Modeling and Prediction of Impact Strength for AISI 304l and AISI 316l Stainless Steel Similar and Dissimilar Welded Joints using Regression Analysis and Artificial Neural Networks Approaches

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Abstract:- In the present investigation, the AISI 304L and AISI 316L austenitic stainless-steel (ASS) plates were welded together using gas tungsten arc welding (GTAW). Several similar butt joints, typically, 304L-304L and 316L-316L as well as dissimilar butt joints, typically, 304L-316L were formed. The dependance of the impact strength of the welded joints were modeled using regression modelling (RM) and artificial neural network (ANN) approaches. The impact energies of the welded joints were evaluated at ambient and lower temperatures up to -75 °C. The results revealed that, at low temperatures, reducing the temperature reduces the absorbed impact energy of the AISI 304L and 316L similar and dissimilar welded joints. The AISI 304L-316L dissimilar welded joints exhibited higher average impact energies when compared with the similar AISI 304L and AISI 316L welded joints. The generated ANN models based on Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) approaches can accurately predict the impact energies of the welded joints with a very high accuracy. The RBF and MLP ANN models having layers structure of 2-8-1 and 2-3-1, respectively, showed the best performance among all the investigated networks for predicting the impact energies of welded joints at different temperatures. The mean absolute error (MAE) resulted from the RBF and MLP ANN models are 4.84 and 4.60, respectively.

Keywords: Gas Tungsten Arc Welding, Stainless Steels, Impact Strength, Low Temperatures, Artificial Neural Networks.

1. INTRODUCTION

Austenitic stainless steels (ASSs) are probably the most used alloys of all the stainless steels (SS). ASSs are more resistant to corrosion due to the high content of chromium (18-20 wt.-%) and nickel (8–12 wt.-%) [1-3]. Generally, ASSs are non-magnetic and non-hardenable by heat treatment. However, they can be hardened by cold working. ASSs are widely used as a structural material in several industries, for example, the petrochemical, vehicle, and aviation industries [4].

Gas tungsten arc welding (GTAW) process has a wide range of applications in various industrial areas due to its capability of fabricating high-quality weld [5]. GTAW is one of the famous welding methods which using an arc between non-consumable electrode and workpiece metal to weld the sections. The broad applications of SSs for construction of equipment working in conditions of elevated as well as low temperatures, require methods for optimization, modelling, and predicting the mechanical properties of welded joints, which often affect the service life of the structure. Therefore, several approaches like the artificial neural network (ANN), machine learning (ML), regression analysis and other statistical and numerical approaches were used for such proposes [6,7].

An ANN is a form of application of an artificial intelligence (AI) system, which consisting of several interconnected processors or nodes, or process elements that are called artificial neurons [8,9]. It has been reported that the prediction results produced by ANN and ML models delivered significantly high relevance with the experimental data over the regression analysis [10]. It has been noticed that few investigations were reported on the modelling and prediction of the mechanical characteristics of ASSs welded joints, especially, as a function of temperature. Therefore, the present investigation aims to develop several models based on ANN and regression modelling (RM) methods to predict the mechanical characteristics of AISI 304L and 316L similar and dissimilar welded joints as a function of the temperature. To perform this task, a series of experiments were performed to collect the data about the impact energies of the welded joints at low temperatures up to -75 °C. The ASSs joints were welded using GTAW using constant process parameters.

2. EXPERIMENTAL WORK

In the present investigations, the AISI 304L and AISI 316L SS were used as base metals (BM). The chemical compositions of the AISI 304L and AISI 316L SS are listed in Table 1 and Table 2, respectively. Filler rods of type ER308L, with chemical compositions listed in Table 3, were used as filler material. The ER308L rods have 2.4 mm diameter. The plates form the AISI 304L and AISI 316L SS, with the dimensions of 60 mm (width)× 600 mm (length) × 10 mm (thickness), were machined to get single V-groove with an angle of 60°. Figure 1 shows a typical configuration for the welded joints.

Table 1. The chemical composition of AISI 304L ASS (wt.-%).

Base Alloy	Elements (wt.-%)							
	Cr	Ni	C	Mn	Si	P	S	Fe
AISI 304L	18.91	10.65	0.028	2.01	1.1	0.04	0.03	Bal.

Table 2. The chemical composition of AISI 316L ASS (wt.-%).

Base Alloy	Elements (wt.-%)							
	Cr	Ni	C	Mn	Si	Mo	P	S	Fe
AISI 316L	17.54	11.89	0.026	2.05	1.02	2.25	0.045	0.018	Bal.

Table 3. Chemical composition of the ER308L filler rods (wt.-%).

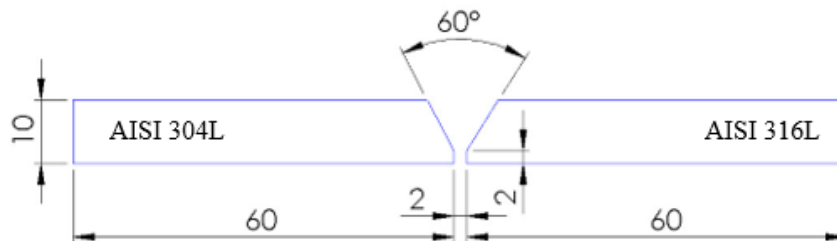| Filler rod	Elements (wt.-%)							
	C	Si	Mn	Ni	Cr	Mo	Cu	N	Fe
E308L	0.02	0.4	1.9	9.8	19.8	0.20	0.15	0.05	Bal.

Figure 1. The joint configuration of stainless-steel plates (dimensions in mm).

The similar welded joints (i.e., AISI 304L-304L and AISI 316L-306L) as well as the dissimilar welded joints (i.e., AISI 304L-316L) were joined using GTAW technique to form butt joints. The GTAW process was performed using Miller Syncrowave 250 CC-AC/DC welding machine. The welding voltage and current were kept constant at 38 V and 210 A, respectively. The GTAW process was carried out manually in four passes with an average welding speed of 11 mm/sec.

The impact energy of the AISI 304L-304L, AISI 304L-316L and AISI 316L-316L welded joints were measured. The Charpy impact specimens have 55 mm long and of square section with 10 mm sides, in the center of length, a V-notch of 45°, 2 mm depth with a 0.25 mm radius of curve at the base of notch located at the weld centerline. Charpy impact tests were performed for welded joints at room as well as lower temperatures of -25, -50, and -75 °C. An ethanol alcohol-based cooling chamber was used to cool the welded SS specimens to the required temperatures. When the required temperature is reached, the impact welded specimen is directly subjecting to impact using computer-controlled pendulum impact tester. The absorbed energy (in Joules) was recorded. At each temperature, the impact tests are repeated, for each welding condition, for a minimum of three times and the mean value and the standard deviation of the impact energy is obtained.

The RM mathematical technique was used to correlate the impact energy of the welded specimens with both the temperature and the type of the base material. Moreover, the ANN technique was also used for modeling the influence of temperature and the base material type on the impact energy welded specimens. The ANN model was based on Multi-Layer Perceptron (MLP) as well as Radial Basis Function (RBF) neural networks. The mean absolute error (MAE) was calculated to define the accuracy of the generated ANN models. It is the difference between the measured value and "true" value. The MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. The MAE can be calculated by using the following equation [11]:

$$\text{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n} \qquad \ldots(1)$$

The MAE is an average of the absolute errors $|e_i| = |y_i - x_i|$, where y_i is the prediction and x_i the true (experimental) value.

3. RESULTS AND DISCUSSION

3.1. Impact Energy of the Stainless-Steel Welded Joints at Different Temperatures

Figure 2 shows the variation of the impact energy of the AISI 304L and AISI 316L SS welded joints with the temperature up to -75 °C. The results revealed that reducing the temperature reduces the impact energy of the welded joints. For instance, reducing the test temperature from ambient to -75 °C reduced the average impact energy of the AISI 304L similar welded joints from 185 J to 108 J, respectively. Similarly, for the AISI 304L-316L dissimilar welded joints, reducing the temperature from the ambient temperature to -75 °C, reduced the average impact energy from 188 J to 112 J, respectively.
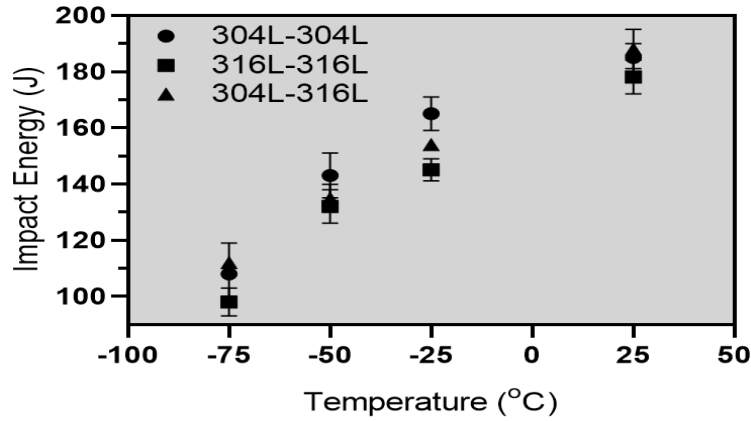
Figure 2. The variation of impact energies of the stainless-steel welded joints with temperature.

The AISI 304L-316L dissimilar welded joints exhibited higher average impact energies when compared with the similar AISI 304L and AISI 316L welded joints. Such observation was noticed at all test temperatures. For instance, the average impact energies at ambient temperature were 185 J, 178 J and 188 J, for the AISI 304L, AISI 316L and AISI 304L-316L welded joints, respectively. While the average impact energies at -75 °C were found to be 108 J, 98 J and 112 J, for the AISI 304L, AISI 316L and AISI 304L-316L welded joints, respectively.

3.2. Regression Modelling of the Impact Energy of The Welded Joints

Figure 3 shows the regression modelling results for the impact energies (IE) of the similar AISI 304L and AISI 316L as well as and AISI 304L-316L dissimilar welded joints. The x-axis represents the temperature in Celsius and the y-axis represents IE in Joules. In Figure 3, the temperature dependence of IE can be approximated by equations (2), (3) and (4).
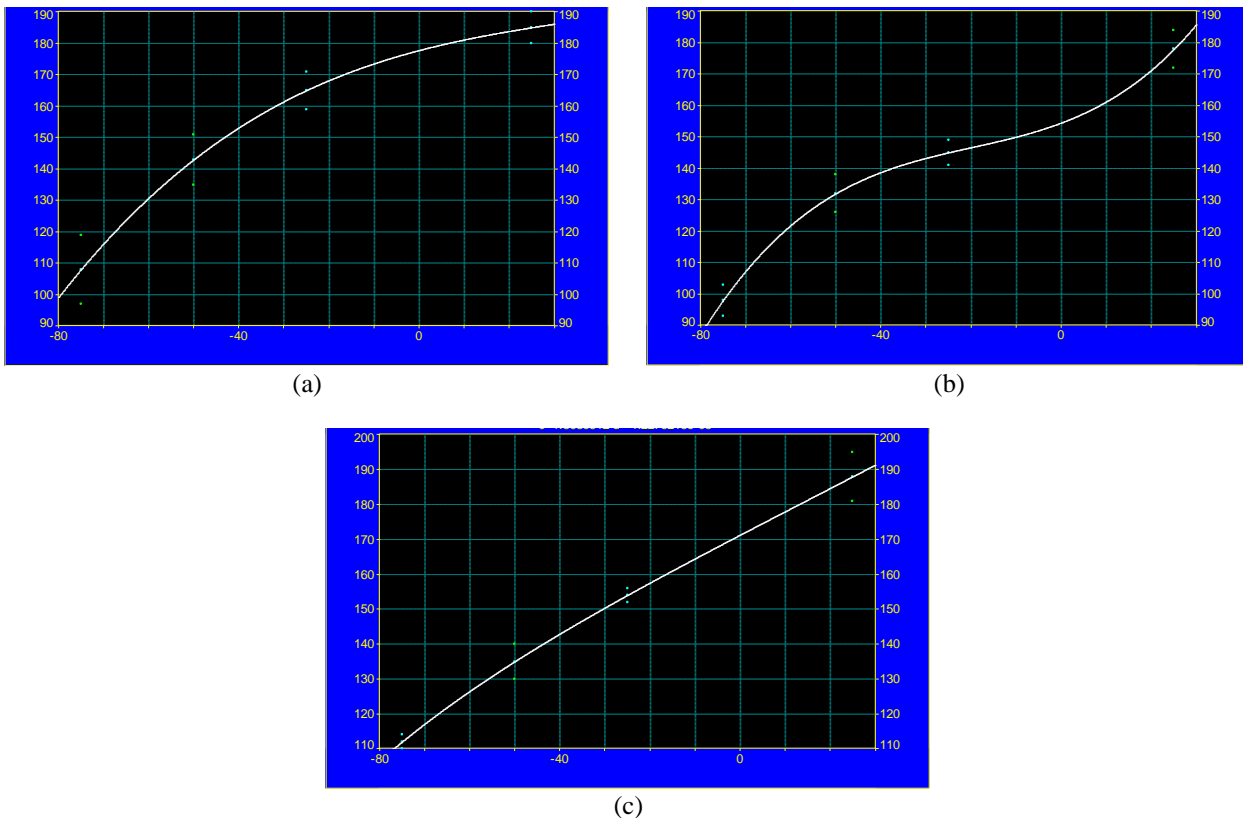

(a)

(b)

(c)

Figure 3. Regression modelling results for the impact energy (IE) of the (a) 304L-304L, (b) 316L-316L and (c) 316L-304L ASSs welded joints; the x-axis represents the temperature in Celsius and the y-axis represents impact energy in Joules.

For AISI 304L similar joints:

$$IE = 177.75 + 0.375 \cdot t - 0.0044 \cdot t^2 + 0.00004 \cdot t^3$$

…(2)

For AISI 316L similar joints:

$$IE = 154.5 + 0.5433333 \cdot t + 0.0112 \cdot t^2 + 0.00018666667 \cdot t^3 \qquad \ldots(3)$$

For AISI 304L-316L dissimilar joints:

$$IE = \frac{171.26189 + 1.3080512 \cdot t}{1 + 0.0037033248 \cdot t - 1.2276215 \times 10^{-5} \cdot t^2} \qquad \ldots(4)$$

Where: IE is the impact energy in Joules and t is the test temperature in Celsius. Equations 2, 3 and 4 have R-Square values of 0.95, 0.97 and 0.98, respectively.

The generalized equation that corelate the IE of the joint with both the temperature as well as the material to be welded (base materials) is shown below:

$$IE = \frac{169.076 + 10.299 \cdot x - 8.700 \cdot x^2 + 2.086 \cdot t + 0.0076 \cdot t^2 + 3.724 \cdot t^3}{1 + 0.098 \cdot x - 0.039 \cdot x^2 + 0.0085 \cdot t} \qquad \ldots(5)$$

Where: t is the temperature in Celsius, x is the weld type and its equal to -1 for AISI 304L, +1 for AISI 316L, and 0 for AISI 316L-304L. Equation (5) has R-Square value of ≈0.977. Figure 4 shows the variation of the impact energy with temperature and the base material(s). In the Figure, the y-axis represents the temperature in Celsius and the x-axis represents joint type.
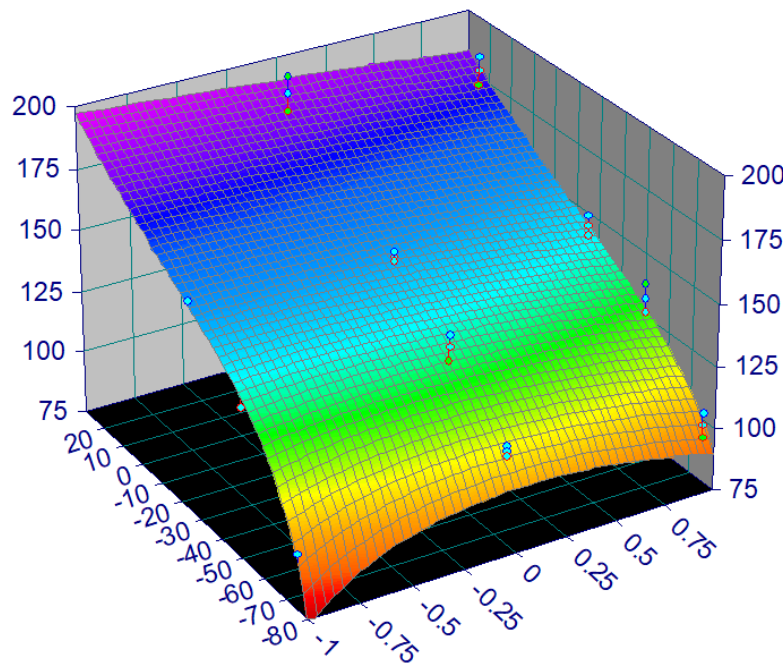

Figure 4. Regression modelling results for the impact energy (IE) of the AISI 304L-304L, AISI 316L-316L and AISI 316L-304L ASSs welded joints; the y-axis represents the temperature in Celsius and the x-axis represents joint type (-1 for AISI 304L, +1 for AISI AISI 316L, and 0 for AISI 316L-304L).

3.2.1. ANN Modelling of the Impact Energy of The Welded Joints

The RBF and MLP ANN models with a structure of 2-8-1 and 2-3-1, respectively, showed the best performance among all the investigated networks. The RBF ANN model showed training, test, and validation performances of 97.68%, 99.60 and 97.01%, respectively. Moreover, the MLP ANN model showed training, test, and validation performances of 97.68%, 99.82 and 96.20%, respectively.

Table 4 lists a comparison between the actual (Target) IE values of the welded joints and the output (predicted) IE values result from the generalized MLP and RBF models. Figure 5 shows a comparison between the target and the output IE values. The MAE resulted from the RBF and MLP ANN models are 4.84 and 4.60, respectively. The results demonstrate that the generated MLP model has a slightly better prediction than the RBF ANN model for predicting the impact energy of the AISI 304L and AISI 316L similar and dissimilar welded joints at different low temperatures. However, the accuracy of the RBF and MLP networks is still very high.

Table 4. The target and output IE values resulted from the generalized ANN modelling for the SS welded joints.

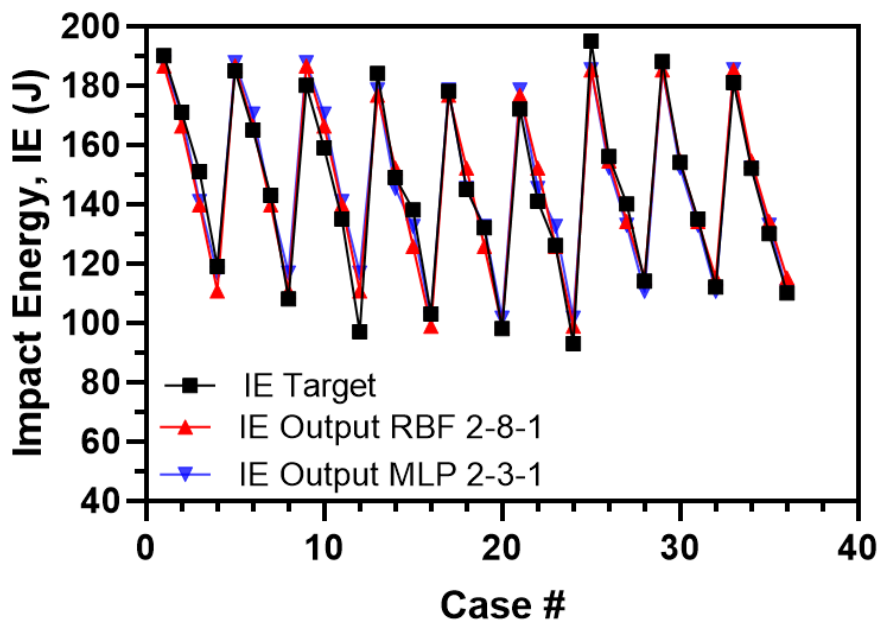| #	IE Target	IE Output RBF 2-9-3	IE Output MLP 2-5-3	#	IE Target	IE Output RBF 2-9-3	IE Output MLP 2-5-3
1	190.0000	186.6428	187.6725	14	149.0000	152.1444	145.2166
2	171.0000	166.3474	170.3196	15	138.0000	125.8291	132.4597
3	151.0000	139.8187	140.8097	16	103.0000	98.8422	101.5971
4	119.0000	110.7182	116.7105	17	178.0000	176.6684	178.5046
5	185.0000	186.6428	187.6725	18	145.0000	152.1444	145.2166
6	165.0000	166.3474	170.3196	19	132.0000	125.8291	132.4597
7	143.0000	139.8187	140.8097	20	98.0000	98.8422	101.5971
8	108.0000	110.7182	116.7105	21	172.0000	176.6684	178.5046
9	180.0000	186.6428	187.6725	22	141.0000	152.1444	145.2166
10	159.0000	166.3474	170.3196	23	126.0000	125.8291	132.4597
11	135.0000	139.8187	140.8097	24	93.0000	98.8422	101.5971
12	97.0000	110.7182	116.7105	25	195.0000	185.2959	185.3065
13	184.0000	176.6684	178.5046	26	156.0000	154.5348	152.2285

Figure 5. Comparison between the target and the output of impact energy values resulted from the RBF and MLP ANN models.

4. CONCLUSIONS

Based on the results obtained from the present investigation, the following conclusions can be derived: -

1. Using the regression modelling approach, a mathematical equation was developed to correlate the relationship between the base materials and temperature with the impact energy of AISI 316L and 304L stainless steel similar and dissimilar welded joints. The equation has R-Square value of 0.977 which is very high.

2. The artificial neural network (ANN) models based on Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) techniques and with layer structures of 2-8-1 and 2-3-1, respectively, showed the best performance among all the investigated networks for predicting the impact energies of welded joints at different temperatures.

3. The RBF ANN model exhibited training, test, and validation performances of 97.68%, 99.60 and 97.01%, respectively. While the MLP ANN model showed training, test, and validation performances of 97.68%, 99.82 and 96.20%, respectively. The MAE resulted from the RBF and MLP ANN models are 4.84 and 4.60, respectively.

4. The developed ANN models based on the RBF and MLP approaches can accurately predict the impact energies of similar and dissimilar AISI 304L and AISI 316L stainless steel welded joints with a very high accuracy. These models can be used to find the dependance of the mechanical properties of the welded joints on temperature.

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