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Artificial neural network-based resistance spot welding quality assessment system★

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Key words:
Resistance spot welding; weld quality assessment; dynamic resistance; artificial neural networks; design of experiments

Abstract – On-line quality assessment has become one of the most critical requirements for improving the efficiency and the autonomy of automatic resistance spot welding (RSW) processes. An accurate and efficient model to perform non-destructive quality estimation is an essential part of the assessment process. This paper presents a structured and systematic approach developed to design an effective ANN-based model for on-line quality assessment in RSW. The proposed approach examines welding parameters and conditions known to have an influence on weld quality, and builds a quality estimation model step by step. The modeling procedure begins by examining, through a structured experimental design, the effect of welding parameters (welding time, welding current, electrode force and sheet metal thickness) and welding conditions represented by typical characteristics of the dynamic resistance curves on multiple welding quality indicators (indentation depth, nugget diameter and nugget penetration) and by analyzing their interactions and their sensitivity to the variation of the dynamic process conditions. Using these results and by combining an efficient modeling planning method, neural network paradigm, multi-criteria optimization and various statistical tools, the identification of the model form and the variables to be included in the model is achieved by executing a systematic model optimization procedure. The results demonstrate that the proposed approach can lead to a general ANN-based model able to accurately and reliably provide an appropriate assessment of the weld quality under diverse and variable welding conditions.

Mots-clés :
Soudage résistif par points ; évaluation de la qualité de la soudure ; résistance dynamique ; réseau de neurones ; plan d'expériences

Résumé – Système d'évaluation de la qualité du soudage résistif par points, mettant en œuvre un réseau de neurones. L'évaluation en ligne de la qualité de la soudure est devenu l'une des exigences essentielles pour améliorer l'efficacité et l'autonomie des procédés automatiques de soudage résistif par points (SRP). Un modèle précis et efficace d'analyse non destructive de la qualité constitue un élément primordial du processus d'évaluation. Cet article présente l'approche structurée et systématique qui a été utilisée pour concevoir un modèle efficace mettant en œuvre des réseaux de neurones pour l'évaluation de la qualité du SRP. L'approche proposée prend en compte les paramètres de soudage ainsi que les conditions connues pour avoir un impact sur la qualité de la soudure pour construire, étape par étape, un modèle d'estimation de la qualité. La procédure commence par un examen, au moyen d'un plan d'expérience structuré, de l'effet des paramètres de soudage (temps de soudage, courant de soudage, effort de soudage et épaisseur de la tôle de métal) ainsi que des conditions de soudage, représentées par les caractéristiques typiques des courbes de résistance dynamique, sur différents indicateurs de la qualité de soudage ; ensuite, les interactions entre ces paramètres et leur sensibilité aux variations dynamiques du process sont analysées. Par utilisation de ces résultats et en combinant, au travers d'une méthode efficace de développement de modèle, différents outils, réseaux de neurones, techniques d'optimisation multicritères, outils statistiques, nous avons identifié la forme du modèle et les variables à y inclure au moyen d'une procédure systématique d'optimisation du modèle. Les résultats obtenus montrent que l'approche proposée conduit à un modèle général, reposant sur les réseaux de neurones, capable de fournir une évaluation convenable de la qualité de la soudure dans des conditions diverses et variables de soudage.

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Resistance spot welding (RSW) is one of the most important joining techniques commonly used for sheet metal assemblies in many industries. Major advantages of RSW are high speed and adaptability for automation in high volume operations, and high rate production. Despite these advantages, RSW suffers from a significant problem of inconsistent quality. This problem results from several sources and complicates automation, reduces weld quality, demands over-welding and increases production costs. Moreover, recent safety and environmental requirements are more rigorous, forcing many manufacturers to develop more rigid and lighter assemblies. To meet these constraints, new advanced high-strength steel and various combinations of thickness, quantity and grades have been used, making the assemblies more complex and significantly increasing the risk of poor quality weld. For this reason, ensuring good weld quality has been and remains a major challenge [1, 2].

To produce and maintain consistent weld quality, the RSW process has to be closely monitored and the welding parameters (Wpar) must be constantly adjusted. The ability to perform on-line quality assessment in order to provide real-time quality control has become significant in RSW and is widely recognized by the industries [2, 3]. Although some conventional quality assessment methods have been developed during the past decade, the accuracy, flexibility and reliability of these methods remain insufficient. Consequently, much more research is required to develop a reliable and cost-effective RSW quality monitoring and assessment system for applications on the shop floor, especially when dealing with unpredictable conditions. Most of the research work conducted so far follows the same framework as that shown in Figure 1. Incontestably, the issues dealing with the understanding of RSW quality monitoring and assessment can be approached according to the development of accurate and reliable on-line measurement of welding parameters and conditions, the selection of appropriate strategies for measurement, processing and analysis, and the development of adequate modeling procedures.

Method development for weld quality evaluation has followed two major trends: destructive testing and non-destructive testing. A variety of available destructive testing methods [4] are useful in order to establish weld nugget strength and can provide precious information on weld quality and adequacy of the selected Wpar. These tests include tension shear, cross-tension shear, twist and peel tests. However, such conventional methods can only ensure the quality of specific spot samples and have limitations in the widely used assembly line system. In addition, the product wastage and the labour costs incurred while performing this type of testing make this approach unattractive. On the other hand, several non-destructive testing methods, using ultrasonic waves or X-rays to examine the quality and defects of the weld, have been investigated. However, applying non-destructive testing to on-line quality inspection causes many problems in terms of cost and facilities. An on-line strategy for quality evaluation in RSW is necessary in order to deal with problems as soon as they occur. This requirement has led to active research for a real-time weld quality control system that can effectively supplement non-destructive testing. Many research efforts have been devoted to the quality control of RSW. In these efforts [5], adaptive control can be considered as a promising strategy to adjust the process parameters, in real time, to the widely varying welding conditions (Wcdt) [2, 3]. Such adaptive systems are difficult to implement in industry. The most important reasons are the absence of measurement systems that reliably and effectively provide weld quality indicators in a hostile welding environment, and the lack of a deep understanding of the process, leading to inadequate modeling strategies.

In order to explore the welding mechanism and to build an effective quality estimation approach, many researchers have investigated the possible effects of various process variables on the birth and growth of nuggets. In addition to Wpar such as welding voltage, current, time and force, the main measurements that have been identified as important quality indicators in RSW include electrode displacement, electrode force, temperature variation, acoustic

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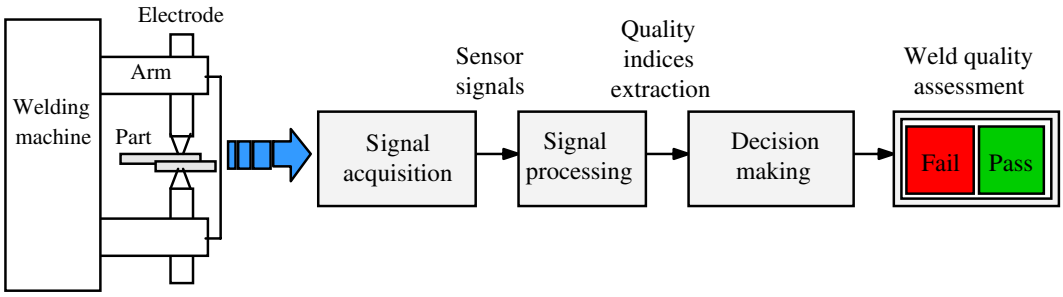


Fig. 1. Schematic diagram of the RSW quality assessment system.
Fig. 1. Représentation schématique du système d'évaluation de la qualité du soudage résistif par points.

emission, ultrasound testing and dynamic resistance [6, 7]. The measured variables are used in models that estimate/predict the quality characteristics. Compared with the destructive and non-destructive testing methods, these approaches provide a more economic and flexible capability, particularly when combined with efficient modeling techniques. Analysis of data from these measurement systems has revealed the difficulties involved in extracting representative characteristics of all process conditions from limited information. It has also shown that two main requirements need to be satisfied when implementing monitoring systems: the measurements must reflect the process behavior under its various operating conditions, and the measured variables must allow discrimination between specific states of the process. Among these variables, the dynamic resistance (DR) gives a relatively clear picture of the welding nugget formation and presents a significant relationship with the quality indicators. Several researchers have explored the use of DR in RSW quality control [8–10]. This research reveals a strong correlation between the various spot welding development phases and the shape of the DR curve. The variations in the DR curve have also been related to various welding settings such as welding current and electrode force [8]. Tested on a variety of materials (mild steels, stainless steels and aluminums), the DR-based methods demonstrate an effective ability to provide a better understanding of the spot welding process formation [9]. Figure 2 presents a schematic illustration of the typical shape of the DR curves and its interpretation based on the evolution stages of the nugget formation. In the short period of stage 1, the contact area increases under the pressure provided by the electrode force, causing resistance to decrease. From stage 1 to stage 3, increase in temperature leads to increase in resistivity, and the DR begins to rise. In the stage 4, the peak point, which is known as the beta peak, is reached [10]. At this point, the increase in resistivity forms an equilibrium with the increase in the cross-sectional area available for current flow and the decrease in resistance caused by the shortening of the current path due to the plastic deformation. After this point, as the size of the molten nugget and the cross-sectional area increase the DR starts to decrease. This interpretation suggests that it is possible to build a dynamic electrical monitoring system to measure and estimate relevant welding conditions during spot welding.

Accordingly, several quality estimation models have been proposed using different modeling methods [13–15]. In order to handle the non-linear dynamic effect, which occurs within a very short time during RSW, and to explain the functional relationship between the process variables and weld quality, attempts are being made to apply artificial neural networks (ANN) and fuzzy algorithms to RSW [11, 12]. A model based on ANN was proposed for on-line nugget size estimation using both controllable process parameters and DR [13]. In this work, only one quality indicator (nugget diameter) has been considered. Also, the force and the electrode displacement included in the experiment were not used in the model because they provide similar information to

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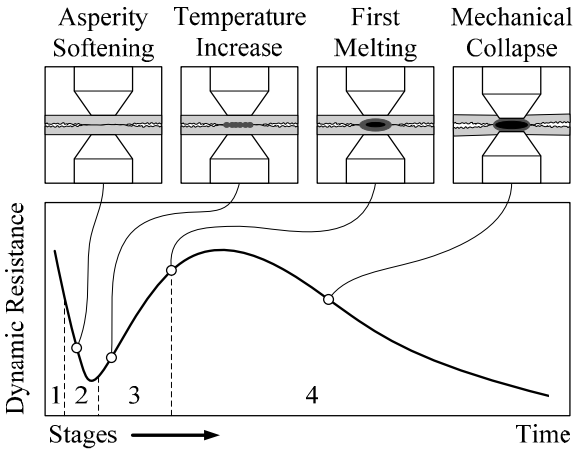


Fig. 2. Theoretical dynamic resistance curve and nugget formation stages.

Fig. 2. Courbes théoriques de résistance dynamique et différents stades de la formation du noyau fondu.

the DR. Based on various DR attributes other attempts using ANN and linear regression have been conducted in order to estimate tensile shear strength as a welding quality indicator for low-carbon steel [14, 15]. Tensile-shear strength limit estimation has also been investigated using a neuro-fuzzy-based approach for zinc-coated steel as a material [11]. Many other methods have been reported as well but most models are based on a single quality indicator and built on specific sheet assembly [2]. It was reported that the reliability of most proposed models is limited under real Wcdt [16].

Recently, attention has been directed to the use of multisensor fusion techniques in order to combine various information sources [17]. Sensor fusion is basically an indirect method using a combination of sensors as input into a mathematical model to extract corroborative and relevant information on the state of the welding operation. Sensor fusion is suggested where only a few sensors measuring specific variables can be applied. However, two difficulties are encountered in this issue: the selection of the most robust modeling technique and the choice of the appropriate sensor combination. No systematic method for sensor fusion can be found in the welding literature. Nevertheless, it is reasonable to assume that sensor fusion is carried out through a series of steps in which decisions are made based on specific statistical tests.

For modeling, two categories of models can be used: theoretical and empirical. Theoretical models are often very difficult to develop because of the reduced understanding of fundamental welding process behavior. The most current theoretical models are limited to very few variables. Empirical modeling methods use experimental data to adapt the parameters of the model in order to compensate for the inability to adequately describe the process mechanisms. As suggested in various works, easily available information on welding operations can be used to establish models using multivariate modeling techniques such as multiple regressions [18–20].

Model building analysis is often conducted with a large set of potential variables. From these variables, only a specific subset is useful. Thus, the identification of important variables is crucial to the modeling success. The identification can be carried out efficiently only if statistical tools are applied systematically. Three existing methods can be used for variable selection. These methods are: engineering judgment, correlation analysis and step-wise regression. However, none of these methods can identify the optimal models systematically. Based on individual knowledge and experience of the welding process, the engineering judgment method is useful to suggest preliminary welding variables for further investigation. However, the use of a limited number of variables without exact knowledge of process behavior is generally risky and cannot lead methodically to the best model. The correlation analysis method selects the highly correlated variables as a model using the correlation coefficients between the welding variables and the welding quality indicators as criteria. In this method, the partial correlations between the selected variables have to be explored otherwise the method is only suitable for finding a model with a single welding variable. Since the partial correlations between the quality indicators and the welding variables are investigated, the stepwise regression method [25] is able to identify r models with multiple variables. This

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method first includes the most strongly correlated welding variables and then adds or subtracts one variable at a time according to the values of an F-distribution that estimates the contributions of the added or removed variables. However, the effect of combining two or more welding variables at a time is never considered. As Wpar and Wcdt are characteristically interrelated, this method could result in models with inconsistent variable selection. In addition to the above three methods, there are two other variable selection methods, forward selection and backward elimination [25]. These methods have similar disadvantages to the step-wise regression. Although the traditional selection procedures offer the possibility of isolating one reduced model, they are unable to identify alternative candidate subsets of the same size or a model considered to be optimal according to various criteria. Hence, these procedures could lead to poor results and often to different subsets since the interactions between variables cannot be considered. Thus, the basic condition to successfully implement an adequate modeling procedure requires a simultaneous application of the selection criteria.

The objective of this study is to develop an effective ANN-based RSW quality assessment system. The proposed approach is built progressively by examining the welding parameters and conditions known to have an influence on weld quality from various aspects and building the quality estimation model step by step. The modeling procedure begins by establishing relationships between Wpar (welding time, welding current, electrode force and sheet metal thickness), Wcdt represented by typical characteristics of the DR curve and welding quality indicators (nugget diameter, nugget penetration and indentation depth), and the sensitivity of these elements to the variation of the process conditions. Using these results and various statistical tools different estimation models are developed. These models combine Wpar and a variety of Wcdt represented by assorted DR curve characteristics. In order to carry out the model building procedure, an extensive number of welding experiments are required to provide the modeling database. For this purpose, Taguchi's efficient experimental planning method is adopted.

1 Experimental assessment

Numerous factors influence welding quality indicators during RSW operations. This study will be restricted to four of them to illustrate the proposed approach. These factors include: welding time (WT), welding current (WC), electrode force (EF) and sheet metal thickness (ST). The effects of the four factors on the DR and on three quality indicators (indentation depth: I_{dep}, nugget diameter: N_{dia} and the nugget penetration: N_{pen}) will be evaluated. The effects of the Wpar and DR and the effects of their interactions on the quality indicators will also be analyzed.

1.1 Quality indicator definition

One of the best-known and most-used quality indicators in industry is the diameter of the spot weld, generally obtained by peeling methods, but the diameter alone cannot guarantee the quality of a spot weld. To attain a better assessment of the weld quality and increase the robustness of the models, we use three geometrical attributes of a spot-weld nugget defined in the AWS D8.1M: 2007 standard of the American Welding Society. The attributes measured from the nugget cross-section shown in Figure 3 are the indentation depth (I_{dep}), the nugget diameter (N_{dia}) and the nugget penetration (N_{pen}). I_{dep} is calculated from the average of the sheets and N_{pen} is the % of the thickness of the nugget out of the total thickness of the assembly. All these attributes have their own standard limit based on sheet thickness and used as criteria of weld acceptation. The resulting nugget was prepared and measured using a standard metallographic procedure.

1.2 Experimental planning

In any experiment, the results depend, to a large degree, on the method used to collect data. In a lot of cases, full factorial experiments are conducted. This approach cannot be implemented when too many factors

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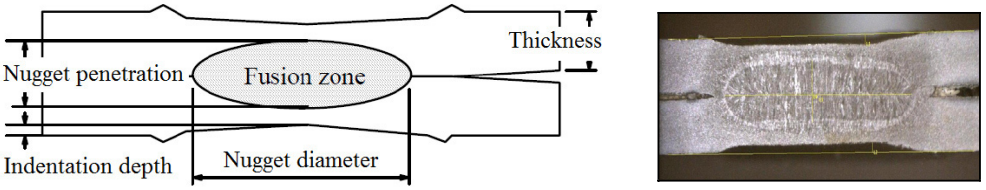


Fig. 3. RSW quality indicators – Weld nugget cross-section geometrical characteristics.
Fig. 3. Indicateurs de qualité du soudage résistif par points – Caractéristiques géométriques de la section du noyau fondu.

are under consideration, because the number of repetitions required would be prohibitive in time and cost. Regular fractional factorial designs cannot produce credible results when interactions among the factors exist. By contrast, the use of a testing strategy such as the orthogonal arrays (OAs) developed by Taguchi leads to an efficient and robust fractional factorial design of experiments that can collect all the statistically significant data with a minimum number of repetitions [25,26]. Accordingly, the OAs are used in this paper for the experimental design.

1.3 Experimental setup

As illustrated in Figure 4, the experiments were carried out on a medium frequency DC portable welding machine. The welding current is measured using a toroidal coil connected to the welding monitor. The electrode force with a pressure sensor is installed on the pneumatic cylinder of the spot welding gun and calibrated according to the arm. The DR is obtained indirectly, using Ohm's law, by measuring the welding voltage across the electrodes as close as possible to the sheets. Since the voltage probes should bypass the steel sheets, the probe cables form a loop in which the magnetic field, created by the welding current, induces noise in the welding voltage measurement. The inductive voltage caused by the magnetic field is measured with a coil installed near the electrodes and used in the evaluation of the welding real voltage component and DR.

The materials used in the experiments are commercially available galvanized low-carbon steel sheets widely used in the automotive industry. Because of their good corrosion resistance and relatively low cost, galvanized steels have attracted much attention over the past decade. However, electrode wear of zinc-coated steels continues to be a significant issue, due to their lower electrical resistance, lower melting temperature and accelerated degradation of resistance welding electrode tips. Electrode wear adversely affects the cost and productivity of the welding process due to reduced weld quality, reliability and robustness. Consequently, large potential cost savings and quality enhancements are anticipated from significant improvements in electrode life [21–24]. To minimize wear and coating effects, the electrodes should be maintained as cool as possible by selecting the appropriate electrode shape and by using water cooling and controlling the rate of welding. Thus, in this research, welding was conducted using a water-cooled 45° truncated cone RWMA C2 electrode (CuCrZr) with 8 mm face diameter. Electrodes were preconditioned before experiments and replaced after a limited number of welds.

In order to acquire several nugget characteristics and a large variety of DR curve shapes, while avoiding cold welds and expulsions and limiting extreme mechanical deformations, the setting limits of control parameters were established during preliminary trials. Cold weld is a consequence of insufficient quantity of energy, low welding current, short welding time and high welding force. Expulsion is a phenomenon that occurs when the energy supplied to the weld region is too abandoned, causing eruption of the molten material. The expulsions are generally considered undesirable due to the lower strength, high energy consumption, high electrode wear and visual appearance of the weld.

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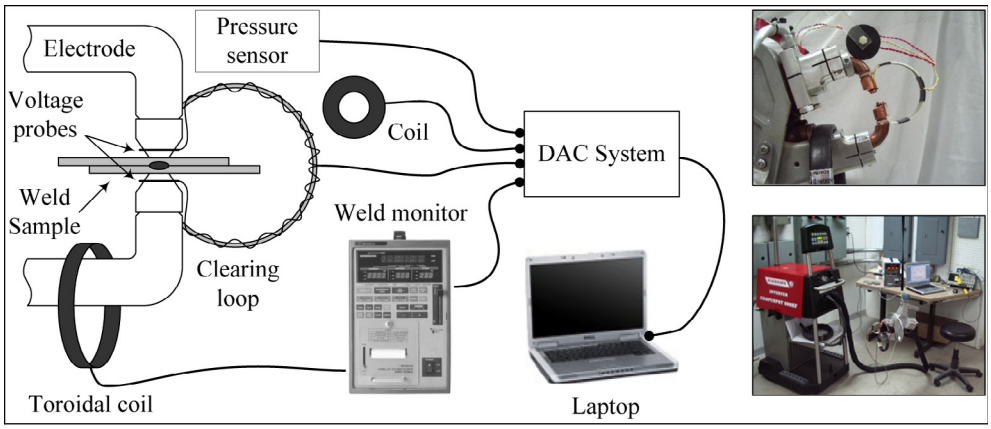


Fig. 4. Schematic diagram of the experimental setup.
Fig. 4. Dispositif expérimental.

Table 1. Factor levels for the experiments.
Tableau 1. Niveau des facteurs du plan d'expériences.

Factors	Training sets	Validation sets
ST: sheet metal thickness (mm)	0.95 to 1.85	0.95 to 1.85
WC: Welding current (A)	6.25 to 9.50	6.25 to 9.50
EF: Electrode force (N)	185 to 400	185 to 400
WT: Welding time (Sec)	300 to 500	300 to 500

Using the established limit values, three levels of settings were determined for each factor. Repetition of the trials to reduce experimental error would require a total of 162 tests to achieve all possible combinations of levels. Since the evaluation of the three quality characteristics by the metallographic method requires a lot of time, the number of trials was reduced to 36 using two OAs (L27 and L9). For the validation of the models, another L8 OA was built, based on the intermediate values used in the L27. The L8 data was also used as cross-validation to optimize the model generalization. The factor levels chosen are given in Table 1.

After welding, all specimens were sectioned through the nugget center cross-section and then polished and etched for nugget geometrical attribute measurement. For etching, the specimens are immersed in a Nital solution consisting of 4% HNO3 (Nitric Acid) in 96% ethanol for a sufficient period of time until the weld nugget, the heat-affected zone encircling the nugget and the macrostructure are revealed with reasonable contrast and definition. The specimens are washed under running water. The specimen surfaces were observed using a light optical microscope (Nikon Optiphot – 100S) at higher magnification. Micrographs of the cross-section were captured with a digital single lens high-quality microscopy camera (PL-A662). The nugget geometrical attributes were determined, based on the average value over three measurements.

1.4 Experimental result analysis

Two statistical indices, derived from ANOVA, are used to analyze the experimental data: the percent contribution and the average effects of each factor. The % contribution of a factor reflects the portion of the total variation observed in the experiment attributed to this factor. Ideally, the total % contribution of all considered factors must add up to 100. The difference from 100 represents the contribution of some other uncontrolled factors and experimental errors. Another interesting way to analyze the effect of a given factor is the graph of average effects. As the experiments were designed using an OA, the estimates of the average effects will

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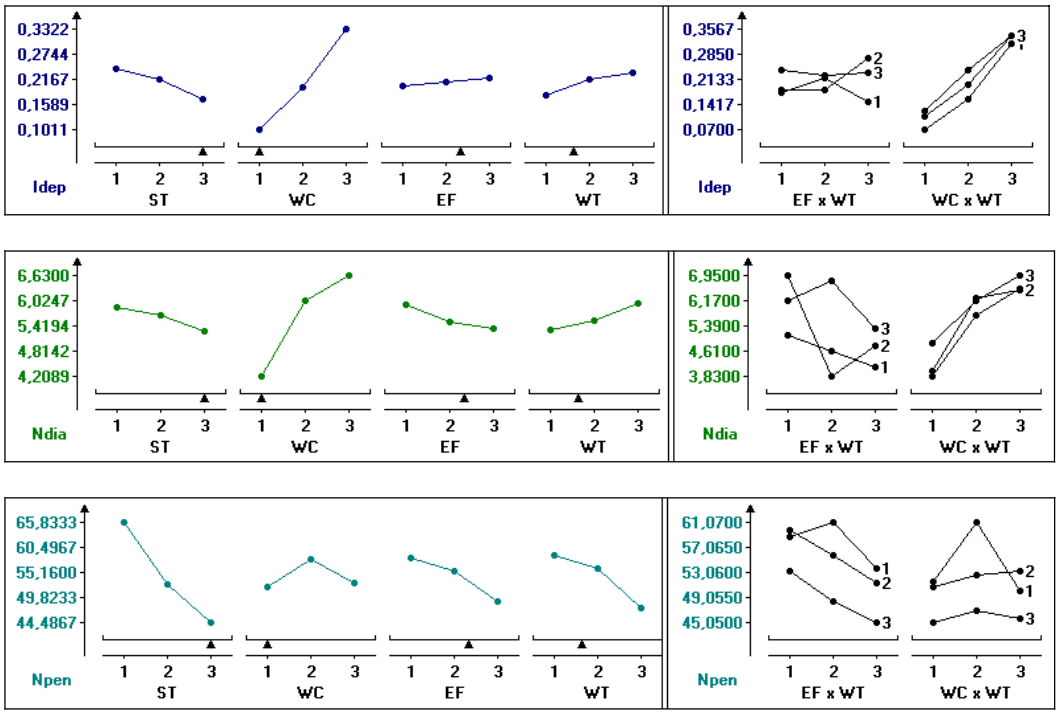


Fig. 5. Effect of Wpar and process conditions on the RSW quality indicators.
Fig. 5. Effet de Wpar et des conditions process sur les indicateurs de qualité du soudage résistif par points.

Table 2. Percent contributions of Wpar in the variation of the quality indicators.
Tableau 2. Contribution (%) de Wpar dans les variations des indicateurs de qualité.

Quality indicators	Welding parameters				Interactions		Error
	ST	WC	EF	WT	WC -WT	EF-WT	
I_{dep}	5.90	73.51	–	2.89	–	4.41	13.29
N_{dia}	3.17	75.02	3.18	3.99	–	2.32	12.32
N_{pen}	53.08	3.54	8.71	14.59	1.96	–	18.12

not be biased. The average effects graph presented in Figure 5 shows that RSW quality is affected by Wpar at different degrees. In this graph, the horizontal axis indicates the factor levels. The plotted points correspond to the averages of the observations realized under each factor level. The factors predominantly affecting quality indicators are ST, WC and WT. Figure 5 also shows the existence of complex interactions between various Wpar and reveals that the effects of different Wpar on the quality indicators are, in most cases, non-linear. Interactions that are not represented in the figure have negligible effects. A similar conclusion can be clearly established from the % contributions reported in Table 2. Presuming a limit of 10%, EF, and the interactions WC-WT and EF-WT were negligible. These results are expected since the WC, which is recognized to have a large effect on the nugget (N_{dia} and N_{pen}), presents the strongest effect. The significant effect of ST on I_{dep} is also predictable.

The limited effect of EF on Idep can be explained by the interaction of EF with the other Wpar and by the variation of the dynamic force (the change in EF from the value preset during the welding sequence). The change in EF is a response to the thermal variation under mechanical constraints. The force change can also be affected by machine characteristics (friction and stiffness), by process parameters through the effects of the thermal-mechanical process (preset force, welding current and welding time) and by workpiece materials through the thermal expansion (sheet thickness and physical properties). The change in electrode

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force can be further complicated by the electromagnetic force and by any non-linearity in response of the welding process. Unfortunately, there is no quantitative description of the dynamic electrode force because of the complex nature of RSW. Therefore, until more fundamental understanding is developed to mathematically describe the behavior of the dynamic electrode force, specially designed experiments and direct measurements may be the only ways available to obtain a quantitative relationship between EF and nugget geometrical attributes. Furthermore, the conclusions of this research focus mainly on global observations.

These results show that the error contribution is relatively high. This implies that important factors that influence RSW quality were not included in the experiments. Accordingly, one can presume that the quality indicators cannot be controlled with ST, WC and WT only. The introduction of some DR characteristics as modeling variables can compensate for the missing factors and reflect the process dynamic conditions. Based on these results, it still remains difficult to select the appropriate variables. A systematic and rigorous procedure for the best variable combination selection is required.

2 Construction of the assessment model

2.1 The proposed modeling strategy

RSW is a complex dynamic process that involves electrical, thermal and mechanical phenomena. The relations between process variables are highly non-linear. In order to establish an effective quality assessment model, two difficulties must be resolved: selecting a robust modeling technique and selecting the number and the type of variables to include in the model. These choices represent the basic ingredients of any modeling procedure. Selecting the model form and modeling technique is not sufficient to produce the best model. In these conditions, because deterministic models are typically valid only for a partial range of a limited number of Wpar, empirical modeling methods using experimental data to adapt the models in order to compensate for the inability to adequately describe the process mechanisms present the best modeling alternative.

As compared with other modeling techniques, ANNs provide a more effective modeling capability, particularly when the relationship between the variables and the characteristics to be identified is non-linear. ANNs can handle strong non-linearity, a large number of parameters, and missing information. This is very useful to reduce the experimental efforts. In addition, because of their inherent learning capabilities, ANNs can be used in cases where there is no exact knowledge regarding the relationships between various variables. While various neural techniques can be used in this approach, the multiplayer feedforward network seems to be one of the most appropriate because of its simplicity and flexibility. In order to extract a cost-effective best combination of variables to be included in the model, Taguchi's OAs are used again. The variable selection is based on the analysis of the effect of each variable combination on the model performances as well as the variable contribution to decreasing the modeling and validation errors.

Many criteria can be used to assess whether a model adequately represents the relationship between the welding quality indices and the Wpar under various Wcdt. Measuring the performance of fitted models is based on the principle of reducing several statistical criteria. These include the residual sum of squared error (SSE), the residual mean square error (MSE), the total squared error (Mallow's C_p), and the coefficient of determination (R^2). For the majority of modeling techniques, the model is determined by minimizing the residual sum of squares (SSE). MSE, C_p, and R^2 are a linear function of SSE. The combination of variables minimizing the SSE creates MSE and C_p as the minimum, and R^2 as the maximum under a fixed number of variables. In this study, the model performance evaluation procedure consists of evaluating the root mean square error (RMSE) and the maximum relative error (MRE) for both training and validation data ($RMSE_t$, $RMSE_v$, $RMSE_{tot}$, MRE_t, MRE_v and MRE_{tot}). These decision criteria provide

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efficient and global estimates of the relationship effectiveness between measured and estimated values, and consequently evaluate the generalization ability of the resulting models.

2.2 Application to RSW quality assessment

To illustrate the proposed modeling procedure, five variables were considered: ST, WC, EF, WT and DR represented by its curve characteristics. While various geometrical indices, such as the absolute values of the monitored DR (initial, maximum, average and final values), the beta peak location, the rising speed, the difference between the minimum and maximum DR, or the maximum value of the variation per cycle, can be used in order to reflect the geometrical type of the DR, a limited number of uniformly distributed points representing the geometric profile of the DR curve seems to be one of the most appropriate because of its simplicity and flexibility. A series of tests was conducted in order to extract the most significant geometric features of the RD curve. The results revealed that it is possible to represent the evolution stages of the nugget formation and the most significant features of the DR curve using a minimum of six uniformly distributed points without significantly affecting the modeling performance. Therefore, the variable DR used in the proposed modeling procedure is represented by the geometrical profiles designed by the points extracted from the DR curves. The illustration of the link between the extracted points and the evolution stages of the nugget formation using a typical DR curve is shown in Figure 2.

Before selecting the variables and training the ANN models, it was important to establish the size of the hidden layer and optimize the training performances. The idea is to approximate the relationship between the size of the hidden layer, the number of input variables and the complexity of the parameters to be estimated. For all trained networks, an adequate knowledge representation with an average error of less than 1% was used, irrespective of the hidden layer size. Consequently, to avoid long training and overfitting that could disturb its accuracy, the $(n)x(2n + 1) \times (3)$ network architecture was selected (n: number of inputs). For variable selection, the procedure begins by selecting the OA for model design where all potential variables are included. The OA that corresponded to this procedure was the L8. The performances of the eighth model design were evaluated.

Using these results, the average effect of each variable on each model performance was calculated. The average effect graph presented in Figure 6 demonstrates that the variables that have decisive effects on the designed models are WC and DR. The presence of WT in the model increases $RMSE_v$ and MRE_v values. The effects of ST, EF and the interaction RD*WC appear consistent but they present less impact than RD and WC whatever the criterion considered. The effects of the other variables and interactions are inconstant and depend on the criteria. Interactions that are not represented in the figure have negligible effects.

A similar conclusion can be clearly established from the average effect of each input variable on the criteria represented by its % contribution in improving the model accuracy, reported in Table 3. These results reveal that WC and DR are sufficient to achieve significantly reduced RMSE and MRE values. Accordingly, the quasi-optimal model (QO_m) including the selected variables was built. Effectively, as shown in Table 4, the QO_m presents the best results when compared with the Wpar-based model (WP_m) and the DR characteristic curve-based model (DR_m). In Table 4, the values (1) and (2) indicate, respectively, whether the variables are used as input in the model or not. The model accuracy is presented as a function of the four selection criteria. Globally, QO_m fit the three quality indicators very well, presenting maximum relative errors less than 6, 8.5 and 8% for I_{dep}, N_{dia} and N_{pen}, respectively. These simulated results are confirmed by the three models' curve fitting graphs illustrated in Figure 7.

3 Conclusion

In this paper, a structured and systematic approach developed to design an effective

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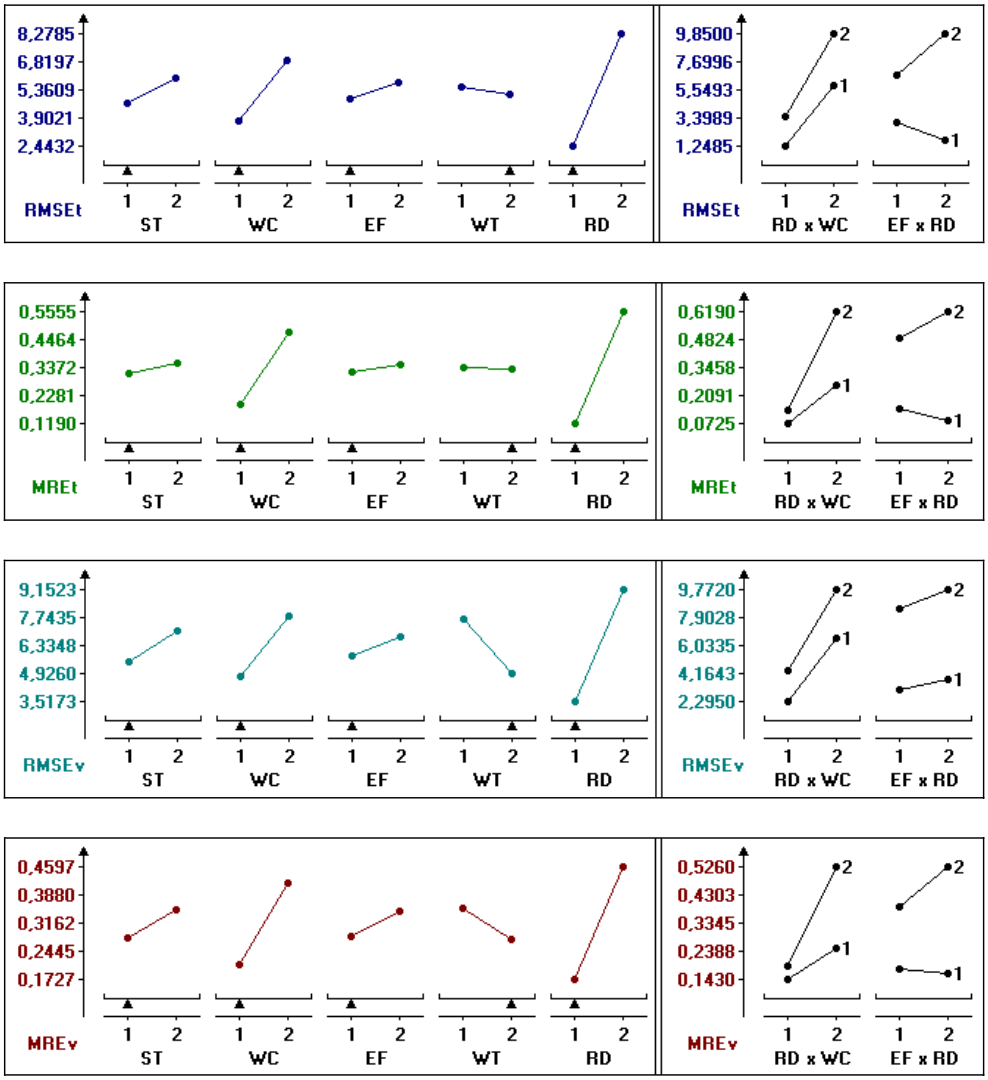


Fig. 6. Average effects of each variable in increasing/decreasing the modeling performance criteria. The values (1) and (2) indicate, respectively, whether the variables are used as input in the model or not.

Fig. 6. Impact de chaque variable dans l'augmentation/diminution des critères de performance du modèle. Les valeurs (1) et (2) indiquent, respectivement, si la variable est prise comme donnée d'entrée du modèle, ou non

Table 3. Percent contributions of modeling variables in the criteria values.

Tableau 3. Contribution (%) des variables du modèle dans les valeurs des critères.

Criteria	ST	WC	EF	WT	DR	WC × DR	EF × DR	Error
$RMSE_t$	2.86	19.4	1.27	–	64.28	1.05	9.31	1.83
MRE_t	0.55	25.03	0.34	–	59.99	11.23	2.7	0.16
$RMSE_v$	4.15	17.92	1.63	14.69	59.97	0.66	–	0.98
MRE_v	1.17	23.29	–	1.59	47.02	10.72	0.91	15.3

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Table 4. Modeling evaluation results

Tableau 4. Évaluation des résultats du modèle.

Model identification			WP_m	DR_m	QO_m
Modeling variables		ST	1	2	2
		WC	1	2	1
		EF	1	2	2
		WT	1	2	2
		DR	2	1	1
Decision criteria	Training RMSE values	I_{dep}	0.0080	0.0268	0.0052
		N_{dia}	0.1061	0.3767	0.1091
		N_{pen}	1.2445	4.9358	0.9146
		$RMSE_t$	1.3586	5.3393	1.0288
	Validation RMSE values	I_{dep}	0.0245	0.0296	0.0184
		N_{dia}	0.3438	0.3408	0.5180
		N_{pen}	2.5737	3.7138	1.4585
		$RMSE_v$	2.9420	4.0842	1.9949
	$RMSE_{tot}$		4.3005	9.4235	3.9641
	Training MRE values	I_{dep}	0.0424	0.1250	0.0322
		N_{dia}	0.0176	0.0637	0.0175
		N_{pen}	0.0192	0.0705	0.0106
		MRE_t	0.0793	0.2592	0.0603
	Validation MRE values	I_{dep}	0.0784	0.0939	0.0650
		N_{dia}	0.0391	0.0515	0.0519
		N_{pen}	0.0266	0.0512	0.0180
		MRE_v	0.1441	0.1966	0.1350
	MRE_{tot}		0.2233	0.4558	0.1953

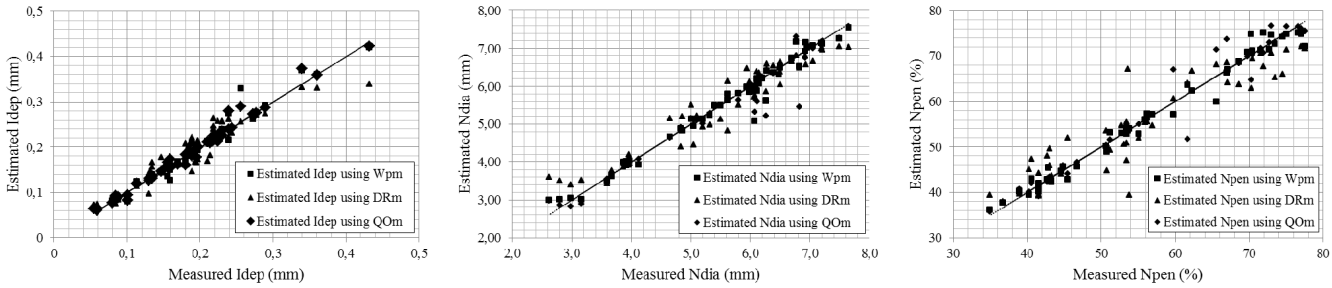


Fig. 7. Model evaluation using measured and estimated quality indicators.

Fig. 7. Évaluation du modèle par comparaison entre les valeurs mesurées et estimées des indicateurs de qualité.

ANN-based model for on-line quality assessment in RSW is presented. Several welding parameters and conditions were analyzed and their correlation with multiple welding quality indicators was investigated under different practical process conditions. Following the identification of the variables that provide the best information about the welding operation, a quasi-optimal model, combining welding parameters and typical characteristics of the dynamic resistance, was developed. The results demonstrate that the resulting ANN-based performance shows significant improvement as compared with conventional methods. With a global maximum relative error less than 10% under various welding conditions, the modeling procedure can be considered efficient, due to the complexity of the analyzed process. The proposed approach can be effectively and gainfully applied to on-line quality assessment for RSW, because it includes the advantages of ease of application,

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reduced modeling time and sufficient model accuracy.

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