by H.-L. Lin, T. Chou, and C.-P. Chou

OPTIMIZATION OF RESISTANCE SPOT WELDING PROCESS USING TAGUCHI METHOD AND A NEURAL NETWORK

There has been a significant increase in the use of high-strength steel sheet in the automobile industry to permit reductions in thickness and thus in vehicle weight.[1] The substitution of high-strength steel sheet for thicker plain carbon steels helps to lower weight and meet federally-mandated improvements in fuel economy. Resistance welding is widely used in mass production, in which production runs with a consistent condition. The resistance spot welding (RSW) process is especially used in the automobile industry.[2] However, high-strength steel sheet has narrow welding current ranges in the RSW process. Sometimes, this limited weldability is a consequence of the interfacial failure of the weld nugget, producing an apparently smaller fusion zone.[3] The physical variables of the metal may include not only the composition of the steels but also the surface condition. Surface effects have been studied and found to have noticeable effects on spot weldability.[4] In summary, it is not easy to obtain optimal parameters of the RSW process on high-strength steel sheet.

Many parameters affect the RSW quality for high-strength steel sheet, such as welding current, electrode force, welding time, and so forth. The desired welding parameters are usually determined based on experience or handbook values. However, it does not ensure that the selected welding parameters result in optimal or near-optimal welding quality characteristics for the particular welding system and environmental conditions. The Taguchi method, a popular experimental design method applied in industry, can alleviate the disadvantages of full factorial design and approaches the optimization of parameter design, although the number of experiments is reduced.[5] However, the Taguchi method has certain limitations when used in practice. The optimal solutions were only obtained within the specified level of control factors. Once the parameter setting is determined, the range of optimal solutions is constrained concurrently. The Taguchi method is unable to find the real optimal values when the specified parameters are continuous in nature because it only addresses the discrete control factors. Neural network (NN) technique with nonlinear function is capable of accurately representing the complex relationship between inputs and outputs.[6–8] The trained neural model was also used to accurately predict the response at given parameter settings. In addition, Khaw et al.[9] proved that benefits could be obtained using the Taguchi concept for NN design. First, this methodology is the only known method for NN design that considers robustness. It enhances the quality of the NN designed. Second, the Taguchi method uses orthogonal arrays (OAs) to systematically design an NN. Subsequently, the design and development time for NNs can be reduced tremendously. In this study, an application involving combination of the Taguchi method and an NN to determine optimal condition for improving the RSW process quality of high-strength steel sheet was presented. The experimental procedure showed that the Taguchi method not only provides systematic and efficient methodology for the initial optimization of the RSW process parameters but is also employed to find out the primary influencing parameters such as welding current and the size of electrode tip that affects tensile shear strength of specimen. A proposed approach that combined the Taguchi method and an NN then was used to resolve the limitations of applying the said method only. This was done instead of the basic backpropagation (BP) algorithm (gradient descent algorithm). The Levenberg–Marquardt backpropagation (LMBP) algorithm with high speed for convergence was adopted. The NN package software MATLAB Neural Network Toolbox (The MathWorks, Inc., Natick, MA) was used to develop the required network. The experimental results were conducted to verify the optimal welding parameter.

H.-L. Lin, T. Chou, and C.-P. Chou are affiliated with the Department of Mechanical Engineering, National Chiao Tung University, Hsinchu, Taiwan.

INITIAL OPTIMIZATION BY TAGUCHI METHOD

The high-strength steel sheet was used in this study; its chemical composition is listed in Table 1. Plates 0.7 mm in thickness were cut into strips of size 30 ×100 mm. The resistance spot welder (FANUC α8/4000is type) had been utilized for the experiment. The schematic diagram of high-strength steel sheet specimen for resistant spot welding is shown in Fig. 1.

Quality Characteristic and Parameters of RSW Process

The study used tensile shear strength of specimens as the quality characteristic in the process. A universal testing machine (MTS 810, MTS Systems Corporation, Eden Prairie, MN) had been used for this study to measure the welding tensile shear strength of the RSW specimens. The speed was set at 0.1 mm/s in the testing. Dr. Taguchi separated all the influencing factors into two main groups, the control factors and noise factors. Control factors are those that allow a manufacturer to control during processing and the noise factors are expensive or difficult to control.[10] As learned from handbook and the practical experience in the production of autobody, the major welding parameters for the processing quality of weldment include welding current, welding time, electrode force, the size of electrode tip, and surface condition of specimens in the RSW process. By making reference to the existing parameter conditions in the production line, the range of experimental parameter value has been initially framed as below: welding current 6200–11,000 A, welding time 8–26 cycles, electrode force 1.8–3.3 kN, and the size of electrode tip ϕ3–ϕ6 mm. The value of each welding process parameter at the different levels is listed in Table 2. Surface condition of the welding area was selected as the noise factor in this study. The specimens at level 1 (N1), without any cleaning treatment, may have been tarnished with dirt and/or grease. The surface impurities were removed and the surface cleaned with acetone at level 2 (N2). The initial conditions of production operation currently were welding current at 7800 A, welding time at eight cycles, electrode force at 1.8 kN, and the size of electrode tip at ϕ4 mm.

doi: 10.1111/j.1747-1567.2007.00186.x

Table 1—Chemical composition of the material used (wt%)

MATERIAL	C	Si	Mn	P	S	Fe
MJSC340D	0.062	0.48	0.95	0.013	0.004	Balance

OA Experiment

Taguchi had tabulated 18 basic OAs that are called standard OAs.[10] Four four-level control factors, in addition to one noise factor, were considered in this investigation. The interaction effect between the welding parameters was not considered. Therefore, there are 12 degrees of freedom owing to the four control factors. The degrees of freedom for the OA should be greater than or at least equal to those for the process parameters. L16 (4^5) OA that has 15 degrees of freedom was employed in this study. An experimental layout with an inner array for control factors and an outer array for a two-level noise factor (N1 and N2) is shown in Table 3. Four repetitions (y_1, y_2, y_3, and y_4) for each trial are used with this experimental arrangement; y_1 and y_2 are N1 specimens (without cleaning); y_3 and y_4 are N2 specimens (cleaned with acetone). The experimental results for the tensile shear strength using L16 OA are shown in Table 4.

Evaluation of Initial Optimal Condition

Taguchi has created a transformation of the repetition data to another value, which is to say a measure of the variation present. The transformation is the signal-to-noise ratio (SNR).[11] There are several SNRs available, depending on the type characteristic being present, such as lower is better (LB), nominal is best (NB), or higher is better (HB). The tensile shear strength of the specimens as discussed earlier belongs to the higher-is-better quality characteristic. The SNRs, which condense the multiple data points within a trial, depend on the three-characteristic LB, NB, and HB. The equation for calculating the SNR for HB characteristic is:

$$\mathrm{SNR} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \quad (1)$$

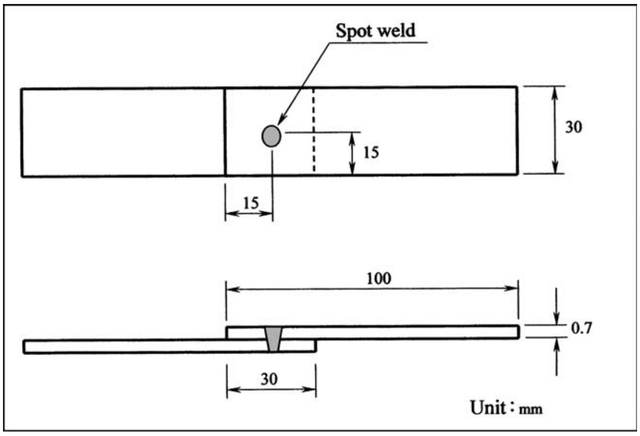

Fig. 1: Schematic diagram of the specimens

Table 2—Control factors and its levels

FACTOR	PROCESS PARAMETER	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
A	The size of electrode tip	ϕ3 mm	ϕ4 mm	ϕ5 mm	ϕ6 mm
B	Welding current	6200 A	7800 A	9400 A	11000 A
C	Electrode force	1.8 kN	2.3 kN	2.8 kN	3.3 kN
D	Welding time	8 cycles	14 cycles	20 cycles	26 cycles

where n is the number of tests in a trial (number of repetitions regardless of noise levels). The value of n is 4 in this study. The SNRs corresponding to the tensile shear strength value of each trial is shown in Table 4. The effect of each welding process parameter on the SNR at different levels can be separated out because the experimental design is orthogonal. The description of the SNR for each level of the welding process parameters is summarized in Table 5. Figure 2 shows the SNR graph obtained from Table 5. Basically, the larger the SNR, the better the quality characteristic (tensile shear strength) for the specimens. The initial optimal conditions of the RSW process parameter levels, $A_1B_4C_1D_3$, can be determined from Fig. 2.

Analysis of Variance

The purpose of the analysis of variance (ANOVA) is to investigate welding process parameters, which can significantly affect the quality characteristics.[12] The percent contribution in the total sum of the squared deviations can be used to evaluate the importance of the welding process parameter change on these quality characteristics. When the contribution of a factor is small, as with factor D (welding time) in Table 6, the sum of squares for that factor is combined with the error. This process of disregarding the contribution of a selected factor and subsequently adjusting the contributions of the other factors is known as "pooling."[11] The welding current and the size of electrode tip were the significant welding

Table 3—Summary of experimental layout using an L16 OA

					NOISE FACTOR			
	CONTROL FACTOR				N1 SPECIMENS		N2 SPECIMENS	
TRIAL NO.	A	B	C	D	y_1	y_2	y_3	y_4
1	1	1	1	1	Measure data			
2	1	2	2	2				
3	1	3	3	3				
.	.	.	.	.				
15	4	3	2	4				
16	4	4	1	3				

Table 4—Summary of experiment data*

	CONTROL FACTORS				TENSILE SHEAR STRENGTH	
TRIAL NO.	A	B	C	D	AVERAGE (kN)	SNR (dB)
1	1	1	1	1	3.317	10.41
2	1	2	2	2	4.098	12.25
3	1	3	3	3	4.105	12.26
4	1	4	4	4	4.392	12.85
5	2	1	2	3	3.299	10.35
6	2	2	1	4	3.758	11.49
7	2	3	4	1	3.950	11.91
8	2	4	3	2	3.855	11.70
9	3	1	3	4	2.622	8.36
10	3	2	4	3	3.735	11.44
11	3	3	1	2	4.168	12.39
12	3	4	2	1	4.083	12.22
13	4	1	4	2	2.318	7.29
14	4	2	3	1	3.572	11.05
15	4	3	2	4	3.637	11.21
16	4	4	1	3	4.139	12.24

*Total average of SNR for all trial $\hat{\eta}$ is 11.213 (dB).

parameters in affecting the quality characteristic, with the welding current being the most significant, as indicated by Table 6.

Confirmation Test and Proper Regulation

The final step of the Taguchi method is to compare the estimated value with the confirmative experimental value, using the optimal level of the control factors to confirm with the experimental reproducibility. The estimated SNR η_{opt} using the optimal level of the control factors, can be calculated as:

$$\eta_{\text{opt}} = \hat{\eta} + \sum_{j=1}^{q} (\eta_j - \hat{\eta}) \tag{2}$$

where $\hat{\eta}$ is the total average of SNR of all the experimental values, η_j the mean SNR at the optimal level, and q the number of the control factors that significantly affect the quality characteristic. Refering to Tables 4 and 5, estimated SNR η_{opt} is computed as:

$$\begin{aligned}\eta_{opt} &= 11.213 + (11.941 - 11.213) + (12.252 - 11.213)\\ &= 12.98\ (\text{dB})\end{aligned}$$

Table 5—SNR response table for the tensile shear strength

FACTOR	PROCESS PARAMETER	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
A	The size of electrode tip	11.941	11.363	11.101	10.449
B	Welding current	9.102	11.558	11.942	12.252
C	Electrode force	11.634	11.507	10.842	10.871
D	Welding time	11.399	10.905	11.571	10.979

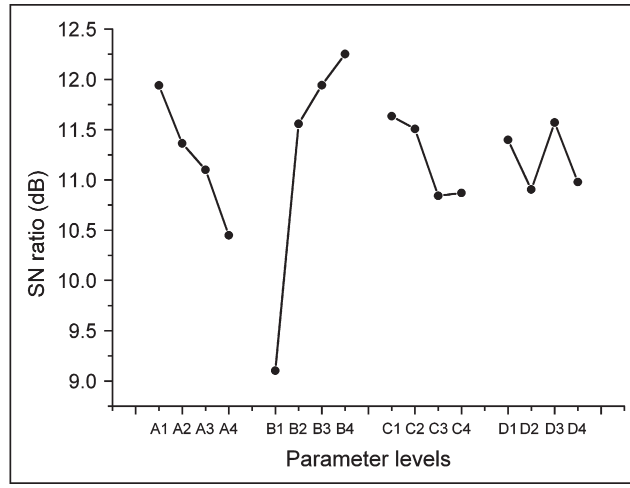

Fig. 2: SNR graph for the tensile shear strength

The confidence interval (CI) is a maximum and minimum value between which the true average should fall at some stated percentage of confidence.[11] The confidence limits of the above estimation can be calculated taking into account the following equation:

$$\text{CI} = \sqrt{F_{\alpha;1;v_e} V_{\text{ep}} \left(\frac{1}{n_{\text{eff}}} + \frac{1}{r}\right)} \tag{3}$$

where $F_{\alpha;1;v_e}$ is the F ratio required for $\alpha = 0.05$ (with a confidence of 95%), v_e the degrees of freedom for pooled error, V_{ep} the pooled error variance, r the sample size for the confirmation experiment, and n_{eff} the effective sample size.

$$n_{\text{eff}} = \frac{N}{1 + \text{DOF}_{\text{opt}}} \tag{4}$$

where N is the total number of trials and DOF_{opt} the total degrees of freedom associated with items used in the η_{opt} estimate. With a CI of 95% for the tensile shear strength, the $F_{0.005;1;6} = 5.99$, and $V_{\text{ep}} = 0.448$, the sample size for the confirmation experiment r is 2, $N = 16$, $\text{DOF}_{\text{opt}} = 9$, and the effective sample size n_{eff} 1.6. Thus, the CI is computed to be 1.738 (dB). The experimental results (Table 7) confirm that the initial optimizations of the RSW process parameters ($A_{\phi 3\text{mm}}B_{11{,}000\text{A}}C_{1.8\text{kN}}D_{20\text{cycles}}$) were achieved.

Although the conformity of reproducibility for the experimental results has been confirmed with an average tensile shear strength of specimens as high as up to 4.406 kN obtained, however, a phenomenon of spark was taken place between

Table 6—Results of ANOVA for the tensile shear strength

FACTOR	DEGREE OF FREEDOM	SUM OF SQUARE	MEAN SQUARE	*F* TEST	PURE SUM OF SQUARE	PERCENT CONTRIBUTION
A	3	4.599	1.533	3.42	3.25	9.54
B	3	24.748	8.249	18.40	23.40	68.61
C	3	2.071	0.690	1.54	0.73	2.13
D	3	1.248*				
Error	3	1.442				
$Error_{(pooled)}$	(6)	(2.691)	(0.448)		6.15	19.72
Total	15	34.109			34.229	100

*The factors are treated as pooled error.

the specimens and the electrode during the spot welding process that leads to a severely shortened life cycle of electrode and a collaterally affected joint quality of weldment for its subsequent welding. With the ANOVA outcomes (Table 6) referenced, a proper regulation of welding current is necessary to cope with the foregoing defects. As learned from Fig. 2 (SNR graph), SNR thereof was slightly increased when welding current regulated from 7800 A to 11,000 A, that is, the tensile shear strength of specimens was not heightened in big magnitude. Therefore, the optimal conditions of parameters obtained from the application of the Taguchi method remained unchanged except the welding current was regulated from 11,000 A to 7800 A. Table 8 lists the results of experiment after adjusting the parameters ($A_{\phi 3mm}B_{7800A}C_{1.8kN}D_{20cycles}$).

LEVENBERG–MARQUARDT BP ALGORITHM

NNs are to be used for modeling of complex manufacturing processes, usually with regard to process and quality control.[13,14] Several well-known supervised learning networks use a BP NN. Funahashi[15] proved that the BP NN may approximately realize any continuous mapping. BP learning employs a gradient-descent algorithm to minimize the mean square error (MSE) between the target data and the predictions of an NN. However, one of the major problems with conventional BP algorithm (gradient-descent algorithm) is the extended training time required. The techniques for accelerating convergence have fallen into two main categories: heuristic methods and standard numerical optimization methods such as the LMBP algorithm.[16]

The LMBP algorithm is similar to the quasi-Newton method, in which a simplified form of the Hessian matrix (second derivatives) is used. When the cost function has the form of a sum of squares, then the Hessian matrix H can be approximated as:

$$H = J^T J \tag{5}$$

And the gradient g can be computed as:

$$g = J^T e \tag{6}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e a vector of network errors. The Jacobian matrix can be computed through a standard BP technique that is much less complex than computing the Hessian matrix.[17]

An iteration of this algorithm can be written as:

$$X_{K+1} = X_K - [J^T J + \mu I]^{-1} J^T e \tag{7}$$

when the scalar μ is zero, this is just Gauss–Newton, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size.

The algorithm begins with μ set to some small value (e.g., $\mu = 0.01$). If a step does not yield a smaller value for e, then the step is repeated with μ multiplied by some factor $\theta > 1$ (e.g., $\theta = 10$). Eventually, e should be decreased since we would be taking a small step in the direction of steepest descent. If

Table 7—Results of the confirmation experiment

TRIAL NO.	TENSILE SHEAR STRENGTH: N1 SPECIMENS		N2 SPECIMENS		SNR (dB)	AVERAGE (kN)	CI (95%)
17	4.562	4.505	4.335	4.209	12.861	4.406	12.98 ± 1.74 (dB)
18	4.426	4.343	4.626	4.243	12.875		

Table 8—Results of the Taguchi method with proper regulation

TRIAL NO.	TENSILE SHEAR STRENGTH: N1 SPECIMENS		N2 SPECIMENS		AVERAGE (kN)
19	4.089	3.945	3.926	3.731	3.851
20	3.878	4.041	3.585	3.611	($N1 = 3.988$, $N2 = 3.713$)

Table 9—Options for different networks

ARCHITECTURE (INPUT-HIDDEN UNIT-OUTPUT)	MEAN SQUARE ERROR FOR TRAINING	RANK OF MSE	SIMULATING ERROR, % (COMPARE WITH AVERAGE VALUE IN TABLE 8)	
			N1 SPECIMENS	N2 SPECIMENS
5-2-1	0.1123			
5-3-1	0.1083			
5-4-1	0.0337	5	−3.81	1.85
5-5-1	0.0282	4	−0.98	6.19
5-6-1	0.2383			
5-7-1	0.0147	2	3.50	−0.54
5-8-1	0.0096	1	−7.92	−6.28
5-9-1	0.0194	3	−4.93	2.36
5-10-1	0.0490			

a step does produce a smaller value for e, then μ is divided by θ for the next step, ensuring that the algorithm will approach Gauss–Newton, which should provide faster convergence.[16] The LMBP algorithm is the fastest algorithm that has been tested for training multiplayer networks of moderate size, even though it requires a matrix inversion at each iteration. It requires two parameters, but the algorithm does not appear to be sensitive to this selection.

TRAINING OF BP NETWORK

Multilayer feedforward NNs are commonly used for solving difficult predictive modeling problems.[18] They usually consist of an input layer, one or more hidden layers, and one output layer. The neurons in the hidden layers are computational units that perform nonlinear mapping between inputs and outputs. A feedforward NN was used in this study. It takes a set of five input values (control factors A, B, C, D, and noise factor) and predicts the value of one output (tensile shear strength of the specimens). The transfer functions for all hidden neurons are tangent sigmoid functions and a linear function is used for the output neurons.[19] Determining the number of hidden neurons is critical in the design of NNs. An overabundance of hidden neurons give too much flexibility that usually leads to overfitting. On the other hand, too few hidden neurons restrict the learning capability of a network and degrade its approximation performance.[18] A total of 64 input–output data patterns were partitioned into a training set, a testing set, and a validating set. Functionally, 60% (38 patterns) were randomly selected for training the NN, while the remaining 20% (13 patterns) were randomly selected for testing and 20% (13 patterns) randomly selected for validating. An efficient algorithm, the Levenberg–Marquardt algorithm, was used to improve classical BP learning in the training process.[17,19] The performance of each NN was measured with the MSE of the testing subset. Table 9 presents nine options for the NN architecture. After comparing all the data for the MSE value, the structures 5-4-1, 5-5-1, 5-7-1, 5-8-1, and 5-9-1 are the five best convergence criteria. The structure 5-7-1 showed the least simulating error and was

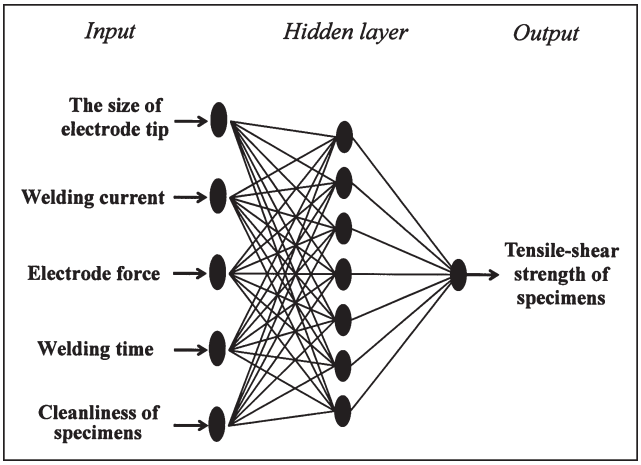

Fig. 3: The BP network topology of the RSW process

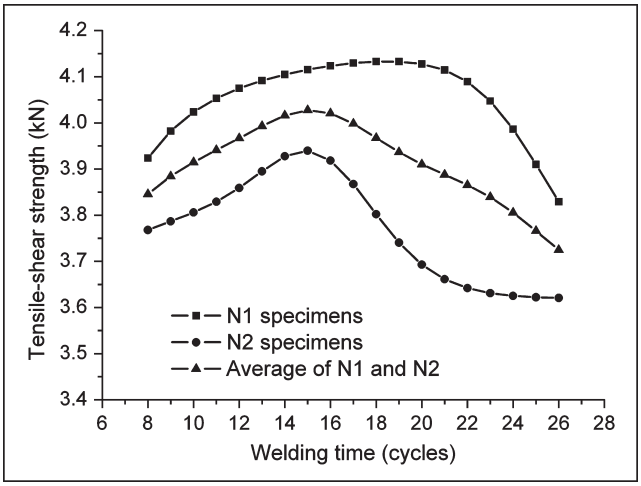

Fig. 4: Results of simulating different welding time

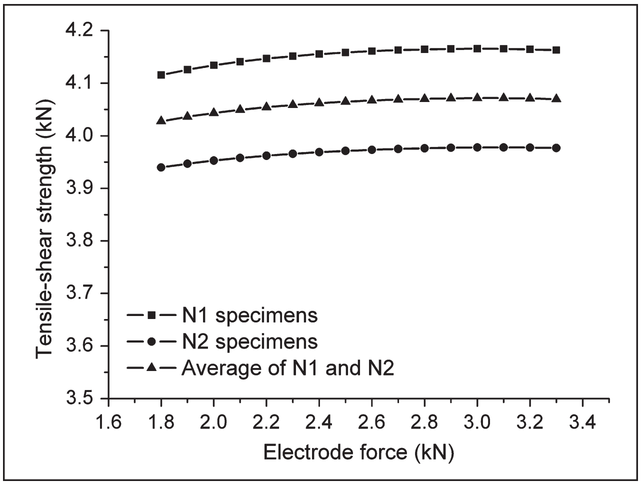

Fig. 5: Results of simulating different electrode force

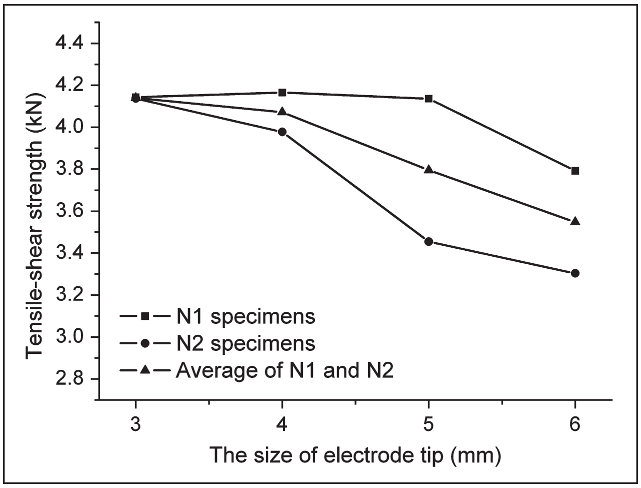

Fig. 6: Results of simulating different size of the electrode tip

therefore selected to obtain a better performance. The topology of the network 5-7-1 with a μ value of 0.001 and a θ value of 10 is shown in Fig. 3.

Simulation with a Well-Trained Network

The control factor D (welding time) is the insignificant welding parameters in affecting the quality characteristic as shown in Table 6. First, the trained network 5-7-1 with 1.47% MSE was employed as the simulating function of the insignificant parameters in this welding process. In Figs. 4–7, the N1 specimens (without any cleaning treatment) had simulated with 0% cleanliness and the N2 specimens (cleaned with acetone) had simulated with 100% cleanliness. Figure 4 shows the comparison of simulating results using the factor D (other conditions $A_{\phi 3mm}B_{7800A}C_{1.8kN}$), from which it can be seen that the tensile shear strength of specimens is best for adjusting welding time to 15 cycles. Second, Fig. 5 shows the comparison of simulating results using the factor C (other conditions $A_{\phi 3mm}B_{7800A}D_{15cycles}$), from which it can be seen that the tensile shear strength of specimens is best for setting electrode force at 3.0 kN. Third, Fig. 6 shows the comparison of simulating results using the factor A (other conditions $B_{7800A}C_{3.0kN}D_{15cycles}$), from which it can be seen that the tensile shear strength of specimens is best for setting the size of the electrode tip at ϕ3 mm. Finally, Fig. 7 shows the comparison of simulating results using the factor B (other conditions $A_{\phi 3mm}C_{3.0kN}D_{15cycles}$), from which it can be seen that welding current and average tensile shear strength are in direct ratio until about 8200 A. The welding current of RSW process for the initial condition is 7800 A. Therefore, the welding current at 7800 A has been selected in this study.

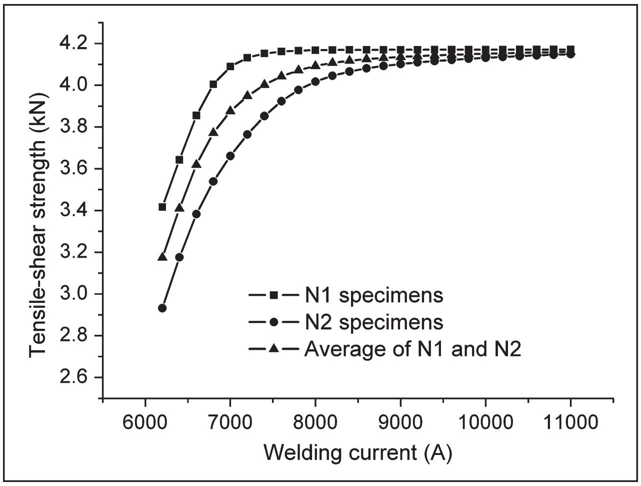

Fig. 7: Results of simulating different welding current

Table 10—Results of the proposed approach

TRIAL NO.	TENSILE SHEAR STRENGTH N1 SPECIMENS		N2 SPECIMENS		AVERAGE (kN)
21	4.310	4.169	4.112	3.746	4.108
22	4.153	3.973	4.522	3.876	

Experimental Results of Proposed Approach

With combination of this Taguchi method and an NN, the optimal welding conditions for tensile shear strength with RSW process were electrode tip size at ϕ3 mm, welding current at 7800 A, electrode force at 3.0 kN, and welding time at 15 cycles. Table 10 shows the experimental results obtained with above optimal welding parameters. Table 11 shows the experimental results with the conditions of production operation currently ($A_{\phi 4mm}B_{7800A}C_{1.8kN}D_{8cycles}$). Comparison of Table 8 with Table 11 shows that the increase in average tensile shear strength from the initial conditions to the initial optimal parameters (apply the Taguchi method only) is 0.309 kN. Comparison of Table 10 with Table 11 shows that the increase in average tensile shear strength from the initial conditions to the real optimal parameters (apply the Taguchi method and NN) is 0.566 kN. The surface condition of specimens for different parameters is shown in Fig. 8. In summary, the quality of RSW process for high-strength steel sheet can be efficiently improved with the proposed approach.

CONCLUSIONS

(1) The improvement of the average tensile shear strength from initial conditions to the initial optimal parameters (apply the Taguchi method only) is about 8.72%. The improvement of the average tensile shear strength from initial conditions to the real optimal parameters (apply proposed approach) is about 15.98%.
(2) The proposed approach is relatively effective and easy for engineers to apply to a range of other processes. In addition, applying the proposed approach allows

Table 11—Results of the initial conditions

TRIAL NO.	TENSILE SHEAR STRENGTH N1 SPECIMENS		N2 SPECIMENS		AVERAGE (kN)
23	3.329	3.518	3.605	3.344	3.542
24	3.673	3.575	3.626	3.669	

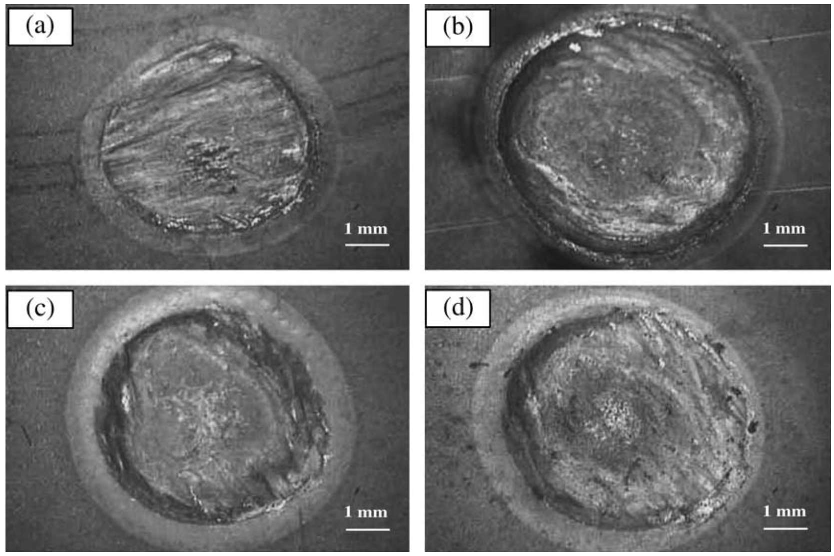

Fig. 8: Surface conditions of specimens for validating the proposed approach: (a) initial conditions, (b) apply the Taguchi method only, (c) apply the Taguchi method with proper regulation, and (d) apply proposed approach

engineers to directly use NN software to optimize the parameters without any theoretical knowledge of neural computing.

ACKNOWLEDGMENT

The authors acknowledge Mr. Liang-Wei Gao, the engineer of the Production Engineering Division of China Motor Co., Ltd., Taiwan, for permitting the use of the resistance spot welder in this study.

References

1. Sawhill, J.M., Jr., and Baker, J.C., "Spot Weldability of High-Strength Sheet Steel," *Welding Journal* **59**(1): 19s–30s (1980).

2. Cary, H.B., *Modern Welding Technology*, 3rd ed., Prentice-Hall, Upper Saddle River, NJ (1994).

3. Han, Z., Indacochea, J.E., Chen, C.H., and Bhat, S., "Weld Nugget Development and Integrity in Resistance Spot Welding of High-Strength Cold-Rolled Sheet Steels," *Welding Journal* **72**(5): 209s (1993).

4. Savage, W.F., Nippes, E.F., and Wassell, F.A., "Dynamic Contact Resistance of Series Spot Welds," *Welding Journal* **57**(2): 43s–50s (1978).

5. Taguchi, G., Elsayed, E.A., and Hsiang, T.C., *Quality Engineering in Production Systems*, McGraw-Hill, New York (1989).

6. Su, C.T., Chiu, C.C., and Chang, H.H., "Parameter Design Optimization via Neural Network and Genetic Algorithm," *International Journal of Industrial Engineering* **7**(3):224–231 (2000).

7. Kim, I.S., Jeong, Y.J., and Lee, C.W., "Prediction of Welding Parameters for Pipeline Welding using an Intelligent System," *International Journal of Advanced Manufacturing Technology* **22**:713–719 (2003).

8. Bhadeshia, H.K.D.H., Mackay, D.J.C., and Svensson, L.E., "Impact Toughness of C -Mn Steel Arc Welds—Bayesian Neural Network Analysis," *Materials Science and Technology* **11**:1046–1051 (1995).

9. Khaw, John F.C., Lim, B.S., and Lim, Lennie E.N., "Optimal Design of Neural Networks Using Taguchi Method," *Neurocomputing* **7**:225–245 (1995).

10. Phadke, M.S., *Quality Engineering Using Robust Design*, Prentice-Hall, Upper Saddle River, NJ (1989).

11. Roy, R.K., *A Primer on the Taguchi Method*, Van Norstrand Reinhold, New York (1990).

12. Ross, P.J., *Taguchi Techniques for Quality Engineering*, McGraw-Hill, New York (1988).

13. Su, C.T., and Chiang, T.L., "Optimizing the IC Wire Bonding Process using a Neural Networks / Genetic Algorithms Approach," *Journal of Intelligent Manufacturing* **14**:229–238 (2003).

14. Coit, D.W., Jacson, B.T., and Smith, A.E., "Static Neural Network Process Model: Considerations and Case Studies," *International Journal of Production Research* **36**(11):2953–2967 (1998).

15. Funahashi, K., "On the Approximate Realization of Continuous Mapping by Neural Network," *Neural Networks* **2**:183–192 (1989).

16. Hagan, M.T., Demuth, H., and Beale, M., *Neural Network Design*, PWS Publishing Co., Boston, MA (1996).

17. Hagan, M.T., and Menhaj, M.B., "Training Feedforward Networks with the Marquardt Algorithm," *IEEE Transactions on Neural Networks* **5**(6):989–993 (1994).

18. Haykin, S., *Neural Networks—A Comprehensive Foundation*, Macmillan College Publishing Co., New York (1994).

19. Demuth, H., and Beale, M., *Neural Network Toolbox—For Use with MATLAB*, MathWorks, Inc., Natick, MA (1998). ■