CORRELATION BETWEEN GMAW PROCESS AND WELD QUALITY PARAMETERS: A NEURAL NETWORK APPROACH APPLIED IN THE AUTOMOTIVE INDUSTRY

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Abstract

The results of a research carried out to evaluate the correlation between GMAW process parameters and weld quality parameters is presented. The GMAW weld process was carrying out and quality parameters according to automotive Industry was measured; the leg size, depth of fusion and gap (root opening) were determined. A neural network model is proposed to explain the contribution of the various welding process parameters (Amperes, Voltage and Travel speed) on weld quality parameters. It is found that the neural network model presented an excellent correlation to predict the weld quality; the leg size is enhanced with the increase of amperage and reduced with the increase of the travel speed and voltage. The relationship of all variables is explained.

The neural model can be used to test initial welding conditions of voltage, amperage and travel speed. The model can predict quality characteristics without repeat the experimental measurements, so it can be used as an inverse model taking the desired conditions of the welds as inputs and give the voltage, amperage and travel speed as outputs.

Keywords: Neural, network, model, prediction

Introduction

The increase of welding productivity has a significant economic impact, estimated in order of several hundred million dollars in yearly worldwide saving. Gas Metal Arc Welding (GMAW) is widely used in the automotive industry. The process's high metal deposition rate makes it well suited to automatic and robotic welding.

Modeling weld quality according to welding process parameters is increasingly important since great financial savings are possible, especially in manufacturing where improved weld process conditions lead to losses in production and necessitate time-consuming and expensive use of materials. Applying the artificial intelligence technology requires the introduction of input and output data to the network. The task of modeling welding process by neural network is to use input data, such as welding voltage and current, speed travel, can be use as variables. After this, the data are processing by neural network model and obtain a response, such as gap, throat, leg, etc.

The main functions of the proposed model are: to simulate the process for purposes of training operators; to improve welding process performance by identifying regions that are insensible to variations on input parameters; and finally to increase the flexibility of a robotic welding cell. The concrete benefits obtained from the GMAW process model development are: optimization of critical variables of the welding process, support for development of virtual process and prototypes, definition of a robust welding procedure, quick response to product change and support in welding training.

Experimental procedure

GMAW experiments were performed with a fully automated welding system. Shielding gas was 90Ar-10%CO_2, power wave 310, rapid arc application, lap joint horizontal position, electrode size 0.045" diameter, Work angle 45° to 55°. Welding was done on a lap joint.

The chemical composition and mechanical properties of the material used to experimental procedure are show in table 1, and the experimental design is in table 2.

Table 1.- Chemical composition and mechanical properties of base metal

	%C	%Mn	%P	%S	%Al	TS (MPa)	YS (MPa)	E (%)
Base metal	0.10 max	0.50 max	0.025 max	0.020 max	0.02 min	270	180-240	38

Spec. GM6409 Grade HR3

Tabla 2.- Experimental design

		V			A			T		G	
Experiment	V1	V2	V3	W1	W2	W3	T1	T2	T3	G1	G2
1	x			x			x			x	
2	x			x			x				x
3	x			x				x		x	
4	x			x				x			x
5	x			x					x	x	
6	x			x					x		x
7	x				x		x			x	
8	x				x		x				x
9	x				x			x		x	
10	x				x			x			x
11	x				x				x	x	
12	x				x				x		x
13	x					x	x			x	
14	x					x	x				x
15	x					x		x		x	
16	x					x		x			x
17	x					x			x	x	
18	x					x			x		x
19		x		x			x			x	
20		x		x			x				x
21		x		x				x		x	
22		x		x				x			x
23		x		x					x	x	
24		x		x					x		x
25		x			x		x			x	
26		x			x		x				x
27		x			x			x		x	
28		x			x			x			x
29		x			x				x	x	
30		x			x				x		x
31		x				x	x			x	
32		x				x	x				x
33		x				x		x		x	
34		x				x		x			x
35		x				x			x	x	
36		x				x			x		x
37			x	x			x			x	
38			x	x			x				x
39			x	x				x		x	
40			x	x				x			x
41			x	x					x	x	
42			x	x					x		x
43			x		x		x			x	
44			x		x		x				x
45			x		x			x		x	
46			x		x			x			x
47			x		x				x	x	
48			x		x				x		x
49			x			x	x			x	
50			x			x	x				x
51			x		x			x		x	
52			x		x			x			x
53			x		x				x	x	
54			x		x				x	x	x

Variable 1= Trim (Volts) V1= 0.80, V2= 0.90, V3=0.95
Variable 2= Amperage (Amps) W1= 380, W2= 400, W3=425
Variable 3= Travel Speed (In/min)= TS1=40, TS2=45, TS3= 50
Variable 4= GAP (mm) = G1=0, G2=1

Discussion and results

The good agreement between the proposed neural network model and the experimental data from the experimental design is encouraging. The output data are in form according to figure 1.

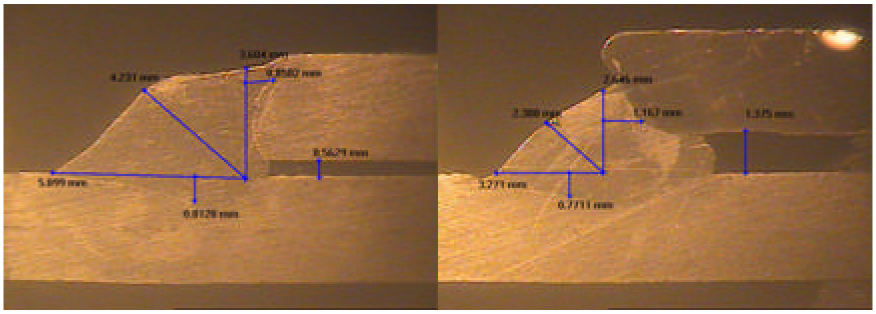

Figure 1.- Two obtained welds in the experimentation

The Neural Network

A neural network is an interconnection of processing elements or artificial neurons. The principal use of this paradigm is the approximation of functions using experimental data. The behavior of the neural network are establishes by their connection weights. The learning rule adjusts the weights to minimize and error between a desired response and the response of the neural network. The desired responses are expressed in a database of patterns of input – output pairs. The response of the processing element is

$$O_n = F_A\left(\sum_{i=1}^{N} W_{n,i} X_i\right) \tag{1}$$

$$F_A(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Where n is an artificial neuron and i is the corresponding element of vector X. Matrix W represents the connection weights between the elements of vector X and the neural element. The activation function F_A regulates the output of the neuron. Sigmoid function is usually used. It is used layers of neurons so it is necessary to adjust several connection weights in the learning rule. There are several learning procedures to adjust the connection weights; nevertheless it is used the Levenberg - Marquardt learning rule. The rule is a variant of the Gauss-Newton optimization method. The connection weights are calculated as follows:

$$W \leftarrow W - (J^T J + lI)^{-1} Je \tag{3}$$

where e is the difference between the actual and the required response. The Jakobi´s matrix for a single neuron can be written as follows:

$$J = \begin{bmatrix} \frac{\partial e_1}{\partial w_1} & \cdots & \frac{\partial e_1}{\partial w_n} & \frac{\partial e_1}{\partial w_0} \\ \vdots & & \vdots & \vdots \\ \frac{\partial e_p}{\partial w_1} & \cdots & \frac{\partial e_p}{\partial w_n} & \frac{\partial e_p}{\partial w_0} \end{bmatrix} \tag{4}$$

Parameter l is modified based on the development of the error signal and p represents the available patterns [ref.]. It was used a neural network with three inputs (voltage, amperage and travel speed) with six outputs (both legs, two deep of fusion, gap, and throat) as shown in figure 2.

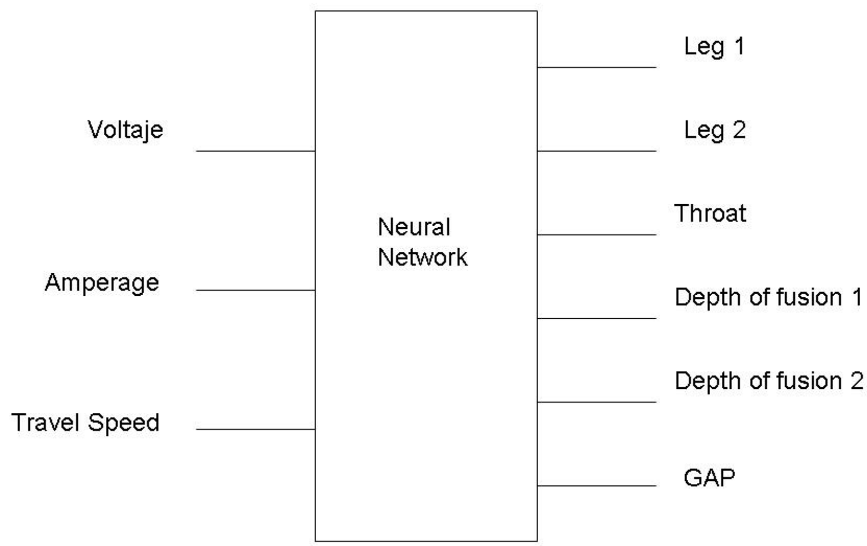

Figure 2. Architecture of the neural network

Training and validation phase

The experimental data was acquired on a robotic Rapid ARC welding process. The inclination of the torch was between 45 and 55 grades. The application mode was horizontal overlap, the work are uses 25 grades of push. It was used a 0.045'' of wire and the protection gas was of 90 percent of Argon and 10 percent of dioxide. The next table shows the information obtained from the experiment.

Table 3. Experimental data of the welding process

V (Volts)	A (Amperes)	TS (mm/seg)	Leg 1 (mm)	Leg 2 (mm)	Throat (mm)	PF 1 (mm)	PF 2 (mm)	GAP (mm)
380	0.87	40	3.08	3.98	2.71	1.25	0.62	1.39
380	0.87	40	3.91	5.14	4.28	0.72	0.58	1.14
380	0.87	40	3.75	5.08	3.47	1	0.64	0.95
380	0.9	40	4.31	5.08	3.49	0.72	1.63	0.97
380	0.9	40	3.56	5.95	4.03	0.7	0.79	0.5
380	0.9	40	3.6	5.89	4.23	0.85	0.81	0.56
380	0.95	40	3.75	5.29	3.33	0.79	0.79	1.12
380	0.95	40	3.66	5.37	3.74	0.73	0.75	1.1
400	0.88	45	2.64	3.27	2.38	1.16	0.71	1.37
400	0.88	45	4.25	4.25	3.11	0.83	0.87	1.04
400	0.91	45	3.91	5.12	3.64	0.6	0.68	1.12
400	0.91	45	3.77	5.08	3.59	0.79	0.85	1.14
400	0.96	45	3.79	4.37	3.13	0.79	0.75	1.2
425	0.89	50	3.58	4.33	3.02	1.27	0.89	1.12
425	0.9	50	3.66	4.08	2.91	0.87	0.89	1.14
425	0.9	50	2.93	4.27	2.75	1.22	1	1.18
425	0.92	50	2.95	4.95	3.11	0.96	0.89	1.12
425	0.92	50	3.12	4	2.9	0.6	0.54	1.45
480	0.95	50	2.93	6.46	4.63	0.45	0.93	0.18
480	0.95	50	2.75	6.29	4.64	0.33	1.33	0.33
480	0.95	50	3.35	4.23	3.03	1.12	0.85	1.18

The physics characteristics of the welded piece depends on three setting inputs, the voltage (V) the amperage (A), and the travel speed (TS) There are several physical parts usually visible on welded pieces (Figure 3) The legs, fusion profusion, gap and throat was taken as experimental data.

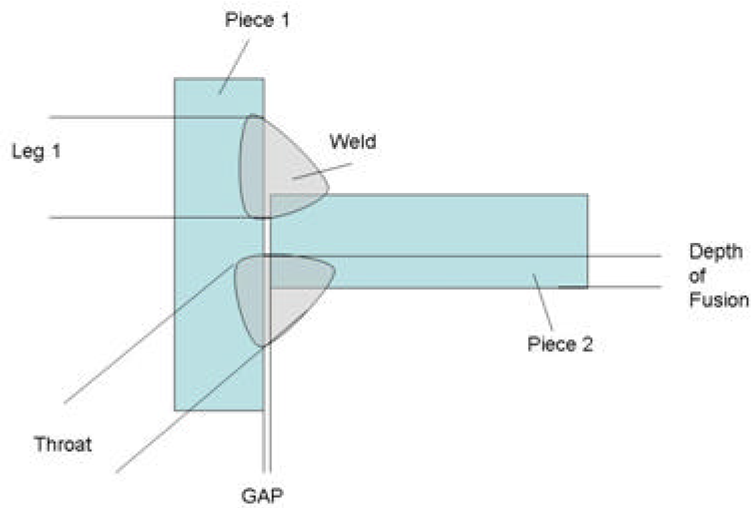

Figure 3. Physical parts of the weld.

The information of the table 3 was normalized and was used in the training process of the neural network. The neural model was validated using extra experimental data not given in the training process given in Table 4. The architecture used of the neural networks is given in figure 2.

Table 4. Validation data

V (Volts)	A (Amperes)	TS	Leg1 (mm)	Leg 2 (mm)	Throat (mm)	PF1 (mm)	PF2 (mm)	GAP (mm)
380	0.87	40	3.58	4.73	3.48	0.99	0.61	1.16
380	0.9	40	3.823333	5.64	3.91	0.75	1.07	0.67
380	0.95	40	3.705	5.33	3.53	0.76	0.77	1.11
400	0.88	45	3.445	3.76	2.74	0.99	0.79	1.20
400	0.91	45	3.84	5.1	3.61	0.69	0.76	1.13
425	0.89	50	3.58	4.33	3.02	1.27	0.89	1.12
425	0.9	50	3.295	4.17	2.83	1.04	0.94	1.16
425	0.92	50	3.035	4.47	3.00	0.78	0.71	1.28
480	0.95	50	3.01	5.66	4.1	0.63	1.03	0.56

The neural networks can be used to analyses the relationship between physics characteristics and welding parameters of voltage, amperage and travel speed.

Voltage:

The impact of the voltage with the welding quality parameters was obtained. According with figure 3, the leg1 shows the major effect, the reason is the quantity of data, the model needs more information to adjust the line, but the relation is directly proportional. The leg2 shows a linear relation with an inflexion point in 0.94 V. The fusion depth 2 has an inconsistent relation, but the curve will be smooth when increase the input data.

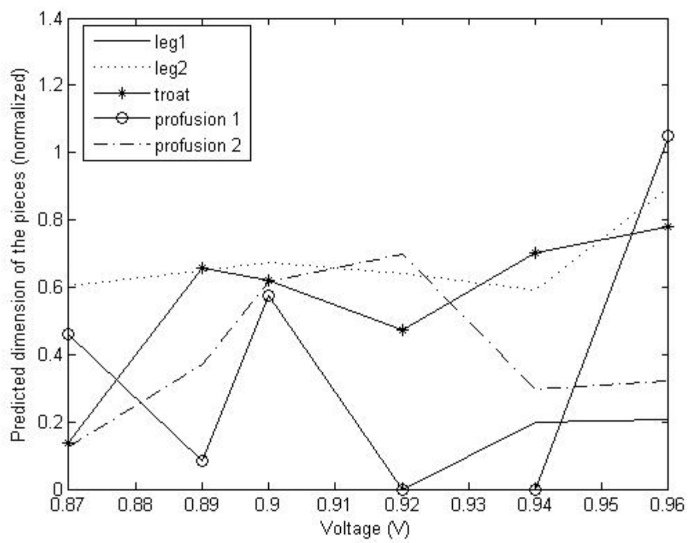

Figure 3. Prediction of the physical characteristic of the welded piece by change in voltage.

Amperage:

The figure 4 shows the effect of amperage in the join characteristics. The amperage has an excellent relation with all the quality parameters. Leg1, Leg2 and throat decrease when the amperage increase, and the fusion depth 1 and 2 are directly proportional with amperage, the fusion depth2 shows an inflexion point in 445 Amps.

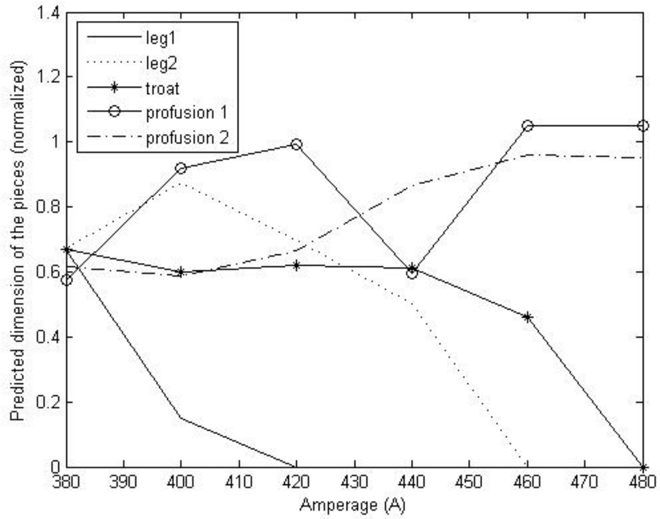

Figure 4. Prediction of the physical characteristic of the welded piece by change in amperage.

Travel speed:

This variable has an important effect with the quality of joins, all of these decrease when travel speed increase, see figure 5, but some of these have inflexion point the will be smooth when increase the input data. The relationship is inversely proportional, except the leg2, that shows and important inflexion point in 44 in/min

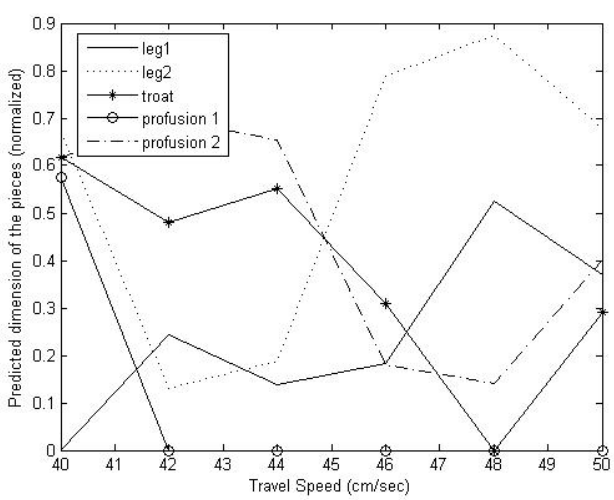

Figure 5. Prediction of the physical characteristic of the join by change in travel speed.

Conclusions

- The neural network model for correlate the influence of GMAW process parameters on the join characteristics has been developed.
- The model shows excellent information about the relationship of independent and dependent variables.
- The model shows some important inflexion points, but those will be smooth when increase the input data.
- The neural network model can calculate the GMAW process parameters to obtain an specific join, with defined characteristics
- The model learning itself, this permit decrease the error
- The use of Artificial Intelligence in general and Neural Network in particular, permit to increase the productivity, eliminate excessive expenses by materials, energy, people, etc.

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