Scientia Iranica B (2016) 23(2), 609–617

Sharif University of Technology
Scientia Iranica
Transactions B: Mechanical Engineering
www.scientiairanica.com

Estimation of mechanical properties of welded S355J2+N steel via the artificial neural network

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Received 22 July 2014; received in revised form 29 October 2014; accepted 4 May 2015

KEYWORDS
Welding;
Yield strength;
Impact test;
Hardness;
Elongation;
ANN.

Abstract. A new estimation study on material features for welding processes is reported. The method is based on the Artificial Neural Network (ANN) for estimation of material features after the gas-metal arc welding process. Since welding is a very common process in many engineering areas, this method would certainly assist technicians and engineers in estimating material features related to the welding parameters before any welding operation. In the proposed method, the input parameters of welding are defined as various shielding gas mixtures of Ar, O_2 and CO_2. As the resulting feature, an estimation is made on the mechanical properties, such as tensile strength, impact test, elongation and weld metal hardness, following ANN. The controller is trained with the scaled conjugate gradient method. It is proven that some estimated values are consistent with the experimental data, whereas some others have relatively higher errors. Thus, this method can be used to estimate, especially, the yield strength and elongation values when the shielding gas proportions are ascertained before the welding. Thus, the method helps to ascertain the welding gas selection in a very short time for engineers, and assists in decreasing welding costs.

1. Introduction

Welding, which combines engineering materials, is one of the most common manufacturing processes in the industry. Strictly speaking, welding of machinery parts is unavoidable for the most engineering applications. Therefore, many researchers work on specific topics in this area to improve the quality of the process, namely, to obtain good joints. Just a few decades ago, the materials were classified as weldable and non-weldable. However, innovations in technology presently allow the joining of most materials by techniques of fusion and solid state welding. Some fusion techniques are applied for a number of materials. However, the typical solid state technique is used for those materials in which the fusion technique may yield to certain problems. Aluminum and Aluminum matrix composites can be mentioned in this context. Many commercially important materials, such as the stainless steel, carbon steel, copper and aluminum, can be welded using this process in all welding positions by adjusting the appropriate parameters for the welding condition [1].

Among the important welding parameters, the composition of the shielding gas mixture depends mostly on the type of material to be welded. The selection of the true shielding gas mixture should be taken into account by considering the chemical-

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metallurgical processes between the gases and the molten pool occurring during welding [2]. There exist various shielding gas mixtures for arc welding in this context, including pure gases and complex quaternary mixtures which consist of Argon (Ar), Helium (He), Oxygen (O_2), and Carbondioxide (CO_2) [3]. According to the literature, the main mixtures of Argon/Helium, Argon/Carbon dioxide, Argon/Oxygen and Argon/Carbon dioxide/oxygen are frequently used in place of pure gases [4]. In addition to the shielding gas mixture, welding current, welding velocity, filler materials, joint types, arc length and some other parameters have also a key influence on achieving good welding. Since the qualities of the welded joint parts are affected by the parameters, a number of experimental studies should be realized on those parameters in order to have good welding. Since design of the experimental setup and work requires many attempts for determination of the best input parameters and creates time consumption and cost, some numerical methods may help to estimate the correct input parameters for the best welding structure. At this point, a number of numerical methods, including Artificial Neural Networks (ANN) and genetic algorithm techniques, have been applied to the material research [5-11]. Among them, Meran [5] applied the genetic algorithm to describe the use of a stochastic search process of welding parameters for joined brass plates. In this respect, he developed the genetic algorithm welding current estimation and genetic algorithm welding velocity estimation models in order to estimate the welding velocity and current. In another study [12], the fatigue strength estimation of an adhesively bonded tubular joint was found using the genetic algorithm approach. As an ANN study, Yilmaz and Ertunc [13] improved a generalized regression neural network model to estimate the tensile strength of the specimens. The predicted values of tensile strength were found to be in good agreement with the experimental values. In recent papers, Udayakumar et al. [14] studied the estimation and optimization of friction welding parameters for super duplex stainless steel joints using the genetic algorithm, while Shojaeefard et al. [8] applied the ANN method to identify the microstructural and mechanical properties of the friction stir welding of aluminum alloys. The performance of the ANN model was excellent and the model estimated the ultimate tensile strength and hardness of the butt joints as functions of weld and rotational speed with good accuracy. In another recent study [15], the welding-induced angular distortions in single-pass butt-welded stainless steel plates were predicted using ANN. For estimation of angular distortions, a multilayer feedforward back propagation neural network has been realized via MATLAB. In another work, Campbell et al. [9] studied the estimation of key weld geometries produced using gas metal arc welding with alternating shielding gases via ANN. His method can be used to predict the penetration, leg length, and effective throat thickness for a given set of weld parameters and alternating shielding gas frequencies. Hamidinejad et al. [10] used the back propagation ANN model for the resistance spot welding of galvanized interstitial free steel sheets, and Sreeraj and Kannan [16] estimated various input process parameters, such as welding current, welding speed, gun angle, contact tip-to-work distance, and pinch, to get optimum dilution in stainless steel cladding of low carbon structural steel plates using gas metal arc welding.

In this paper, an estimation of the material features of S355J2+N steel has been realized before the gas metal arc welding via ANN. Apart from our earlier paper [7], we have proposed a larger training set with different shielding gas composition in order to estimate the mechanical features of the welded samples of a different steel material, which has a wide usage area in the manufacturing industry. Thus, highly accurate ANN test results are expected from the analysis. In the previous study, all mechanical features were defined in a single network. However, this caused high error values in the calculations. Thus, in the present study, we have considered all the mechanical tests as a single output in different network schemes.

2. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are among biologically inspired intelligent methods. This method uses many elements which are highly interconnected in terms of a specific feature. The interconnection of these elements organizes a specific network which is made by specific layers. The elements (i.e. neurons) are important for their dynamic state responses in order to proceed further from the information given as learning patterns. Therefore, many external inputs are given to the network. In the learning process, the weights and thresholds of the processing elements are adjusted automatically. When one finds minimum difference between the ANN output and the target output, the network is accepted as trained.

According to the literature, ANNs can use many structures and architectures [17-19]. Among them, multilayered perceptions (MLPs) are among the most simple and common neural network architectures [7,19]. An MLP consists of at least two layers. Strictly speaking, in addition to input and output layers, an intermediate or a hidden layer exist in the MLP. Neurons in the input layer only act as buffers for distributing the input data, x_i, to neurons in the hidden layer. Each neuron, j, in the hidden layer gets the data, x_i, after weighing them with the strengths of the respective connections, w_{ji}, from the input layer,

Table 1. The chemical composition of the material S355J2+N.

Element	Fe	C	Mn	Si	P	S	Cu
Weight %	bal	0.23	1.70	0.60	0.035	0.035	0.60

and computes the output, y_i, as a function, f, of the sum:

$$y_i = f\left(\sum w_{ji}x_i\right). \quad (1)$$

Here, f is a Purelin transfer function, but any other functions, such as sigmoidal or hyperbolic tangent functions, can also be used in this manner. From the hidden layer, the data is transferred into the output neurons and the output layer calculations are done similarly. Different learning algorithms are used to adjust the weight of ANNs. Among them, the delta-bar-delta algorithm, extended delta-bar-delta algorithm, back-propagation algorithm, and directed random search algorithm can be counted [7,20-22].

3. Experimental process and ANN

The material S355J2+N used in this study had the elemental composition given in Table 1. Two steel plates (15 × 150 × 450 mm) were welded under the welding current 180 A and welding voltage 28 V. In the welding process, a MIG/MAG welding machine was used and different mixtures of shielding gases, such as O_2, CO_2 and Ar, were used. These gas mixtures create a shielding media during the welding process. The flow rate of the gas was 13 l/min through the study. The experiments were performed by setting the distance as 15 mm between the contact tip and the workpiece. The wire used as an electrode had a diameter of 1.2 mm.

The post-welding specimens were cut into small pieces; 15 × 25 × 80 mm for yield and elongation tests, 15 × 25 × 50 mm for impact tests, and 15 × 25 × 30 mm for weld metal hardness, using a slow speed diamond wheel saw through the transverse direction of the bonding interface. Yield strength, impact, elongation and weld metal hardness tests were measured to check the mechanical performance of the welded materials.

The ANN model used in this study is summarized in Figure 1. It has three inputs from the shielding gas ratios used in the welding process, two hidden layers and one output, as one of the tests for each network scheme. While the input layer has 3 neurons representing the gas mixtures and one of the corresponding mechanical features (i.e. hardness, tensile strength, elongation, impact test), the hidden layers have 9 and 7 neurons, respectively. The output layer has only 1 neuron due to reasons of accuracy for estimation of mechanical features.

In the creation of the network scheme, the feed-forward backprop was considered a network type due to its better training results. In two hidden layers, the Tansig function was used, whereas the Purelin function was used in the output layer calculations. In the training part, the scaled conjugate gradient method was considered. Due to very-restricted experimental conditions, only 21 experimental data could be applied to the network for the training aim. Since conventionally restricted shielding gas mixtures can be applied in the welding industry, we are not allowed to enlarge the training network by adding additional mixtures. These data were obtained from the experimental results for each specific shielding gas mixture (i.e. Ar, O_2 and CO_2). After the analysis, the ANN algorithm gives the output neurons, such as tensile strength, elongation, impact test and hardness. 21 data are shown in Table 2 for the training. The other 6 experimental data are used as testing data for the ANN estimation, and the errors of the method are calculated.

4. Results and discussion

Experimental study results of the welded specimens are given in Tables 2 and 3. According to the tests, the highest yield strength of 43 MPa was obtained from the sample (no. 14) welded under Ar93% + $CO_2$7% gas mixture. The lowest yield strength of 34.6 MPa was obtained from the specimen (no. 4) under the gas mixture of Ar85% + $O_2$15%.

In the case of elongation, it was understood that the amount of heat input and gas mixture ratio play an important role in the specimens. Higher heat input causes much elongation in the specimens. The specimen (no. 4) welded under the Ar85% + O_2 15% mixture gives the longest elongation, namely 21.5%. The minimum elongation amounts were obtained under the mixtures of Ar93% + $CO_2$7% and Ar93% + $O_2$2%+ $CO_2$5% for specimen nos. 14 and 23, respectively.

According to the hardness tests, welded specimens

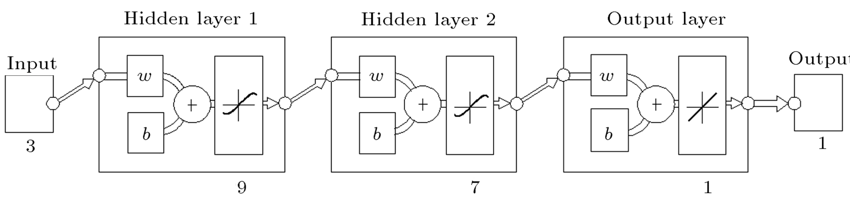

Figure 1. ANN configuration for for all the mechanical property (i.e. hardness, tensile strength, elongation, impact test).

Table 2. Experimental results of the welded specimens for training.

Experiment no.	Ar	O_2	CO_2	Yield strength (MPa)	Elongation (%)	Weld metal hardness (HV_5)	Impact test at -20°C (joule)
1	95	5	0	354.98	20	210	48
2	92	8	0	372.63	19.5	210	45
4	85	15	0	339.29	21.5	180	40
5	98	2	0	348.11	20	170	50
6	90	10	0	364.78	18.9	180	47
7	98	0	2	392.24	16.8	210	48
8	95	0	5	374.59	16.9	210	58
10	85	0	15	372.63	19.7	210	75
11	75	0	25	371.65	17	230	59
12	82	0	18	375.57	19.2	210	45
13	80	0	20	392.24	17.7	220	44
14	93	0	7	421.66	16	210	50
15	90	5	5	393.22	17.5	230	49
16	85	5	10	394.20	17	200	45
17	77	3	20	344.19	20	210	45
19	90	3	7	370.67	16.8	230	40
20	87	5	8	392.24	17.7	210	41
21	80	5	15	354.00	19	190	45
24	86	2	12	372.63	19.8	215	48
25	78	2	20	354.9772	19	210	48
27	0	0	100	391.2594	17.4	200	42

Table 3. Experimental results of the welded specimens for the ANN estimation.

Experiment no.	Ar	O_2	CO_2	Yield strength (MPa)	Elongation (%)	Weld metal hardness (HV_5)	Impact test at -20°C (joule)
3	88	12	0	343.21	18.8	190	44
9	90	0	10	391.26	16.1	230	49
17	80	10	10	364.78	18.6	190	44
22	78	5	17	370.67	16.5	200	43
23	93	2	5	382.43	16	220	40
26	100	0	0	362.82	18.5	165	47

give a number of values from 165 HV_5 to 230 HV_5. The highest hardness was obtained from specimen nos. 9, 11, 15, 19 under the mixtures of Ar90% + $CO_2$10%, Ar75% + $CO_2$25%, Ar90% + $O_2$5% + $CO_2$5% and Ar90% + $O_2$3% + $CO_2$7%, respectively. Besides, the lowest hardness of 165 HV_5 was measured in welding under the Ar 100% gas atmosphere for specimen no. 26.

In terms of impact test measured at -20°C (Tables 2 and 3), the highest impact test results were measured as 75 joules from the specimen (no. 10). This specimen was welded under Ar85% + $CO_2$15%. In addition to this measurement, specimen no. 11 also showed the second highest result under the mixture of Ar75% + $CO_2$25%. The lowest impact test results gave the value of 40 joules from specimen nos. 4, 19 and 23. The welding gas mixtures were Ar85% + $O_2$15%, Ar90% + $O_2$3% + $CO_2$7%, and Ar93% + $O_2$2% + $CO_2$5%, respectively.

4.1. Estimation of weld metal hardness using ANN

In order to make an estimation of the weld metal hardness, ANN training has been realized using 21 different samples, as shown in Table 2. The test values

Table 4. The ANN test values for weld metal hardness.

Experiment no.	Ar	O_2	CO_2	Hardness (ANN)
3	88	12	0	219.582
9	90	0	10	207.4865
17	80	10	10	210.9468
22	78	5	17	208.3572
23	93	2	5	204.6504
26	100	0	0	204.0309

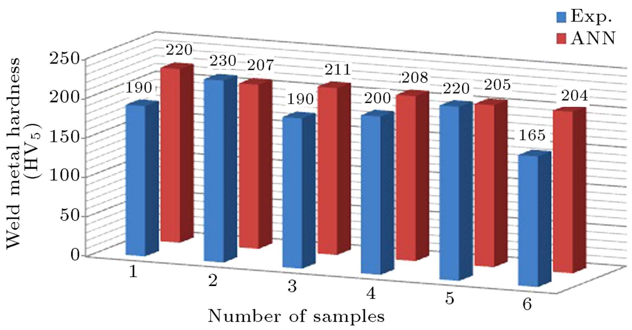

Figure 2. Comparison of ANN prediction with experimental results for six experiments.

for the experimental nos. 3, 9, 17, 22, 23, and 26 related to weld metal hardness are given in Table 3, and these values are compared with the ANN results shown in Table 4.

While the maximal hardness is found for Experiment no. 3 from the ANN estimation, the lowest one is obtained for Experiment no. 26. This proves that the ANN can predict medium hardness values more correctly than the lower and higher values. This situation will be handled in detail with corresponding error graphs in the next section. According to these, the experimental and ANN results are depicted in Figure 2. The ANN estimations are close to experimental results, although the ANN values are slightly higher than the experimental ones in general. According to Figure 2, the overall trend can be predicted correctly for hardness values.

4.2. Estimation of yield strength using ANN

In the case of yield strength, 6 test values from Table 3 have been used for the ANN analysis, as in the previous subsection. The trained algorithm finds the ANN results presented in Table 5.

While the yield strengths have maximal value for Experiment no. 22, the minimal yield strength is obtained for Experiment no. 3. These values have the same trend as the experimental findings. The error values are expected to be relatively lower compared to the hardness values in that respect. Thus, one can claim that this ANN algorithm would be most useful in the estimation of yield strengths. Figure 3 presents both experimental and ANN estimation data. The most recognized errors are obtained for the sample numbers of 9 and 22.

Table 5. The ANN test values for yield strength.

Experiment no.	Ar	O_2	CO_2	Yield strength (ANN)
3	88	12	0	351.5098
9	90	0	10	368.9204
17	80	10	10	366.3414
22	78	5	17	382.5164
23	93	2	5	373.6861
26	100	0	0	368.6134

Table 6. The ANN test values for elongation.

Experiment no.	Ar	O_2	CO_2	Elongation % (ANN)
3	88	12	0	19.0657
9	90	0	10	17.6407
17	80	10	10	19.0793
22	78	5	17	19.111
23	93	2	5	18.1007
26	100	0	0	17.4362

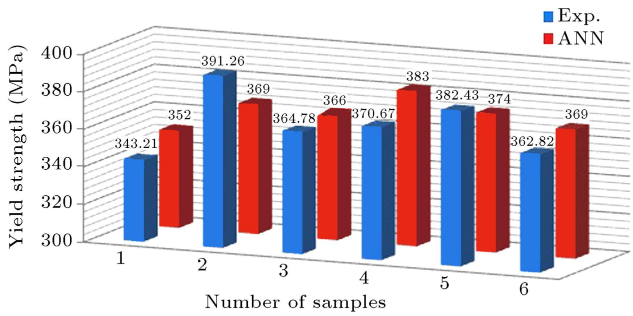

Figure 3. Comparison of ANN prediction with experimental results for six experiments.

4.3. Estimation of elongation using ANN

The estimation of elongation values was carried out from experimental values in Table 3. The trained ANN algorithm finds the ANN results presented in Table 6.

It is obvious that the ANN results are parallel with the experimental findings in general. However, the maximal elongation was found for Experiment no. 22 with the shielding gas mixture of Ar78% + $O_2$5% + $CO_2$17%. In the experiment, the maximal one was measured for specimen no. 3, with the shielding gas mixture of Ar88% + $O_2$12%. In the case of minimal elongation values, the estimation finds specimen no. 26, while the experiments give the lowest elongation for specimen no. 23. However the difference between the gas ratios of the specimens is low and can be ignored in that sense.

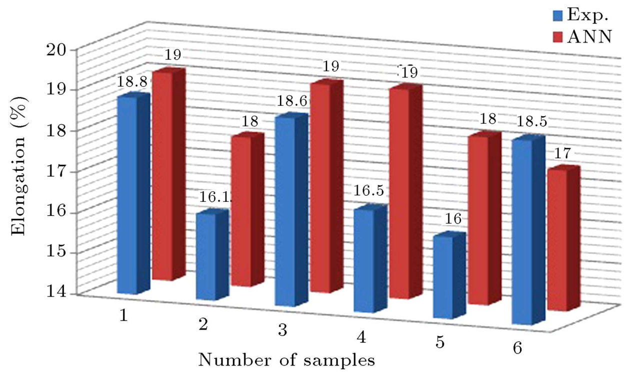

Figure 4. Comparison of ANN prediction with experimental results for six experiments.

Table 7. The ANN test values for impact test.

Experiment no.	Ar	O_2	CO_2	Impact test at -20°C (ANN)
3	88	12	0	38.7541
9	90	0	10	51.6303
17	80	10	10	41.4069
22	78	5	17	47.0086
23	93	2	5	47.3277
26	100	0	0	48.9121

Both experimental and ANN estimations are presented in Figure 4. The general trend of the results is similar, but the estimations are higher than the experimental findings.

4.4. Estimation of impact test using ANN

Table 7 gives estimations of the impact test. According to the table, test values present different experimental results, from 40 to 49, for the impact test at -20°C. In the case of ANN results, the values change from 38 to 48, which are similar to each other. By comparing the minimal and maximal values, we conclude that the maximal experimental impact test has been obtained for specimen no. 9, and the ANN gives the maximal impact test for the same specimen. While the minimal experimental impact test measured for specimen no. 23 in the experiments, the ANN gave the minimal value of 38 for specimen no. 3.

Figure 5 indicates the experimental and ANN results on the impact test. The ANN values are higher compared with experimental ones. The maximal error occurs for specimen no. 3. However, it is proven that the estimations are better than the hardness and yield values.

4.5. ANN errors

The ANN results presented in the previous sections have different errors, depending on the material mechanical properties. However, the maximal percentage error has been found at around 7.91%. This value has

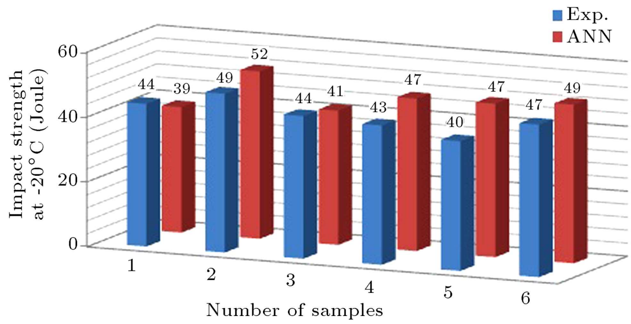

Figure 5. Comparison of ANN prediction with experimental results for six experiments.

Table 8. The errors of ANN test values for weld metal hardness.

Experiment no.	Ar	O_2	CO_2	Error	Error (%)
3	88	12	0	29.582	15.56
9	90	0	10	22.5135	9.78
17	80	10	10	20.9468	11.02
22	78	5	17	8.3572	4.17
23	93	2	5	15.3496	6.97
26	100	0	0	39.0309	23.65

Table 9. The errors of ANN test values for yield strength.

Experiment no.	Ar	O_2	CO_2	Error	Error (%)
3	88	12	0	8.299798	2.41
9	90	0	10	22.33905	5.70
17	80	10	10	1.558173	0.42
22	78	5	17	11.84957	3.19
23	93	2	5	8.747933	2.28
26	100	0	0	5.791424	1.59

been calculated by:

$$\text{Overall error (\%)} = \frac{\sum_{i=1}^{N} E_i}{N} \times 100. \tag{2}$$

Here, E_i and N indicate the ANN absolute percentage errors given in Tables 8-11 and the test number for all mechanical tests (i.e. $N = 24$), respectively. This error value is an acceptable error percentage, since it includes four different experimental mechanical tests. Thus, all tests include experimental errors, which may then affect the results of the ANN algorithm. Besides, due to the lack of large training data because of the welding procedures, the errors have been found in this order.

According to the study, our analysis includes: Database collection of shielding gas mixtures for 4 different mechanical tests (i.e. hardness, yield strength, elongation and impact test), training of 4 neural

Table 10. The errors of ANN test values for elongation (%).

Experiment no.	Ar	O_2	CO_2	Error	Error (%)
3	88	12	0	0.2657	1.413298
9	90	0	10	1.5407	9.569565
17	80	10	10	0.4793	2.576882
22	78	5	17	2.611	15.82424
23	93	2	5	2.1007	13.12938
26	100	0	0	1.0638	5.75027

Table 11. The errors of ANN test values for impact test.

Experiment no.	Ar	O_2	CO_2	Error	Error (%)
3	88	12	0	5.2459	11.92
9	90	0	10	2.6303	5.36
17	80	10	10	2.5931	5.89
22	78	5	17	4.0086	9.32
23	93	2	5	7.3277	18.31
26	100	0	0	1.9121	4.06

networks with 21 training sets, and the application of 6 test data to the trained networks for the estimation. According to the overall percentage errors, estimations of mechanical features for different gas mixtures can be realized within 23.65% by the ANN algorithm. However, the errors show different behaviors in accordance with the applied mechanical tests (i.e. output neurons). For instance, while the errors increase for hardness values, the best results are obtained for yield strength.

Initially, Table 8 gives the errors of metal hardness for test specimens. The algorithm can better estimate the metal hardness, when the percentage of Ar gas is reduced. Otherwise, it gives 23% error for the highest Ar percentage. Thus, it can be understood that the training sets should include various intermediate gas mixtures in the network training in order to achieve a better accuracy (see Table 2). However, the high proportions of O_2 (maximal proportion 15%) and CO_2 (maximal proportion 25%) cannot be used in any industrial applications for gas-metal arc welding processes. Therefore, in our training process, we have only one set that has 100%CO_2 in the gas mixture. This condition may limit the training sets and cause high errors in the network, as pointed out previously.

Figure 6 gives the error graphs of test and training groups. While the errors get lower for training sets, the errors for the test group become slightly higher, according to Figure 6(b).

In the case of yield strength, the ANN estimations are better within the percentages of 0.42-5.70%. Here, the best estimations are found for Ar80% + $O_2$10% + $CO_2$20% and Ar100% (see Table 9).

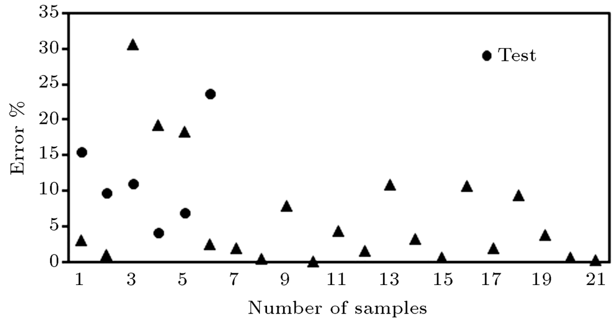

Figure 6. The ANN metal hardness errors of test and training specimens.

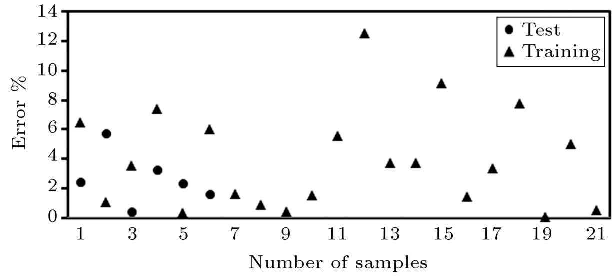

Figure 7. The ANN yield strength errors of test and training specimens.

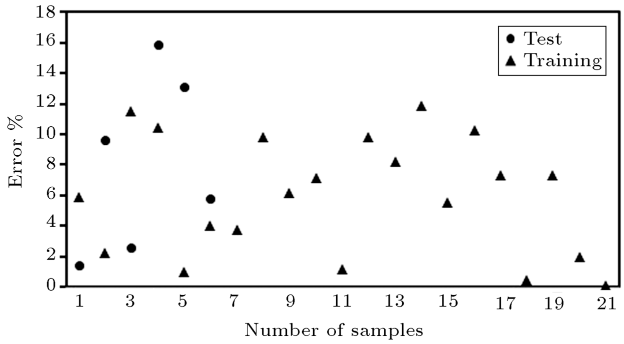

Figure 8. The ANN elongation errors of test and training specimens.

Figure 7 presents the errors of test and training groups. Here, the error values of the training set are generally larger. If we compare the estimations of hardness and yield strength, the estimations of yield strength are more accurate.

Table 10 gives the errors of elongation (%) within the values of 1.4-15.8%. These estimations are better than the estimations of hardness, but worse than the estimations of yield strength. Apart from the previous mechanical tests, here, the errors are generally higher for different proportions of gas mixtures, such as Ar78% + $O_2$5% + $CO_2$17% (see Table 10).

Figure 8 shows the errors of both training and test groups. Similar to the errors of yield strength, the errors in the test and training sets are generally similar. But, the errors in the test set are slightly higher.

In the case of an impact test, the errors are

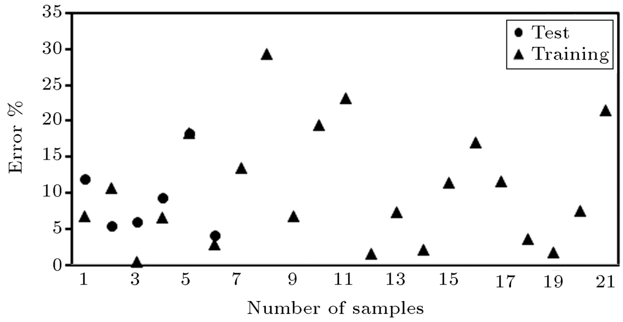

Figure 9. The ANN impact test errors of test and training specimens.

relatively higher (Table 11). They differ between 4.06-18.31%. Figure 9 proves that estimations of the impact test are bad as in the hardness estimations. Note also that the errors of the test set are lower than the errors of the training set, as in the yield strength.

In one of our previous papers [7], a test group was also included into the training set. It has been found that such a result may lower the errors of the mechanical tests and the maximal error percentage was obtained as 8.8. However, in a real study, the test data should not be incorporated into the training data in order to prove the accuracy of the network.

5. Conclusions

In this ANN study, we constructed four networks for each mechanical test by considering different proportions of shielding gases as the input parameter. It is proven that this method can estimate the yield strength and elongation values with better accuracy, when the gas mixtures are determined. However, the ANN estimations require highly comprehensive training tests with different proportions of shielding gases in order to determine hardness and impact test values. Since all the gas mixtures cannot be tried experimentally in gas metal arc welding, we believe that this condition may lead to such high errors which cannot be avoided. In its present stage, it can be concluded that the estimations of mechanical tests, depending on the shielding gas mixture of welding, using the current ANN method can help engineers and technicians get an idea of some mechanical features of the specimens. The benefits of ANN estimation for such a process can be described as being less time consuming and less expensive, especially for the measurements of yield strength and elongation. On the other hand, yield strength and elongation values are the leading features in order to determine the material which will be used.

Acknowledgments

This work has been granted by the EU Commission and Turkish Ministry of EU Affairs under the Erasmus IP Project, entitled: II. European Workshop on Renewable Energy Systems (www.ewres.info), with Project no. 2013-1-TR1-ERA10-48722 and Innovative European Studies on Renewable Energy Systems with Project no. 2015-1-TR01-KA203-021342.

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