Original Article

Performances of regression model and artificial neural network in monitoring welding quality based on power signal

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ABSTRACT

In this study, a systematic research was conducted to compare the performances of the regression model and artificial neural network in predicting the nugget diameter of spot-welded joints by monitoring the dynamic power signature. The TC2 titanium alloy with a thickness of 0.4 mm was used as the welding material, and a high-frequency precision spot welder was used to join the titanium alloy sheets. The dynamic welding current curve was obtained using the Rogowski coil, while the voltage curve was detected via two leads clipped onto the upper and lower electrodes during the entire welding process. The variations in the welding power signal in the welding process were investigated, and the characteristics of the power signals for different welding currents and electrode forces were analyzed. The power signals of different types of welding joints varied significantly. Five characteristics were extracted from the power signal to describe the shape of the curve. The stepwise regression analysis and back propagation neural network were respectively used to classify the welding joints into three categories: bad welds, good welds, and welds with expulsion. The performances of the two established prediction models were compared, and their behavioral discrepancies were attributed to their own data-mapping capabilities.

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1. Introduction

Resistance spot welding is a frequently-used welding technique that has the advantages of low cost, high degree of automation, and small work load. It is often used for joining steel sheets for car bodies and comprises approximately 3000–5000 spot welds [1]. Resistance spot welding methods can be categorized into two types in terms of welding power supply. One method employs alternating current (AC), and the other employs direct current (DC) [2]. With the development of science and technology, high-frequency welding power supply has attracted extensive attention. Li et al. [3] found that the...
DC welding process generally produced larger welds than the AC welding process even though the same root-mean-square welding current was employed. Thus, to obtain welding joints of a particular size, the AC welding process consumed more energy than the DC welding process. Alfaro et al. [4] used a high-speed filming technique to investigate the nugget formation and growth in the resistance spot welding process in case of an AC and a DC spot welding machine. They indicated that the DC welding machine offered a greater possibility of obtaining uniform nuggets. Lee et al. [5] developed a fuzzy controller for an inverter DC resistance-spot-welding system to control the constant current and more complex current waveforms for realizing the adaptive control of resistance spot welding. Hence, it can be observed that the DC resistance-spot-welding machine consumes less power owing to its higher energy efficiency, introduces less electrode wear, and results in a wider weld lobe and more uniform nugget sizes. While there exist several research works focused on the monitoring of the welding quality of AC welding machines, few studies have focused on a specially designed system for predicting and assessing the welding quality of a DC welding machine.

The dynamic resistance curve of the welding process is considered to contain information regarding nugget development, and widespread research interest has thus been focused on it. Summerville et al. [6] estimated the nugget diameter directly from the dynamic resistance of the welding process by using principal component analysis, autocorrelation, and multilinear regression; their research findings indicated that the dynamic resistance curve was potentially useful for reducing the production time and cost. Fan et al. [7] used the dynamic resistance to monitor the stainless-steel single-spot-welding process and studied the effects of different welding conditions on the dynamic resistance curves, and they found that the dynamic resistance curve could be monitored to prevent the occurrence of expulsion. Xing et al. [8] proposed a scheme for the online quality monitoring of the resistance spot welding process using random forest classification featuring based on dynamic resistance signals. A number of characteristics were extracted to describe each dynamic resistance plot, and they were then treated as the inputs of the random forest classification model, while the outputs of the model comprised three types of welds: cold weld, good weld, and expulsion weld. Wang et al. [9] analyzed the complex electrical impedance by dividing the voltage by the current in order to obtain the dynamic resistance curve. They extracted several features from the dynamic resistance curve and analyzed the correlations between the extracted features and weld strength. Luo et al. [10] highlighted that the nugget growth status in the resistance-spot-welding process could be classified as the initial stage, growth stage, and stable stage based on the dynamic resistance curve, and these represented different periods of the nugget growth process. Wang et al. [11] implemented a fast, self-organizing, map-based quality classification with windowed feature extraction for the purpose of welding-quality classification using dynamic resistance signals. The results of the spot-welding experiments indicated that the classification accuracy was approximately 92.9%.

From a review of the relevant literature, it was observed that nearly all the existing studies are focused on the dynamic resistance of the steel and aluminum alloy used in the AC welding process. Titanium and titanium alloys hold a unique place in the aeronautics and chemical industries owing to their low density, high specific strength, good high-temperature properties, and corrosion resistance [12]. As the DC welding machine can be used to replace the AC welding machine [13], an effective method of monitoring the welding quality of a titanium alloy during the DC welding process is urgently required.

To advance an affordable and highly accurate technique of online quality monitoring from the laboratory to the plant environment, the use of a more reliable and cheaper dynamic signature was proposed for welding-quality examination in this study. A real-time detection system was presented, after which the welding current and voltage were obtained in the secondary circuit. The power signal was acquired, and variations in the power signal were analyzed to characterize the welding qualities. The welding qualities could be classified as bad welds, good welds, and expulsion welds. The profile quantities with physical meanings were extracted from the power signal to identify the variations in the signal, and they were then treated as the inputs of the artificial neural network and regression model. The prediction accuracy of the models was also discussed.

2. Materials and methods

The material used in the experiments was a 0.4-mm-thickness titanium alloy TC2, which is a type of α + β titanium alloys that provides a complex microstructure in addition to its excellent combination properties and working temperature of up to 400°C. The TC2 titanium alloy is considered an ideal building material for bulkheads and wall panels used in high-temperature applications. Its chemical composition and mechanical properties are listed in Tables 1 and 2. The TC2 metal sheets were cut to a size of 100 × 30 mm and then soaked in a 20%-hydrofluoric acid, 45%-nitric acid, and 35%-water mixture for 2 min. The welding plates were thoroughly cleaned using clear water and dried via air drying. The base metal sheets were overlap-welded with a length of 30 mm, high-frequency alternating-current pedestal welder, and air-cooled flat-tip copper-alloy electrodes. The tip face diameter of the electrode was 3 mm.

A weld schedule usually comprises four key process parameters, which include the welding current, electrode force, welding time, and holding time. The welding current, welding time, and electrode force control the heat input supplied to the welding zone, while the holding time is related to the cooling rate of the nugget. The nugget rapidly nucleates and grows with the help of the electrode force during the holding time. The holding time was set as 2 ms in this study. Table 3 presents the detailed welding parameters.

The layout used for obtaining measurements is shown in Fig. 1. The welding current was measured using the Rogowski coil positioned at the lower arm of the welding machine, and the electrical voltage was calculated based on the voltage difference between the upper and lower electrodes. The leads clamped onto the two electrodes were twisted to reduce the inductive noise. The analog signals of the welding current and
Table 1 – Chemical compositions of TC2 titanium alloy.

<table>
<thead>
<tr>
<th>Alloying elements</th>
<th>Impurities (not more than)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ti</td>
<td>Al</td>
</tr>
<tr>
<td>Main</td>
<td>4.0</td>
</tr>
</tbody>
</table>

Fig. 1 – Measurement system used in the welding process.

Table 2 – Mechanical properties of TC2 titanium alloy.

<table>
<thead>
<tr>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>σb</td>
<td>825 MPa</td>
</tr>
<tr>
<td>σ0.2</td>
<td>757 MPa</td>
</tr>
<tr>
<td>E</td>
<td>111 GPa</td>
</tr>
<tr>
<td>δ5</td>
<td>18.8 %</td>
</tr>
</tbody>
</table>

Table 3 – Welding process parameters employed in the welding experiments.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Lower limit</th>
<th>Upper limit</th>
<th>Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Welding current</td>
<td>kA</td>
<td>1.0</td>
<td>2.4</td>
<td>0.2</td>
</tr>
<tr>
<td>Welding time</td>
<td>ms</td>
<td>4</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>Electrode force</td>
<td>N</td>
<td>76.2</td>
<td>203.2</td>
<td>25.4</td>
</tr>
</tbody>
</table>

Voltage were transformed into an array of digitized data using the analog-to-digital conversion card.

Tensile shear tests were conducted to determine the mechanical performances of the welding joints. During the tensile shear test, the specimens were subjected to a pair of parallel forces until it was fractured and destroyed. The tensile shear test was performed using a loading velocity of 1 mm/min at room temperature, and the peak load was recorded on plotting a load-displacement curve. The nugget diameter was measured using a Vernier caliper from the fracture section of the specimens. It follows that the quality of welding joints is function-related to the nugget size, peak load, and failure mode. The predominant failure modes comprise interfacial failure (IF) and pull-out failure (PF) [14]. There exists a critical nugget diameter that induces the IF and PF modes. Therefore, the nugget diameter appears to be the key index for determining the welding quality [15].

3. Results and discussion

3.1. Quality-class selection for welding joints

Fig. 2 demonstrates the typical load-displacement curves of the tensile-shear-tested specimens for the cases of IF mode, PF mode, and expulsion. The failure modes of the welding joints can be easily distinguished from their fracture sections. In the IF mode, the failure is controlled by the shear stress at the interface of the two sheets. In the PF mode, the resulting tensile stress around the nugget controls the occurrence of failure [14,16,17]. The PF specimens demonstrate an advantageous tensile-shear-load-bearing capacity with a good combination of strength and ductility; consequently, they are considered good welds. The welding joints with expulsion display a downward trend in failure energy, although their peak load presents a similar value to that in the case of the PF specimen. It is apparent that its lower failure energy is due to its brittle fracture. In addition, expulsion is considered one of the most common defects in the resistance-spot-welding process, and it is usually caused by local overheating at the workpiece-workpiece or workpiece-electrode interface. Metal splash can cause severe damage to the working environment and severe injury to humans; it should thus be prevented. A bad weld with the IF mode exhibits the worst load-bearing capacity and apparent lowest peak load. Its failure mainly occurs in brittle failure. Fig. 3 displays three typical types of welding joints after performing tensile shear tests. The specimen in Fig. 3a presents the IF mode, thus indicating that it is an undersized welding nugget. Fig. 3c presents the tensile fracture interface of the PF mode. It is generally recognized that the crack is first formed in the heat-affected zone, which signifies that the weld has good ductility [18,19]. The expelled molten metals are observed at the faying surface in Fig. 3b, the results of previous studies indicate that the majority of welds with expulsion more easily undergo brittle fracture in the tensile shear test [20–22]. Even though some welds with expulsion display a sound peak load, their failure energy is still low [23]. In addition, expulsion a welding defect and should thus be prevented. Therefore, welds with expulsion are thought to be undesirable and should be treated differently from other welds. Based on the load-displacement curves, failure modes, and expulsion, the welding qualities could be classified into three levels: bad weld, good weld, and expulsion weld.
The nugget diameter is the key factor used for assessing the welding quality, and it determines which failure mode will occur [24]. There exists a critical nugget size, and the failure mode transforms from interfacial into pull-out as the nugget diameter increases. On the basis that the critical nugget diameter is the minimum value that induces pull-out failure, it is necessary to determine this critical value. The American Welding Society, American National Standards Institute, and Society of Automotive Engineering define the equation for the critical nugget diameter as follows [25]:

$$ D = 4\sqrt{t} $$  

(1)

where, $D$ is the critical nugget diameter, and $t$ is metal-sheet thickness. The critical nugget size for 0.4-mm thickness metal sheets should be 2.53 mm based on this equation. However, the experimentally determined critical nugget diameter is 1.76 mm, which is much smaller than that obtained using Eq. (1). This value is thus inconsistent with the experimental value.

Another equation for the critical nugget diameter was derived by Chao [26]. The weld nugget size criterion was calculated on the basis of the fracture toughness and strength of the material. The model is given as follows:

$$ D = 3.41(t)^{\frac{1}{3}} $$  

(2)

Based on this equation, the critical nugget size for a 0.4-mm thick titanium alloy is 1.0 mm. This value seems too small, and it is not adequate for ensuring the occurrence of the PF mode.

Sun et al. [27] presented the integrative determination formula under which the pullout failure mode could be ensured:

$$ D > \frac{1}{f} $$  

(3)

where $f$ is the weld porosity factor, which is dependent on welding properties such as porosity and irregularity. On assuming that the value $f$ is equal to 0.8, the critical nugget diameter is 1.6 mm, which is smaller than that in the experimental data, i.e., 1.76 mm, and can not ensure the quality of the welding joints of a titanium alloy with 0.4-mm thickness.

Thus, it is necessary to create a valid methodology for determining the critical nugget size for the 0.4-mm-thickness TC2 titanium alloy such that the welding joints can bear the expected load. The contact interface of the welding joints bears the shear force in the case of IF mode, while the entire nugget sustains tensile force in the case of PF mode. The failure mode is determined based on the resultant of the tensile and shear forces applied to the nugget. If the maximum shear force applied at the interface of the nugget exceeds the tensile force imposed on the cylindrical regions of the nugget, the nugget fails in PF mode; else, it fails in IF mode. Based on this phenomenon, an analytical model for the critical nugget diameter was developed by Zhao et al. [28]:

$$ \frac{H_{HAZ}}{H_{FZ}} x^3 - \frac{3}{4} \frac{H_{HAZ}}{H_{FZ}} x + \frac{1}{4\pi} = 0 $$  

(4)

where $H_{HAZ}$ is the mean value of the Vickers hardness of the heat-affected zone, and $H_{FZ}$ is the hardness of the nugget. In the case of the TC2 spot welding joints, the hardness of the nugget was approximately 385 Hv, while this value in the heat-affected zone was approximately 245 Hv, such that the expression for the TC2 titanium alloy is as follows:

$$ \frac{245}{385} x^3 - \frac{147}{308} x + \frac{1}{4\pi} = 0 $$  

(5)

The acceptable solution for this cubic equation is as follows:

$$ x = \frac{1}{d} = 0.174 $$  

(6)

where the diameter of the nugget is $d$, and the height of the nugget is $L$.

The indentation depth of the welding joints is usually approximately 20% of the sheet thickness [29].

$$ \frac{0.8t}{d} = 0.174 $$  

(7)

Finally, the critical nugget diameter $d$ for the 0.4-mm-thickness titanium alloy is as follows:

$$ d = 4.60t $$  

(8)

The critical nugget diameter was calculated using Eq. (8) as 1.84 mm, which was consistent with the experimental critical nugget diameter of 1.76 mm. Thus, this empirical formula can be said to have a superior accuracy in the case of spot-welded TC2-titanium-alloy sheets of 0.4-mm thickness. Table 4 illustrates the critical nugget diameter obtained based on reference models and actual experimental results. It is apparent that the model developed using Eq. (8) most closely approximates the actual value.
Table 4 – Remarks on various models with respect to critical nugget diameter.

<table>
<thead>
<tr>
<th>No.</th>
<th>Model</th>
<th>Model equation</th>
<th>Critical nugget diameter (mm)</th>
<th>Error (mm)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Existing industrial model</td>
<td>$D = 4\sqrt{t}$</td>
<td>2.53</td>
<td>0.77</td>
<td>Very high factor of safety</td>
</tr>
<tr>
<td>2</td>
<td>Chao</td>
<td>$D = 3.41(t)^{\frac{4}{7}}$</td>
<td>1.00</td>
<td>−0.76</td>
<td>Unsafe</td>
</tr>
<tr>
<td>3</td>
<td>Sun et al.</td>
<td>$D = \frac{18.2}{t}$</td>
<td>1.60 (considering $f = 0.8$)</td>
<td>−0.16</td>
<td>Unsafe</td>
</tr>
<tr>
<td>4</td>
<td>Zhao et al.</td>
<td>$D = 6.60t$</td>
<td>1.84</td>
<td>0.08</td>
<td>Satisfactory</td>
</tr>
</tbody>
</table>

Fig. 4 – Constant-welding-current curve.

Fig. 5 – Typical power signal and its corresponding dynamic resistance curve.

3.2 Characteristics of dynamic power signatures for different welding conditions

The welding current and voltage signals were measured and processed to estimate the power signal. The power signal can be evaluated by multiplying the welding current and voltage:

$$P(t) = V(t) \times I(t)$$  \hspace{1cm} (9)

where $t$ is the welding time, $P(t)$ is the dynamic power, $V(t)$ is the voltage, and $I(t)$ is the welding current. The power can also be written as follows:

$$P(t) = V(t) \times I(t) = I^2(t) \times R(t)$$  \hspace{1cm} (10)

$R(t)$ is the dynamic resistance in the welding process. As the constant welding current mode is employed in the welding process, as shown in Fig. 4, it is easy to deduce that the power signal should exhibit a similar tendency to that of the dynamic resistance. Fig. 5 presents the typical power signal of a titanium alloy. The power value first increases to a peak point and then it exhibits a descending trend until it reaches the terminal point. This trend of the power corresponds to a specific physical phenomenon that occurs in the welding process. The first increase phase comprises two physical phenomena. With the help of the electrode force and welding heat, the asperities of the faying surfaces break, and the contact area increases, as a result of which, the resistance decreases. As the welding current increases significantly at the same time, the power thus increases owing to the effects of these two phenomena. As the temperature increases in the welding zone, the metal melts and a nugget forms. The effect of bulk resistivity plays a leading role while the current is constant at this stage, thus resulting in an increase in the power signal. The peak point is also referred to as the $\beta$ peak. In the decreasing stage, the effects of the enlarged nugget diameter and decreasing welding current overpower other effects, thus accounting for the decrease in the curve until the end point is reached.

The power signal not only exhibits a similar change trend to that of the dynamic resistance but also corresponds to all the physical phenomena in the welding process. In addition, compared with the dynamic resistance, the power has a greater effect on the welding heat supplied to the welding zone, which is the essential factor determining the formation and growth of the nugget. Furthermore, a single resistance value appears to be irrelevant to the welding heat as it is required to be used in combination with the welding current or voltage to obtain the heat value.

Fig. 6 presents the power signals for welding currents varying from 1.2 kA to 2.0 kA. The rate of increase in the power signal in the first few seconds increases steadily along with the different welding current levels. The peak value of the power signal increases, and its corresponding arrival time advances with the increase in the welding current. This behavior indicates that the heating rate is relatively slow in the case of a low current; therefore, more time is required to achieve a similar nugget growth and mechanical breakdown in the metal sheets as required in the case of a higher welding current. As the welding heat is proportional to the heat input of the power supply, the higher the current level is, the faster
the welding heating will be, and the shorter the time required for nugget formation will be. In the following stages, as the current increases, the power curve decreases slightly faster.

The electrode force has a significant influence on the welding quality. In order to investigate the influences of electrode forces on the power curve, the power curves for various electrode forces were recorded and presented in Fig. 7. As the electrode force increases, the known β peak value reduces and shifts; at the same time, the entire dynamic power curve presents a general upward trend as the electrode force decreases. The electrode force is the main factor affecting the electrode-workpiece and workpiece-workpiece contact surface area. The contact surface area increases as the electrode force increases, while the length of the conductive pathway decreases as the electrode force increases, thus resulting in a lower resistance value. As a consequence, the welding heat is reduced. All the welding experiments were performed at the same current level, and thus, the welding zone heats up more slowly under a larger electrode force than that under a smaller electrode force. Therefore, the peak point presents earlier, and as the electrode force increases, the formation of the nugget is delayed.

Three levels of welding qualities and their corresponding power signals are plotted in Fig. 8. It is observed that remarkable differences exist among the curves. The peak β point of the bad weld appears to be less apparent, thus indicating a slight local melt and insufficient nugget formation. The power signal for a good weld exactly presents the typical power signal. It can be noted that the peak time for the good weld markedly advances as compared with that of the bad weld. The power signal of the weld with expulsion significantly drops after it reaches the β point owing to the molten metal splashing out of the welding zone as expulsion occurs. The power signatures are quite different from each other owing to their different physical characteristics.

It is generally considered that the extraction of several characteristics for expressing each power plot according to the previous discussion is feasible. Five features were selected to illustrate the power signature. The extracted features comprise the peak time, peak power, inflection point, power decrease rate, relative velocities, and the welding heat. Some of these are schematically presented in Fig. 9. Detailed descriptions of the features extracted from the power signal are scheduled in Table 5.

4. Establishing model for quality inspection

4.1. Regression modeling

The regression models commonly comprise linear and nonlinear regression. The regression model is employed to establish a relationship between the independent variables \((x_1, x_2, \ldots, x_n)\) and dependent variables \(Y\). The response function can be expressed as follows:

\[
Y = f(x_1, x_2, \ldots, x_n) \tag{11}
\]
Table 6 - Coefficients and analysis-of-variance results of the regression model.

<table>
<thead>
<tr>
<th>Source</th>
<th>Coefficient</th>
<th>F value</th>
<th>P-value</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td></td>
<td>352.1170</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$p_n$</td>
<td>0.1596</td>
<td>7.4689</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$P_n$</td>
<td>801.2810</td>
<td>0.1195</td>
<td>0.9051</td>
<td></td>
</tr>
<tr>
<td>$\Delta P$</td>
<td>−801.2810</td>
<td>0.1195</td>
<td>0.9051</td>
<td></td>
</tr>
<tr>
<td>$P_s$</td>
<td>5.1538</td>
<td>9.7480</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$Q$</td>
<td>0.05728</td>
<td>12.3352</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$p_nP_n$</td>
<td>0.0070</td>
<td>1.1771</td>
<td>0.2409</td>
<td></td>
</tr>
<tr>
<td>$p_n\Delta P$</td>
<td>0.0131</td>
<td>0.7052</td>
<td>0.4817</td>
<td></td>
</tr>
<tr>
<td>$p_nP_s$</td>
<td>1.0963</td>
<td>5.3631</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$p_nQ$</td>
<td>−0.0006</td>
<td>−0.4125</td>
<td>0.6805</td>
<td></td>
</tr>
<tr>
<td>$P_n\Delta P$</td>
<td>0.0308</td>
<td>1.1621</td>
<td>0.2469</td>
<td></td>
</tr>
<tr>
<td>$P_nP_s$</td>
<td>−2.38315</td>
<td>−6.6793</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$P_nQ$</td>
<td>−0.0004</td>
<td>−0.2536</td>
<td>0.8001</td>
<td></td>
</tr>
<tr>
<td>$\Delta PQ$</td>
<td>0</td>
<td>0.0000</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>$\Delta PQ$</td>
<td>−0.0035</td>
<td>−0.7332</td>
<td>0.4645</td>
<td></td>
</tr>
<tr>
<td>$P_sQ$</td>
<td>−0.0535</td>
<td>−1.8026</td>
<td>0.0733</td>
<td></td>
</tr>
<tr>
<td>$P_s^2$</td>
<td>0.0050</td>
<td>1.0886</td>
<td>0.2780</td>
<td></td>
</tr>
<tr>
<td>$P_s^2$</td>
<td>0.0085</td>
<td>1.1416</td>
<td>0.2553</td>
<td></td>
</tr>
<tr>
<td>$\Delta P^2$</td>
<td>−0.0176</td>
<td>−0.3113</td>
<td>0.7560</td>
<td></td>
</tr>
<tr>
<td>$P_s^2$</td>
<td>−9.6121</td>
<td>−7.9393</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>$Q^2$</td>
<td>−0.0007</td>
<td>−7.528</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0933</td>
<td>R-square</td>
<td>0.9383</td>
<td></td>
</tr>
<tr>
<td>Adj R-square</td>
<td>0.9357</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The second-degree regression model is the most frequently used, and it is given as follows:

$$Y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j$$  \(12\)

where $a_i$, $a_{ij}$, and $a_{ij}$ are the coefficients to be calculated, which are usually obtained via the least square method.

In this paper, the features extracted from the power signal are the independent variables, and the nugget diameter is the dependent variable. The coefficients are determined using the stepwise regression method. The stepwise regression procedure is used for assessing the significances of the variables. The stepwise regression method is a statistical method that can be used to select several important variables to establish the regression equation. Using the stepwise regression method, the importance of each term in the regression model can be easily detected based on its F value [30].

The regression coefficients were estimated using the first 170 couples of experiment data based on the software MATLAB 2013a. The remaining 80 groups of data were used to validate this regression model. The F value of each term is tabulated in Table 6. The results show that the multiple-stepwise-regression method could make a selection from many free variables and eliminate some unimportant factors. The F-value of each term of the model indicates whether it is significant. A F-value of less than 0.05 is thought to be statistically significant while the terms with a F-value greater than 0.1 are eliminated. A determination coefficient of 0.9383 is observed for this model; this value is close to 1, which means the model is of high reliability and practicability. The final quadratic regression model used for calculating the nugget diameter based on the features selected from the power signal can be expressed as follows:

$$D = 0.1596p_n + 5.1538P_s + 0.05728Q + 1.0963P_mP_s - 2.38315p_nP_s - 9.6121P_s^2 - 0.0007Q^2$$  \(13\)

4.2. Neural network modeling

Artificial networks are considered very efficient for application to complicated and highly interactive problems, as they can realize free linearity or non-linear function mapping. The BP (back propagation) network, being a widely applied neural network model, is a feed-forward neural network practiced by the BP algorithm. The BP neural network can learn and store a large amount of input-output mode-mapping relationships without having to reveal the mathematical equations for the mapping relationship beforehand. These characteristics give it some good properties such as self-learning, and self-adapting ability, and strong robustness. In this study, a BP neural network was employed to distinguish the complex relationship between the extracted features in the power signal and the nugget diameter.

The learning rule of the BP neural network is the gradient descent method, which constantly adjusts the network weights and threshold using back propagation to minimize the error sum of squares. The topological structures of the BP neural network include the input, hidden, and output layers. The first layer is the input layer and consists of a group of processing units that are responsible for the acceptance of the data imported to the network. The number of neurons for the input layer equals that of the independent variables. The neurons of the hidden layer perform the pattern matching of the process input information and respond to the input patterns, while there are one or several nodal points in the output layer, which generates the output data.

In the case of the BP neural network being used for predicting the nugget size on the basis of the power signal, the input parameters for the input layer comprise the full range of features extracted from the dynamic power signal, while the output is the nugget diameter of the welding joints. The numbers of hidden layers and hidden units significantly affect the output accuracy of the BP neural network. However, there is neither theoretic nor strategic guidance available for determining the topological structure [31]. The ill-structured BP neural network is easily trapped in a local optimum or could require too much training time [32]. One hidden layer was used as it has been proved that a single-hidden-layer network can approximate any nonlinear mappings [33]. The number of hidden layer neurons changed from 3 to 10, and it was established as 7 by trial and error. Fig. 10 presents the topological structure of the BP neural network with one hidden layer.

The software MATLAB 2013a was employed to construct the BP neural network model. The transfer function of the hidden layer was set as the tan sig function and the purelin function was employed for the output layer. The training function was trainlm. The learning rate was set at a level of 0.001. The performance-function mean-square error was minimized with an iteration plan, and its goal was set as 0.00001.
The initial weights and biases of the BP neural network were achieved using the offline training method and the 170 couples of the experimental data were taken as the training data. After studying the network, the coefficient matrix of each unit, which includes the input, hidden, and output layers, was obtained. By adjusting the weight and, computing error rate and modifying the parameters of the hidden nodes, optimal results were achieved in the learning procedure. Using the collected data in the training the neural network, an appropriate welding-quality-assessment neural-network model was established.

4.3 Selecting an accurate model

The 80 couples of experimental data were used to test the prediction accuracies of the prediction models using the power signal. The scatter diagrams of the predicted versus measured nugget diameters for the regression model and BP neural network model are presented in Fig. 11 and used to verify the prediction accuracies of these models. The performances of the models were determined based on their errors and the variance of the errors. Fig. 12 presents the absolute errors of the two models based on the validation data. The statistical characteristic values of the absolute errors of each model are tabulated in Table 7.

It can be concluded that owing to the lower mean value and standard deviation of the absolute error of the BP neural network, it performs much better than the second-order regression model. One of the principal reasons for the superior performance of the BP neural network model is that it displays a better predictive capability than the regression model in actual application, owing to its random non-linear mapping ability. Therefore, the BP neural network can approximate nonlinear functions with arbitrary accuracy by regulating the variable weight connection.

5. Conclusions

(1) The power signal contains useful information regarding the dynamic resistance, which indicates the weld nugget states in the welding process, and it significantly affects the heat input generated; thus, it can be observed as a signal that is highly correlated with the welding quality, and it is valuable for the novel welding-quality-control method.

(2) The power signal in the welding process is analyzed, and its five features are extracted. The extracted features can not only provide information regarding the power signal but also reduce the scope for supervising the variations in the signal.

(3) The quadratic regression model was illustrated based on the experimental results using the stepwise-regression method. In the case of the quadratic polynomial regression model, the variance analysis indicates that $P_m$, $P_n$, $P_e$, and $Q$ are very significant ($P < 0.05$), whereas the value of $\Delta P$ has no significance ($P > 0.1$).
The experimental results prove that, as compared with the quadratic regression model comprising the use of stepwise regression analysis, an artificial neural network can provide more accurate results of nugget-diameter-prediction and target much better. Furthermore, the quadratic-polynomial-stepwise-regression method may not provide precise values of certain points for some highly nonlinear equations.

**Conflicts of interest**

The authors declare no conflicts of interest.

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