the different stages of weld formation. The work obtained that the electrode force could clearly show a decreased trend upon the onset of melting, and this trend can be used as an indication of weld formation. Also, other characteristics of electrode force can also be related to the weld quality. Finally, the work concluded that monitoring the force signal can enable the welding quality. In addition, Cullen et al. [108] also developed a sensor cluster to monitor the RSW, which included a current sensor, a voltage sensor, a photoelectric infrared diode and a weld ultrasonic system. All the data from these sensors was recorded using a PC through corresponding acquisition system. Then a multilayer perceptron feed forward, BP neural network was employed. The input of the neural network included current (I), voltage (V), dynamic resistance (R), infrared (IR), force (F) and ultrasonic (US), while the output was weld nugget size. Through adjusting several parameters of the network, including the number of hidden layers, the number of neurons and transfer function, the correlation between predicted result and actual results can be improved. At last the optimum network structure can be chosen and the nugget size prediction can achieve a high accuracy. This type of work can be considered as a combination of the works using one or few sensors, they used the same principle to relate the collected data and mathematical tools. More information was employed, and more accuracy of model could be established. However, the models were more complex than that of others using few data, which can induce the generality relatively lower.

In summary, the nugget formation and growth occurs at the interface between workpieces, and is hard to directly monitor and analyze. A lot of scholars employed various methods to analyze the process, estimate or classify the welded spots for nondestructive test or other objectives. Apart from preceding part which reviewed the auxiliary measuring signals from external sensors, this part focuses on the intrinsic signals, which can be collected during the RSW production process. The variation of signals is closely relative to the nugget formation and growth, so they can be employed to reflect the internal physical variation of the metal sheets. Dynamic resistance and electrode displacement were the most commonly-employed signals, and other signals, such as electrode force, were also be used. There is a difference in between large scale RSW and small scale RSW, which is that the electrode displacement signal was used few in small scale RSW because the magnitude of the signal was very small and difficult to collect, and the force signal was used more under this circumstance. Kinds of neural networks, regression methods or curve fittings were usually employed to establish the model using kinds of signals. However, each method required a lot of preliminary data to train the reference model, and some criterions were proposed based on the welding or mathematical knowledge. The model, which was obtained based on the collected data, was determined under the special welding conditions and productions environments. Then the new testing data was processed and the results can be obtained. Majority of works cannot provide general methods and had their limitations in reality, also, some methods involved sophisticated data collection and particular modeling process, which seriously limited the generality of the methods. Combining various signals and sensors, the methods can provide approaches for majority of actual requirements. It is easy to find the common points from the previous works, no matter which sensors or mathematical tools were employed, the variations followed relatively fixed rule which can be employed to test new collecting data for weld samples. However, it was difficult to conclude whether the approaches can be extended to general applications, because the exploration of the rules lacked enough physical support, and relied on the preliminary training data which had their limitation in reality. In addition, many mathematical tools were employed in quality estimation and NDT, not only the traditional BP and LVQ neural networks, but also the recent RF and SVM, and other relative tools, they provided convenient modeling method to relate the various input variables and selected output variables. It is hard to conclude that which tool was the most suitable for RSW application because the performance is determined by data coupling strategies, variables selection, and other relative conditions. According to review previous works, the BP neural network is the most commonly-employed tools to predict the nugget size, while the LVQ is the most frequently used classifier. Though recently the SVM and relative frontier analysis tools presented good performance, their mass application is still limited. Though the previous works provided valuable contributions in academic researches and practical application, the relative works in this aspect are required to be more considered, and much simpler as well as more general methods are expected to be obtained and then serve the production in the future.

3. Welding process control

To obtain welds with satisfactory quality, at the same time the energy loss is as less as possible, appropriate control actions should be taken during the process. Be different from the online process analysis and quality estimation, online welding process control should concern both of quality and process optimizations. The control strategy must be designed based on the characteristics of nugget formation and growth, and the goal should be obtaining welds with satisfactory quality. In this work, we considered using internal and intrinsic conditions to achieve good welding quality through employing appropriate control strategies. We found that some works employed external tools to improve the welding quality, under some special conditions, such as using external magnetically assisted method [109,110]. However, those methods are not included in this paper because the works of this paper focused on using different control strategies to adjust the energy delivery modes, so as to obtain the welds with satisfactory quality and high energy efficiency during the process, instead of employing other extrinsic tools to assist the quality improvement. In early works, some scholars focused on the control parameters optimization, and explored how the specific welding parameters affected the weld quality. Lately, other scholars combined the quality estimation and control strategy design, and then proposed proper control strategies to achieve satisfactory goals.

3.1. Parameters optimization

During the process, welding current, welding time and electrode force are three variables which determine the welding process and weld quality. The conventional welding schedule are composed of these three variables. There is no difference between RSW machines using single-phase AC power source and three-phase medium frequency DC RSW power source in welding schedule design, only except the description of welding time. Traditionally, in single-phase AC RSW operation, the welding time is described by welding cycle, while in that of three-phase medium frequency DC RSW, because the welding current is successive and no idle exists, the welding time is usually described by direct counted by milliseconds.

Apart from the welding time, welding current and electrode force have their special ranges to achieve acceptable welding process and weld quality, which are called as welding lobe [111,112]. The welding lobe should be confirmed by actual experiences and experiments. Too small value of welding current may induce cold weld, while excessive welding current may induce expulsion, and may not avoid internal porosity or cracking of the nugget after welding completion. On the other hand, too small value of electrode force may easily induce expulsion, while large value of electrode force may reduce the efficiency of heat energy and produce small weld, because of no sufficient contact resistance and consequently heat generation [113,114]. Currently, though the different workpieces sizes can affect the efficiency of energy absorption and nugget growth rate [115], almost all of the control systems dealt with the workpieces with the same sizes, in other words, the effect of different workpieces sizes was few considered in previous works.

In previous works, some scholars wanted to obtain a steady welding process together with welds with satisfactory quality by means of optimizing the operational parameters. Kasih et al. [116] used two types of low carbon steels and made corresponding experiments and analyses, and then obtained optimum ranges of welding current and welding time, based on welding quality, which was described by nugget diameter and corresponding tensile-shear load. The work revealed that both of welding current and welding time had great influences on the quality of the spot welded joints. Similarly, Zhang et al. [117] explored the effects of RSW parameters on microstructures and mechanical properties on dissimilar material joints. In the work, a three-phase medium frequency DC RSW machine, was employed, so the welding time was counted by milliseconds instead of welding cycle, and constant current control was used. The workpieces used in the work were galvanized high strength steel and aluminum alloy. Because the workpieces were dissimilar, some particular phenomena appeared. According to change the nugget diameters and interfacial layer structure, welding current and welding time had obvious effects on the tensile-shear load of the spot welded joints. Based on the experiments and analyses, an optimum range of welding current and welding time which can obtain the maximum value of nugget diameter can be provided. Also, the interfacial intermetallic compound layer has higher nanohardness than that of aluminum alloy nugget and galvanized steel. Wan et al. [118] established a model to explore the effect of welding current on RSW process, the workpieces were DP600 steel. The experiments were conducted with the welding current between 6 kA and 12 kA, and FEM tool was also employed to predict the nugget size. The final results showed that the welding current had slight effect on the micro-properties of the spot welds, according to the microstructure examination. However, the nugget size and shape were highly dependent on the welding current. Also, the expulsion phenomenon was also considered in the work. It occurred at 12 kA and unsatisfactory partial interfacial failure can be detected. An approximate work was conducted by Vignesh et al. [119]. The workpieces were two types of dissimilar stainless steels. According to examine the microstructures and other analyses, it was concluded that the welding current majorly indicated the tensile-shear strength, followed by the welding time, while the least effective factor was the electrode tip diameter. After using Taguchi's L27 orthogonal array design to select an optimum schedule, the final result showed that the weld nugget consisted of ferrite and austenite and there was no precipitate of detrimental phases in the weldment, which showed a satisfactory quality. The majority of previous works used constant welding current during the process, however, to employ more effective welding current, Md et al. [120] examined the effects of different reference welding currents on increasing of nugget diameter, and then proposed an adaptive reference welding current compensation function to achieve an optimum welding schedule. In addition, the effects of different welding times on the quality were also be considered. Aslanlar et al. [121] investigated the effects of welding time on the tensile-peel and tensile-shear strengths of welding joints in RSW operations. According to the experiments, the optimum combination of welding time and welding current which can achieve the maximum strengths were obtained after several experiments using various combinations. A similar work was also found in work [2]. In addition, through evaluation by peeling tests, cross-tension tests and weld lobe with various welding currents and welding times, Lin et al. [122] obtained an optimal welding time. Also, the work proposed that using two-step RSW scheme, which introduced an additional pre-heat stage, could result in a larger nugget than that of traditional one-step scheme, and then the actual experiments supported the statement.

In majority of previous works, electrode force was a constant during the process. This is because the majority of electrode forces are controlled by a pressure differential of the two air pressure gauges, which is hard to online adjust during the welding process. However, the characteristics of electrode force were also monitored and investigated in previous works. Sun et al. [123] divided the electrode force into three types: squeeze force, welding force and forging force. To online change the electrode force, an electrical servo gun was employed in the work. For three types of forces, higher squeeze force was required to ensure the closely contact of sheet metal before welding, while lower squeeze welding force can lead to higher electrical resistance of sheet metal, and the highest forging force can reduce solidification defects like cracks and porosity. Hence, the electrode force during the process was better to be a varying value instead of a constant one. According to usage of the design of experiment (DOE) approach, optimum parameters of the forces can be confirmed by experiments and corresponding analyses. The final results showed that a varying electrode force can improve the weld quality, and also evidently enlarging the weldability lobe. Apart from this work, Venugopal et al. [124] also explored the effect of the time-varying electrode force on the nugget size in three-phase medium frequency DC RSW system. The work was based on the numerical simulation using a professional RSW simulation software, which was SORPAS, and actual experiments. The simulation presented the effects of constant electrode force and time-varying electrode force on the increasing of the nugget size. Using specific welding condition and parent metal sheets, the relation between increasing of electrode force and growths of nugget size was nonlinear, when a constant electrode force was employed during each process. When a time-varying electrode force was employed, the changes of time of force in percentage significantly affected the nugget size, under the condition that the same welding current and welding time were used. Apart from just adjusting one parameter, two parameters, which were welding current and electrode force, can be adjusted according to the online detection results during one welding process. Ji et al. [125] used three-phase medium frequency DC RSW machine to explore the effects of electrode displacement and electrode force on the RSW process of aluminum alloy 5182. Apart from that the two parameters were proportional to the welding current, they both presented important characteristics during the nugget formation and growth process, such as their increasing rates were proportional to the welding current, and can detect when expulsion occurring. Then based on the characteristics, two possible strategies for quality control, which employed different values of welding current, were designed. In the strategy, the welding current was firstly set according to changes of electrode displacement or force, then kept it constant until the force reaches the peak or the total displacement reaches an experimentally predetermined value. Both strategies would produce nugget with satisfactory sizes.

Above works denoted that three significant parameters can seriously affect the welding process and nugget formation and growth. Moreover, other welding operational conditions were also considered during the welding process, such as machine stiffness, friction and moving mass [126,127]. The works can conclude that the machine stiffness had a positive influence on expulsion prevention and welding quality, so that it is recommended, while the machine friction and contact error had negative effect on welding quality, and machine moving mass and touch behavior had no influence on weld quality. Dennison et al. [128] examined the RSW operations and corresponding robotic equipment, and then focused on the optimization of the mechanical and control systems for the RSW process, especially referred to the existed robotic spot welding system. During the process control of a robot RSW system, some system characteristics influenced the process duration, such as weld controller latency, gun close time and gun open time. Two aspects should be considered for the process optimization. The first was the process improvements via modifications to mechanical system design including the mechanical and electrical system design and corresponding optimizations, while the second was the closed loop control methodologies including the online monitoring of the electrical parameters and corresponding analyses, as well as the results from some external auxiliary sensors. The robots were employed to conduct the optimization process, and then an optimum control strategy was produced a further 5% improvement in the process cycle time. This work was based on the robotic RSW system and considered the mechanical, electrical and control elements, and then used comprehensive methods to optimize the welding process. Though the final results were obtained from a series of experiments, it can be a general method for optimizing the robotic RSW system and possible extended to other RSW process.

In summary, though RSW system is so complex, the commonly adjustable parameters were only welding current, electrode force and welding time. Three parameters have significant influences for the welding quality. Table 1 shows their influences on the welding process or weld quality, and the corresponding commonly-used optimization measures, according to review previous works.

It can be seen that the optimization measures of welding current and welding time always were taken together. The design of welding schedule is trying to find an optimum combination of three parameters for a special welding process, and the goal is obtaining welds with larger nugget size or higher tensile-shear strength, in the meanwhile, some negative phenomena, such as expulsion, splash, cold or undersize weld, must be avoided. This part only considers the optimization of the control parameters for achieving an optimum welding quality. According to review previous works, because the welding current is the main parameter which can determine the amount of energy delivering into the system, as well as its value

Table 1
Influences on the welding process and weld quality, and optimization measures of the three main variables.

Variables	Influences on the	Optimization Measures
Welding Current	Nugget size and shape; Expulsion occurring; Tensile-shear strength, micro-properties of the weld	Using numerical analyses and experimental to seek an optimum combination for one specific process
Welding Time	Tensile-peel and tensile-shear strengths of welding joints	
Electrode Force	Energy efficiency; Expulsion occurring; solidification features of the spot weld	Varying instead of constant value during the process

can be easier adjusted than that of others, it is considered by a lot of previous works. Also, recent works considered using varying electrode force by means of electrical servo gun and found that it can improve the welding process and weld quality. Many combinations were derived from actual experiments and corresponding comparisons. In this section, the majority of schedules were a fixed combination during the whole welding process, or preliminarily set a varying mode. Hence, the control optimization process was offline and the online adjustments were not included, which had limitations because there were various disturbances and uncertainties during the RSW process. Though the works can provide references for other welding schedule designs and control process optimizations, these reported methods were not general and should be improved to further achieve online control to obtain welds with satisfactory quality. In the next section, the works which dealt with the real time control operation collaborating with online quality estimation will be considered.

3.2. Control process optimization

Apart from the control parameters optimization for the RSW process, some control actions were conducted by combining the online quality estimation results. In these works, different control strategies were employed and presented different effects related to the weld quality, based on the application of mathematical tools, control system designs and quality estimations of the RSW process.

The external energy is delivered into the welding system through two types of power sources, and some previous works only considered the process control for the power sources without the optimization for weld quality. The works focused on the characteristics of electrical structures and provided solutions to achieve stable welding process and expected control strategy for energy delivery. For example, in our previous work [54], constant current control strategy was properly realized in single-phase AC RSW machine, whose electrical system is highly nonlinear and time-varying. The work was based on the mathematical modeling of the electrical structure and can be easily extended to other control strategy, such as constant power control in our other work [129]. Also, in the three-phase medium frequency DC RSW machine, the magnetic saturation in the iron core of the welding transformer may induce disastrous negative phenomena. Klopčič et al. [130,131] analyzed the electrical structure and proposed a new advanced hysteresis control method to control the actual output welding current, and reduce the current spikes and eliminate the magnetic saturation. These works benefited the current RSW operations. Though they were relative to the control process optimization, the operations only concerned energy delivery part rather than the quality information, they are not seriously considered and reviewed in detail in this section.

The simplest control mode for the RSW operation was open-loop controller. The parameter setting and process control followed a predetermined welding schedule, which was obtained from offline experiments or experiences. However, the method cannot consider the quality estimation results because the operational parameters were preliminary fixed, and no any feedback information and adjustment can be used during the process. Then to combine the online quality estimation result, close-loop control should be employed together. The most commonly-used close-loop controller was Proportional–Integral–Derivative (PID) Controller. Cho et al. [132] and Chang et al. [133] developed two similar feedback controllers to achieve good quality. Single-phase AC type machines were used in both works. The controllers were based on a microprocessor, and adjusted the energy input to make the actual electrode movement track a preliminary desired curve, which was obtained offline and denoted the welds with satisfactory quality could be obtained. The P controller and PI controller were respectively employed in these two works. The characteristics of final products approached the desired characteristics very much, so the preliminary goals were achieved under the circumstances of the experiments. Also, Haefner et al. [134] developed a real time adaptive controller using the same basic idea. Single-phase AC RSW machine was also used in this work. An integrated PID controller was used, and the gain was obtained using advanced Smith-Predictor, which could continuously modify the gain by the linear least squared estimator to follow the actual process gain variation during the welding process. The preliminary electrode displacement curve, which denoted the welds having desired quality, was an ideal condition for controller adjustment. Finally, through adjusting the gains of the PID controller, the actual energy delivery was changed to make the actual electrode displacement curve approach the preliminary ideal one. Fig. 16 showed the control scheme of this kind of controllers.

These feedback controllers can achieve the goal which obtained welds with satisfactory quality, under the specific welding conditions. However, it has more limitations. Firstly, it may not be able to obtain general desired curve of the reference model, which was the electrode displacement moving trajectory in above works, no matter using numerical calculation or actual experimental method. Numerical calculation has some limitations, which were the same as why the FEM cannot precisely describe the RSW process, as mentioned in preceding section. For an actual experimental process, because the system

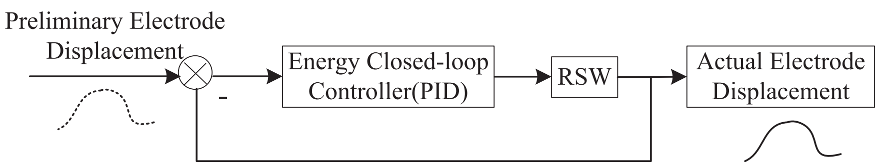

Fig. 16. Control scheme of close-loop feedback controller.

was so complex, the desired curve obtained from one series of experiments cannot be generally employed in other occasions. In addition, the electrode movement was affected by electrode force, or other relative mechanical and electrical conditions. Similarly, as another process variable which was commonly employed to describe the process characteristics, dynamic resistance was also considered as desired control condition in previous work [135]. However, establishing a precise and reliable model to seek a desired dynamic resistance curve may be even more difficult than that obtaining a desired electrode displacement, because the dynamic resistance related to more elements and more sensitive to kinds of noises affecting the parent sheet metals than those of electrode displacement, and the phase change can affect dynamic resistance more than that of electrode displacement. Hence, based on the same reason, it was harder to establish a corresponding general relation between varying dynamic resistance and varying energy delivery.

As the significantly developing of artificial intelligent (AI) controller and high technology of computer application, intelligent control methods were also widely employed in RSW process control. Firstly, fuzzy logic controller was used more frequently in practical mechanical systems, also in RSW system control. Araki et al. [136] proposed a model reference fuzzy adaptive control (MRFAC) system for RSW process control, which was a nonlinear and time-varying system for realizing online control and improving output performance. The input of the system was a voltage signal to firing SCR of the single-phase AC RSW machine, while the output was the welding energy. The goal of the control action was obtaining expected output performances, which were expected nugget and reduced energy loss. An adaptive welding energy reference model, which was established based on expected welding information, such as characteristics of different welding stages, welding current and so on, provided online feedback information to the fuzzy logic controller, which could adjust the gain and output new voltage input signal for the next control cycle. The simulation showed that the actual output could converge to the desired demands. This work only considered how to use fuzzy controller in RSW process control, and focused on the characteristics of different welding stage instead of quality control for RSW operation. However, the reference model might not be sufficiently reliable, and the work was not an integrated actual welding operation and no weld quality information appeared in the work. Hence, the work can only be an important reference for the further works. Another typical application of the fuzzy logic control was developed by Chen et al. [137], and the authors were also the members of the group who conducted the preceding work. Based on the dynamic resistance calculation and input energy, they can calculate the nugget size using FEM, and a welding current model reference in different welding stages, which was based on characteristics of dynamic resistance, could be established. The nugget size in this work included both of the penetration and distance, which were width and height. The error of the welding current was the input of the proposed fuzzy logic controller, while the output was the input of the RSW machine, which was also a voltage signal firing SCR. According to FEM calculation of nugget size based on the actual welding dynamic resistance and welding current, the proposed method could obtain bigger nugget size than that of constant current control. In these two works, fuzzy logic control was used to calculate the input of RSW system based on the output of the machine. Also, fuzzy logic control was a powerful tool to deal with a lot of input information and make a decision for control system. Khoo et al. [138] employed a two-stage RSW machine and selected four important variables, which were welding currents in two stages, welding time and electrode pressure, as the inputs, and the outer diameter of the HAZ as the output, to establish a prototype fuzzy RSW system. The rule-base contained 125 heuristic control rules derived from experiences, literatures reviews and through actual experiments, to relate the necessary actions to obtain welds with good quality. The system had the ability to imitate the decision-making process of a specialist and to provide simultaneous control of more parameters. Hence, it is possible to achieve good welding quality even the initial parameters setting was not perfect, because the prototype system can provide a bi-directional adjustment of outer diameter of the HAZ which was like the specialists' behaviors, and prevent the machine from operating under undesirable conditions. Recently, to increase the cost effectiveness in the production, Podržaj et al. [139] employed the fuzzy logic to detect the expulsion occurring. The variations of three important variables, which were dynamic resistance, electrode displacement and welding force, could be inputs the fuzzy logic, and the expulsion was the output, and each varying range is between 0 and 1. If the output was changed to 1, the welding process should be stopped immediately so that the electrode can be protected and the energy can be saved. Compared to the preceding works, the last work did not focus on the welding quality and process control. It was just an actual application of fuzzy logic in online expulsion detection.

Apart from fuzzy logic control, neural network was also employed in RSW control action. In many cases, it was combined with fuzzy logic to generate expected results in RSW relative works. An intelligent control system was developed by Messler et al. [140]. In the work, neural network was used to describe the electrode displacement as a function of percentage maximum heat input and welding time. It used a lot of actual experimental data and trained the network offline using BP algorithm. The data was collected under normal welding condition with different percentages of heat input. Then a fuzzy logic was used to adjust the actual heat input based on the electrode displacement and velocity. The control actions began from the third control cycle because the effect of surface roughness or contaminations dominated the first two cycles, and then the fuzzy rules were adjusted based on the difference between actual and desired electrode displacements, together with the difference between actual and desired electrode velocities at the comparison point in the first zone, while in the second zone, the fuzzy rules were adjusted only based on the difference between actual and desired electrode displacements. The desired values came from experimental and theoretical deduction based on the electrode movement characteristics. The border of the two zones was confirmed in preliminary stage. This combined controller can compensate for variations and errors, and improve the welding quality during the RSW process, according to the simulation of three anomalies that frequently occurred during the process, which were worn electrode, poor fit-up and contamination. Also, Zhang et al. [141] proposed a neuro-fuzzy algorithm to control the weld quality, through adjusting the welding current, when the part fit-up fault

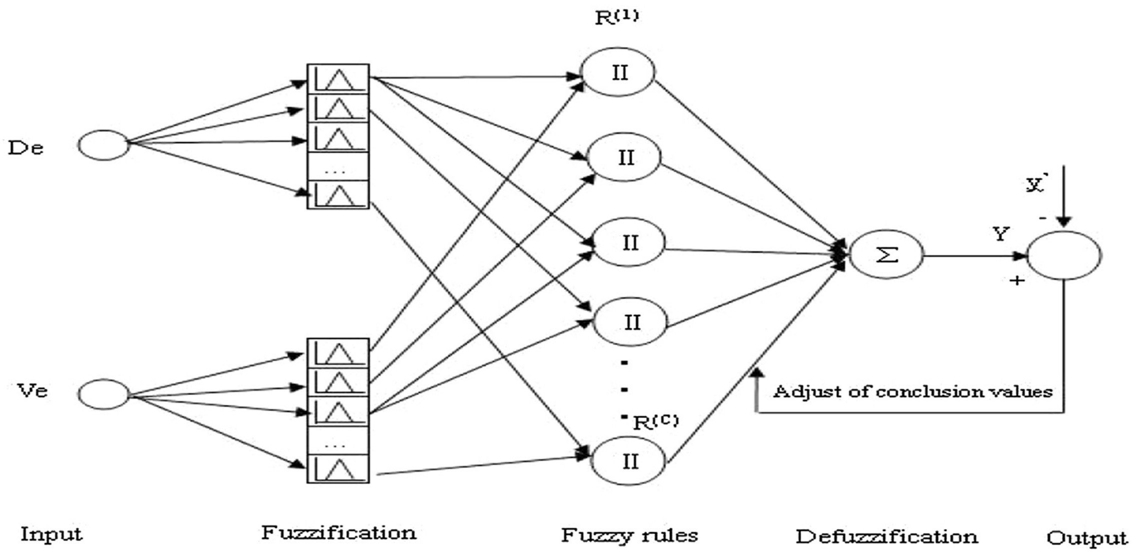

Fig. 17. Structure of neuro-fuzzy system in work [141].

existed. The proposed inference system had two input variables, which were electrode displacement and electrode velocity, while the welding current was the output variable. The desired value of the input also came from preliminary deduction, as the same as the preceding work. The errors between desired and actual values of the two input variables were codified into linguistic values by special membership functions, and then the activation degrees to each rule can be calculated. At last, the inference mechanism weighted each conclusion values. The error signals were used by the gradient-descent method to adjust each rule conclusion. Fig. 17 [141] showed the structure.

The final experimental results showed that when the proposed system was applied, the actual electrode displacement was very close to the desired electrode displacement, when compared to that without the proposed system, which meant that the proposed neuro-fuzzy system was able to compensate for the quality variation caused by part fit-up fault conditions.

According to above works using AI control methods for RSW operations, it can be concluded that the applications of intelligent controllers in practical RSW operations are remaining limited. Because the RSW system is so complex, and a lot of elements affect the welding quality, it is hard to cover all the elements by means of AI modeling. Firstly, as the same as the usual feedback control, intelligent control needs a preliminary desired reference condition, electrode displacement and dynamic resistance were commonly used as the conditions, however, it was hard to obtain a general reference model to instruct the energy delivery. In majority of previous works, the desired curves were only proper under some specific conditions. Secondly, the fuzzy logic and neural network are based on former experimental data or experts' experiences, which are not general and ideal actually. In addition, RSW system has a lot of special features during the process, so that the fuzzy logic requires a lot of fuzzy set to cover all the elements. Also, precisely setting each linguistic value is difficult because the variation range cannot be precisely confirmed. Moreover, making up the fuzzy logic set require a lot of rules. Too many rules may decrease the generality and increase the complexity of the method, while too less rules many decrease robustness of the system, which is a dilemma actually. While neural network requires a lot of data for preliminary training to establish a map, however, the data may not cover all of conditions which will occur in reality, and the data may be obtained in one condition and may not ideally cater to other conditions. For example, the map between dynamic resistance or electrode displacement and input energy can be established according to a lot of actual experimental data, however, the variation of the two vari-

Table 2
Characteristics and shortcomings of the controllers.

Controller	Characteristics	Shortcomings
Open-loop control	Followed a predetermined welding schedule	No quality information, no online adjust
Close-loop control (PID)	Tracked a predetermined reference condition	Ideal and general reference cannot be obtained
Fuzzy logic control	Adjusted the energy delivery to follow a reference model established by quality information	The models might not be reliable; Precisely setting each linguistic value was difficult; Fuzzy logic set required a lot of rules
	Adjusted the input according to experts' experiences	Using fuzzy set to cover all the elements was difficult
Neuro-fuzzy Control	Neural network established the relation between input and output, while fuzzy logic adjusted the energy delivery	The results were experimental condition dependent and might not be general in actual application

ables are affected by a lot of elements, in addition to the input energy, such as mechanical, electromagnetic or thermal elements, so the map may not be normally worked in other welding operations because the effects of the affecting elements may be diverse. In other words, they are experimental condition dependent and may not be general in actual application. Furthermore, the difference between parent metal sheets may be very large, the experiences, models or other types of references obtained from previous collected data may not be available for the new parent metal sheets. In addition, the methods directly adjusted the energy input, no matter in types of the firing voltage of SCR, or the duty cycle of the PWM, were based on the preceding system output. Once one sudden disturbance came, it may induce the energy delivery in next control cycle significantly vibrate, which may lead to system cannot be convergent, and the threshold setting may be not able to adequately deal with the sudden change of the system, under some special conditions. Hence, it was expected to use other advanced control system design for this process. To clearly present the characteristics of the different controller, combining the preceding open-loop and close-loop controllers, Table 2 shows the characteristics and shortcomings of above four controllers.

To obtain reliable and precise control, the energy delivery control and the online quality estimation can be coupled in recent works. A significant work using this mode was conducted by El-Banna et al. [142]. The work simultaneously employed constant current controller and the online quality estimator. A medium frequency DC RSW machine was used to operate the welding action. In the work, an intelligent control algorithm replaced the conventional “stepper” type constant current control scheme. The welding current remained constant, which was realized by a fuzzy control algorithm. The control action in the primary coil of the welding transformer was continuously adjusted based on two online intelligent sensors. The first was a LVQ neural network responsible for quality estimation, while the second was an online expulsion detection sensor based on dynamic resistance online monitoring. The online nugget quality estimation sensor, which used a two layers LVQ artificial neural network, was employed to classify the welds as three types: normal weld, expulsion weld and cold weld. The expulsion detection sensor was to detect the dynamic resistance variation, if sudden drop appeared in the dynamic resistance curve, it meant that the expulsion occurred. The control action of the welding current employed a fuzzy logic controller to modify the changes of the output current to achieve intelligent current adjustment to compensate the effects of electrode degradation, and the results of quality estimation and expulsion detection were utilized by the controller. The overall control scheme of the work was shown in Fig. 18 [142].

In the work, the online quality estimation, expulsion detection and realization of control strategy were properly combined. The work was a remarkable improvement when compared to previous works. Though the neural network was employed, it was just a weld classification sensor, and the expulsion detection also used general characteristics of RSW process. The fuzzy logic algorithm was used to achieve constant current control, and the algorithm did not fully rely on the results of online quality estimation and expulsion detection. The discipline was much general than that of previous other works. In other word, this type of work was the most suitable method when compared to other works, especially which employed the AI tools.

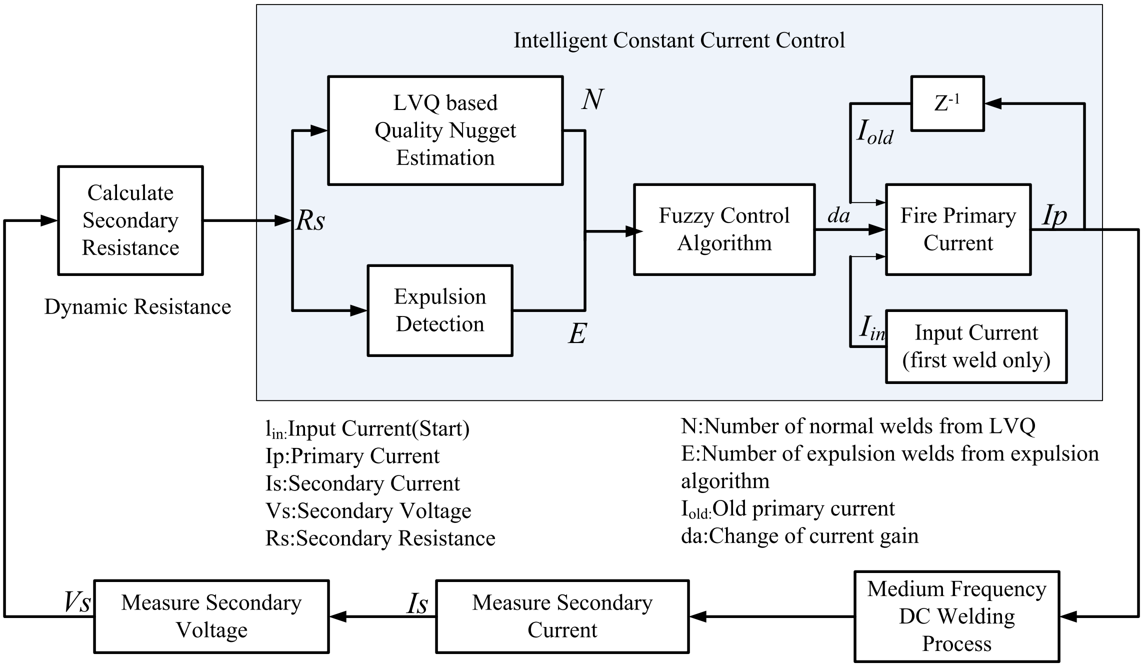

Fig. 18. Control scheme in the work.

In the preceding reviews, though the control systems were designed based on the effects of quality monitoring, two parts are dependent each other. In other words, if energy delivery followed a predetermined mode, such as constant current, constant energy or parameters optimization modes, the online quality estimation cannot instruct the control system design. On the other hand, if the online quality estimation was employed to generate control strategy for instructing the energy delivery, the energy delivery must abandon its intrinsic mode and follow it. In addition, if the feedback control mode was employed, the feedback signals must affect the predetermined energy delivery mode or quality estimation algorithm.

To achieve an appropriate control, the energy delivery and the online quality estimation should be absolutely separated, in other words, the energy delivery was independent and not affected by quality estimation result during the whole process, while the online quality estimation was just a sensor and provided the quality information to the system.

In our previous work [13,143], we designed a similar system to conduct the process control of RSW system. In this work, we employed a constant current controller, which was designed fully based on the electrical characteristics of single-phase AC RSW machine and can guarantee the value of the welding current approximately constant during the whole process. An online nugget diameter estimator was used to provide diameter value after each control cycle, based on a model which was established offline. The model in the work was based on the metallurgical experiment, while the process analysis based on dynamic resistance characteristics and mathematical deduction, and the results were verified by a series of experiments. The online dynamic resistance measurement in this work employed a new processing method, which used the historical information to eliminate the noises and errors, and obtained the values with very high frequency, at the same time the accuracy was similar to that of the calculation by RMS values of electrode voltage and welding current. The form of the quality estimator was mathematical equations based on the data curve fitting between energy absorbed by the workpieces and nugget diameter, and coefficients of equations were obtained based on the experiments under different welding currents. The overall control scheme was shown in Fig. 19 [143].

In the work, the actual welding time of the system was determined by the result provided by the online nugget quality estimator. If the output of the estimator achieved the predetermined value, the process terminated, otherwise, the external energy continued to be delivered into the system. The energy was calculated using welding current and dynamic resistance following Eq. (1). The work properly combined online quality estimation and constant current control. However, the two parts were independent with each other. The result of online quality estimator did not affect the action of constant current control, it only supplied the estimated nugget diameter values after each control cycle, in other words, a terminating signal of the action. In addition, the detection of expulsion which was based on the fierce and abnormal change of dynamic resistance was also added to terminate the operation when expulsion occurred. Hence, the system was adequately safe during the process. The final experimental results showed that the error of the nugget diameter control can be limited to less than 0.1 mm.

According to review above control methods for RSW operation, the RSW system has only one input, such as percentage of energy input, or welding current, or other employed parameters, which were realized by adjusting the firing angle of SCR in single-phase AC RSW machine or duty ratio of PWM wave in three-phase medium frequency DC RSW machine. All of the system operations and strategies must relate the input and the preliminary confirmed goal, which might be the nugget diameter, welds classified results or others in general cases. A lot of nonlinearities, uncertainties, or mechanical elements affect the welding quality, hence, precisely establishing the model of the relation between input and output is difficult. This reason is the same as why no proper or general method to be proposed to online analyze RSW process or do NDT. In addition, because the welding time is so limited, control actions cannot be conducted in many times. In this section, firstly, the works which focused on optimizing the process parameters have been reviewed. These works analyzed the welding process and explored how the parameters affected the nugget formation and growth process, then used offline methods to optimize the process. However, the optimization cannot enough deal with the complexities and nonlinearity in real time, its applications were so limited. Secondly, the works which used the feedback control to improve the welding quality were reviewed. The works combined the characteristics of RSW process and nugget formation and growth, and many commonly employed control strategies were employed in reality. The control strategies included the traditional PID control and recent AI control methods. The methods were based on a lot of offline training and experiences, and some methods were so complex and required a lot of inputs, which limited the generality and university of the methods. In addition, the control actions generated from the control models may induce the system instability, because the quality estimation was accomplished and the

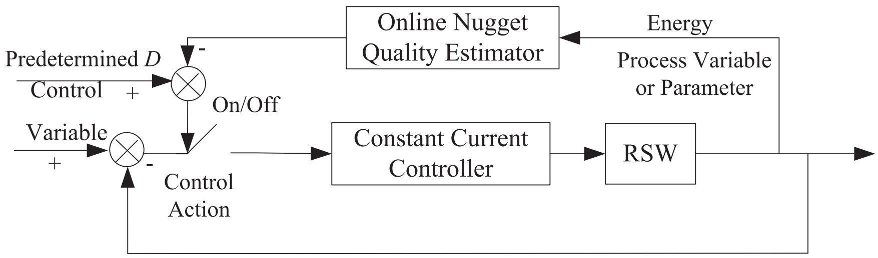

Fig. 19. Overall control scheme in the work.

control decision was made in the secondary coil of the transformer, while the control action was conducted in the primary coil, a tiny change in the second coil may induce large changes in the primary coil because the welding transformer was step-down. Hence, relying on the decision made in the secondary coil to adjust the energy delivery in the primary coil may be difficult and can induce a lot of errors. Then two works, which combined online quality estimation and confirmed control strategy were presented for respectively three-phase medium frequency DC RSW machine and single-phase AC RSW machine. The constant current control strategies were conducted in both of two works, in the first work, though it used the results of online quality estimation, the current control strategy was confirmed and cannot be changed by the results; while in the second work, the results of online process analysis and quality estimation were just a sensor to determine when to terminate the energy delivery. However, preliminary knowledge or offline data training are still required under current circumstance. The designs were more general than those of previous works and can assure the stability of the control process and obtaining welding products with high quality, though there are some drawbacks existing in these two works. It can be seen that the real time control system design for RSW operation is still a big challenge issue in current academic research and practical industrial application.

4. Conclusion

The recent advances of process analysis and quality control in RSW area have been reviewed in this paper. Online process analysis and non-destructive quality estimation are very important in RSW application because it can help to understand the process, and then take corresponding measures to reduce energy loss, improve the energy efficiency and weld quality, and reduce the costs of the production. It is derived from the exploration of the characteristics of RSW process, especially involving the nugget formation and growth features. Firstly, a lot of scholars employed mathematical analysis tools to interpret the RSW process and obtained some significant achievements. Though various models were presented, majority of models were based on the same principle and used the similar methods. That is, axisymmetric and thermal-electrical-mechanical models were employed to calculate the process, and display the important characteristics, such as temperature or current density distributions, magnetic variation, as well as the effects of process parameters on the nugget formation and growth process. However, under current circumstances, because the governing equation cannot sufficiently and exactly describe the phase change process, some important characteristics parameters cannot be precisely obtained. Also, some operational conditions, such as welding current in single-phase AC RSW machine, used approximate assumptions, the mathematical tools, mainly the FEM, had some limitations actually and cannot be precisely describe the process. Also, external monitoring tools, which included the digital high-speed camera, SEM, acoustic reflection, IR camera, PZT-based sensor, magnetic signals and so on, were employed. Though kinds of auxiliary measuring signals collected by majority of sensors can include enough information of the welds by means of preliminary models or data processing algorithms, some limitations cannot be avoided. Proper setting the sensors is so difficult, and the quality of the signals transmission is affected by various welding environment. Also, some experimental platforms are so complicate and many uncertainties elements exist in the measuring and analysis process. In addition, the information directly obtained from the sensors should be related to the characteristics of RSW process and nugget formation and growth, which require a lot of experimental data and offline training works. Moreover, the intrinsic process variables were also frequently employed to reflect the welding quality. Dynamic resistance, electrode displacement, which were the most commonly employed intrinsic variables, together with other variables, such as electrode force, electrode velocity, and so on, were combined various mathematical tools, such as kinds of neural networks or other data fitting methods to reflect the characteristics of RSW process. Though some remarkable achievements have been gained, the methods which used a lot of offline experiences and complex modeling methods lacks enough generality and could only be applied in limited occasions. In other words, it is difficult to extend the methods to general applications, no matter in process analysis or non-destructive quality estimation.

The goal of welding process control is obtaining welds with satisfactory quality by means of proper control actions. At the same time, the energy loss should be less and efficiency should be high. RSW control process is different from other common control systems. The process is absolutely unidirectional, because if the energy is delivered into the system, it cannot be removed. Also, the control action can be conducted in limited points, especially in the systems which employ the single-phase AC power source, so the accuracy of the system control is difficulty to be assured. Previous works employed various strategies and methods to achieve the goal. Firstly, some previous works focused on the operational parameters optimization. Apart from optimizing process variables to avoid negative phenomena, a lot of optimized parameters combinations, which were various welding lobe, were confirmed according to theoretical analyses or corresponding actual experiments. In addition, the works explored the effects of different parameters on welding quality, and then made corresponding adjustments or optimizations. Then to realize the feedback control, advanced control methods, such as PID tracking control, fuzzy logic control, and neuro-fuzzy control, were incorporated in the RSW operation, and gained some achievements. However, because the desired control goal was derived from or collected by limited experimental data, and offline data trainings were required. Each welding process involves a lot of special elements, the actual welding condition may not be the same as that when the offline data collection and training are conducted. In other words, the methods lack generality and has limitations in actual applications. Also, the control action for energy delivery in the primary coil of the welding transformer is affected by the predetermined control goal in the secondary coil of the transformer, which may deteriorate the stability of the system operation. Then two comprehensive control designs, which properly combined the online quality estimation and control strategies application, were presented. The works referred to respectively medium frequency DC RSW machine and single-phase AC RSW machine. Under the circumstances, two parts were effectively combined and could achieve more general design for the RSW control operation. The control action employed fixed control strategy and can guarantee the steady of energy delivery during the process, while the online quality estimation was used to optimize the performance of control strategy, or provided a signal of terminating the welding process.

According to review previous works in RSW related area, it is easily noticed that the amount of previous works dealing with online quality estimation or NDT including expulsion monitoring is extreme more than that of papers in other aspects of RSW related works, it may because the online quality estimation can be realized by means of different sensors or mathematical tools. As for other aspects, such as electrical structure and corresponding operations, materials characteristics analysis and control system design, the relative contributions were fewer. It may because that separately researching the electrical structure, process optimization or control system design were more difficult to obtain new significant achievements. However, based on above reviewing works, to achieve the goal of obtaining welds with satisfactory quality, different aspects should be comprehensively combined. For example, a general quality estimation or control system requires a stable energy delivery, which is provided by electrical structure. However, the variation of load resistance affects the consistency of energy delivery, and the knowledge is closely related to the metal melting and material characteristics variation. On the other hand, the quality estimation method requires materials characteristics, energy delivery features together with the application of reliable mathematical analyzing tools.

Because the RSW system is multi-field coupled and so complex, nonlinear and full of uncertainties, no matter in online process analysis and non-destructive quality estimation, or process control for obtaining products with high quality, there are some challenges in actual application. The general models which can eliminate the noises and disturbances have not been appeared so far. The majority of previous works were based on special working conditions or experimental conditions, or required many offline trainings or experts' experiences. In addition, because the surface differences between parent metal sheets are so large, and the welding condition also have differences, the reference models derived from previous experimental data have big limitations. Hence, it is expected that the important aspects for RSW researches will remain an active research items for a long time, especially in the general model of process analysis, quality estimation including NDT and online control system design. The future work should combine the characteristics of nugget formation and growth, as well as the operational features of RSW process, and consider the different parent metal size on the nugget formation and growth, and then establish general models which can avoid disturbances and cater to majority of occasions. Then the effective and general control system for stable RSW process and obtaining welds with satisfactory quality can be developed. This work can provide references and enlightens no matter in academic researches or actual production of RSW relative works.

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