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Development of an Artificial Intelligence-Based Algorithm for Predicting the Mechanical Properties of Weld Joints of Dissimilar S700MC-S960QC Steel Structures

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Abstract: Recent developments in the application of artificial intelligence (AI) in predicting weld quality and mechanical properties make it important to investigate the viability of AI in helping to eliminate human efforts. This paper contributes to this development by developing an artificial intelligence (AI) algorithm to determine high-strength steel's mechanical properties, particularly in weld joints created through dissimilar gas metal arc welding of S700MC and S960QC steels. A mathematical model based on artificial neural networks (ANNs) was employed to demonstrate its viability. Sixteen experiments were conducted, generating data on yield and tensile strength concerning the welding parameters and a filler wire with a similar carbon equivalent. Initially, the algorithm was set up to predict joint characteristics using only welding parameters as input variables. However, to enhance the accuracy of the predictions, the carbon equivalent of the filler metal was incorporated as an additional input variable. This adjustment resulted in improved prediction outcomes compared to those obtained without considering the filler wire. The implementation of the AI algorithm was carried out using MATLAB, specifically its R2017b version. The algorithm's ability to predict mechanical properties based on the given input variables showcases its potential in optimizing welding processes and ensuring the desired mechanical properties of weld joints in high-strength steels are achieved. The findings are beneficial for the welding industry and serve as an educational tool.

Keywords: Gas-arc welding, dissimilar welding, high-strength steels, artificial neural network, S700MC, S960QC.

I. Introduction

The use of new materials in modern industries has boosted the need for new developments in predicting weld mechanical properties. Thick and thin metal plates of increasingly diverse materials are used throughout the industry and hence the need to effectively predict the mechanical properties is in high demand. Considering that the mechanical properties of weld metal are influenced by both its chemical composition and thermal history during welding. The study of the mechanical characteristics of materials is a critical area of mechanical engineering since it ensures that the parts used in various mechanisms will be able to withstand different loads while operating. The welding of mechanical parts, although it allows parts to be joined in a sufficiently homogeneous manner, has the disadvantage of not preserving the characteristics of the materials at the welded joint (Bayock et al., 2020). This disadvantage is even more pronounced in the case of dissimilar welding. The study of the new mechanical characteristics at the joint is therefore essential to ensuring the conformity of the welded parts. These mechanical characteristics depend not only on the type of welding process used but also on the mechanical characteristics of the base metal and the filler wire, the welding time, and the applied contact force. (Bayock et al., 2019), (Palanivel et al., 2017), (Winiczenko et al., 2016). The choice of a given welding process depends, among other factors, on the mechanical and thermal characteristics of the base metal (Mishra et al.,2020). However, dissimilar welding presents an additional challenge given the differences in the mechanical and thermal characteristics of the base metals. This limits the choice of welding method Odebiyi, et al., 2019), (Penttilä et al., 2019). The application of dissimilar is to ensure that the different melting points of the materials do not prevent a homogeneous weld joint which is very important in achieving good welded mechanical properties (Bayock et al., 2020). To achieve good mechanical properties, gas-metal arc welding is one of the methods used. Its main parameters are current intensity, welding speed, and thermal energy input (Uhrlandt et al., 2016), (Rajamanickam, et al., 2017). In addition to these parameters, the physical and chemical characteristics of the materials, their geometries, and the properties of the filler metal must be considered to obtain a welded joint of good quality (Uhrlandt et al., 2016), (Park et al., 2024), (Singh et al., 2022).

The weld quality is determined by the quality of the joint obtained, which must have mechanical characteristics as close as possible to those of the original materials. To ensure this closeness, several research methods are used, the most important of which is experimentation. This method consists mainly of destructive testing and requires the use of several samples. Artificial intelligence methods are increasingly being considered for consolidating experimental methods to reduce costs (Mishra, 2020), (Merayo et al., 2020) . The most used methods are artificial neural networks and genetic algorithms. (Gyasi et al., 2017), (Tran et al., 2023) showed that, after comparing several artificial intelligence techniques, algorithms based on artificial neural networks produce better approximation results. The mechanical characteristics studied in their work included tensile strength, yield strength, hardness, and grain size (Gupta et al., 2016), (Payares-Asprino et al., 2021).

However, determining the mechanical characteristics of welded joints experimentally is expensive, given the ratio of time to cost. The value of the materials, therefore, makes any waste expensive. The use of artificial intelligence methods is one solution used to overcome this challenge (Azizi et al., 2016), (Mishra et al., 2020).

The rise of artificial intelligence has led to the investigation of the use of various machine learning techniques in welding. Some studies focus on the geometry and welding parameters (Agbulut et al., 2020), while others focus on the mechanical characteristics of welds. (Park et al., 2024) used an artificial neural network to predict the yield strength of austenitic stainless-steel welds. (Akshansh et al., 2020) compared the effectiveness of an artificial neural network against that of a decision tree regression model to predict the tensile strength of weld joints obtained by friction stir welding of 6061-T6 aluminium alloy from the work of (Elatharasan et al., 2013). The control of weld joint characteristics was studied in the work of (De Filippis et al., 2016), who used an artificial neural network to predict and control the mechanical properties of aluminium plates welded using the friction welding process. (Gupta et al., 2016) proposed an approach based of a multi-objective optimization on friction stir welding of dissimilar AA5083-O and AA6063-T6 aluminium alloys. (Ajith Raj et al., 2018) Investigated several machine learning methods to predict the quality of a welded 304 stainless steel weld joint through its tensile strength and hardness. (Azizi et al. 2016) used a ring probabilistic logic neural network and genetic algorithm to study grain size during friction welding. Very few techniques have been investigated, hence the importance of extending this field to other welding techniques.

This work considers the dissimilar welding of high-strength steels, which are widely used in mechanical engineering due to their combined strength and malleability (Kim et al., 2024), (Wang et al., 2020).

This paper investigates a method for predicting the tensile strength and yield strength of welded materials. The algorithms implemented are based on an artificial neural network, and the welding method chosen is a gas metal arc. In addition, the work draws an analogy in highlighting the importance of the carbon equivalent of the filler material, which evaluates the effect of its alloying material in welding by using the predicting mechanism. The algorithms used in the literature mainly consider welding parameters, such as welding current, welding speed, heat input, and carbon equivalent. To know the viability of AI predictable developed, the work of (Bayock et al., 2020) , (Bayock et al., 2019), which focused on the study of the microstructure and mechanical properties of dissimilar S700MC/S960QC high-strength steels was used. In their work, the specimens were welded using a gas metal arc welding process, and the thermal profile and cooling time, along with the mechanical properties of the welded joint, were investigated using various experimental techniques (Kim et al., 2022), (Chaki et al., 2019). The values obtained for the tensile strength and yield strength and the corresponding welding parameters are the datasets used in this research. The deployment of the algorithm is performed in MATLAB R2017b, and two models are considered. One in which the input parameters are exclusively the welding parameters; a second model which includes the carbon equivalent of the filler metal as an additional variable was applied.

II. Materials and methods

The experiment was conducted using dissimilar S700MC and S960QC materials whose mechanical characteristics are displayed in Table 1 along with those of the filler wire used. The carbon equivalent of the investigation steels was calculated according to the following equation (Banik et al., 2021):

$$\mathrm{CE} = \%\mathrm{C} + \frac{\%\mathrm{Mn}}{6} + \frac{(\%\mathrm{Cr} + \%\mathrm{Mo} + \%\mathrm{V})}{5} + \frac{(\%\mathrm{Ni} + \%\mathrm{Cu})}{15} \quad (1)$$

Carbon equivalent is an essential predictor of steel hardenability. It can be a cause of reduction of hydrogen-induced cracking (Alhassan et al., 2021).

Table 1: Chemical characteristics of the based metal and filler wire

Material	C	Si	Mn	Al	B	Nb	Ti	V	Cu	Cr	Ni	Mo	N	P	S	CE*
S700MC	0.056	0.16	1.18	0.027	0.002	0.044	0.12	0.006	0.02	0.062	0.066	0.0150	0.005	0.01	0.005	0.38
S960QC	0.09	0.21	1.05	0.03	0.002	0.003	0.032	0.008	0.025	0.82	0.04	0.158	0.175	0.01	0.004	0.49

Metal	C	Si	Mn	P	S	Ni	Cr	Mo	Cu	Al	Ti+Zn	CE
16834-A G 69 6 M21 Mn4Ni1.5CrMo	0.0 7	0.5 0	1.70	0.0 12	0.0 2	1.6 0	0.2 0	0.4 5	0.3	-	0.05	0.55
EN ISO 16834-A - G 89 5 M21 Mn4Ni2.5CrMo AWS A5.28: ER120S-G	0.0 56	0.1 6	1.1 8	0.0 1	0.0 05	0.0 66	0.0 62	0.0 15	0.0 2	0.0 27	0.12	0.38
NiCrMo700	0.1 2	0.2 1	1.9	-	-	2.3 5	0.4 5	0.5 5	0.3 0	-	-	0.34

*CE: Carbone equivalent

Table 2 : Mechanical characteristics of the samples and filler wire

	Yield strength (MPa)	Tensile strength (MPa)	Elongation (A5%)	Vickers Hardness (HV5)
S700MC	768	822	12	280
S960QC	960	1000	18	320
16834-A G 69 6 M21 Mn4Ni1,5CrMo	780	830	17	270
EN ISO 16834-A - G 89 5 M21 Mn4Ni2,5CrMo AWS A5.28: ER120S-G	960	1038	20	390
NiCrMo700	780	830	≥ 17	270

Gas metal arc welding was performed with Ar + 18% CO_2 as the shielding gas at a flow rate of 17 l/min. Figure 1 shows the setup used during the welding process. The ABB IRC 5 robot control unit, which is an automated gas-arc welding robot using a preregistered laser profile, was used to carry out the welding process. Welding is performed after two passes in this work, and we consider the results obtained from those two passes separately.

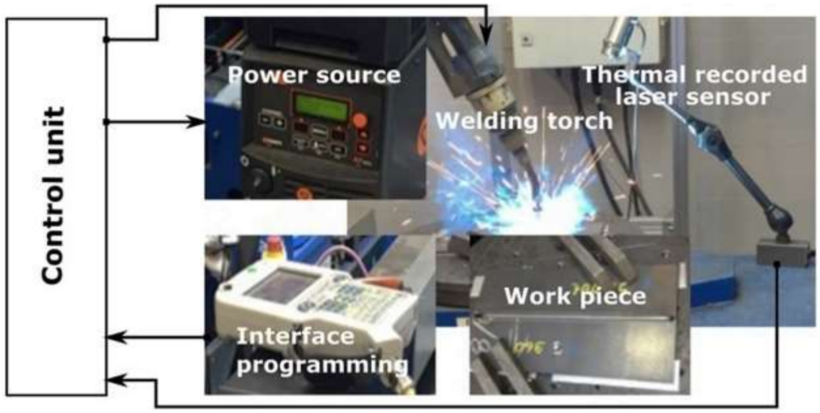

Fig. 1 . Welding setup (Bayock et al., 2020)

Non-destructive testing was carried out using a Vickers Wilson Wolpert 452SVD hardness-testing machine (ITW, Chicago, IL, USA). The microstructure analysis of the materials and the chemical composition of the heat-affected zone were determined using a Hitachi SU3500 instrument (Hitachi High-Technologies America, IL, USA). Destructive tensile testing was carried out using ZWICK/ROZ Z 330 RED (Zwick Rowell, Ulm, Germany).

The MATLAB R2017b built-in neural network function was used for this work. The neural network-based algorithm was set up using the following variables: the intensity of the electric current [in A], the welding speed [in mm/s], the heat input [in kJ/mm], and the carbon equivalent of the filler wire. To ensure that the ranges of all variables were the same and therefore improve the accuracy of the prediction, the data were normalized using Equation 2 (Gupta et al., 2016), (Kesse et al. 2020):

$$\hat{x} = \frac{0,8}{\Delta}x + \left(0,9 - \frac{0,8x_{max}}{\Delta}\right) \quad (2)$$

where $\hat{x}$ is the normalized value of the data, x Is its original value, and $\Delta = x_{max} - x_{min}$. Table 3 displays the actual values of the variables used during the experiments and the corresponding yield strength and tensile strength (Bayock et al. 2020), (Rubio-Ramirez et al.,2020), (Wang et al., 2020). Table 4 shows the normalized values obtained.

Table 3: Experimental results

N°	**Welding current [A]**	**Welding speed [mm/s]**	**Heat input [kJ/mm]**	**Q**	**Carbon Equivalent (EC)**	**Yield Strength [MPa]**	**Tensile strength [MPa]**
1	203	6.2000	0.7000		0.5500	762	813.3000
2	203	4	1		0.3400	789.6000	795.0000
3	203	6.2500	0.8000		0.4500	776.3000	833.3000

4	206	4	1.1	0.3400	761	795.4000
5	206	4	1	0.55	716	813.0000
6	206	3	1.5	0.34	720	773.5899
7	208	6.2	0.71	0.45	752	831.5900
8	208	4	1.2	0.45	700	823.9000
9	210	3	1.5	0.55	706.3	770.3000
10	211	4.5	1.8	0.45	716.3	790.3090
11	212	4.67	0.7	0.34	788	831.5900
12	215	6.2	0.7	0.55	795	818.3890
13	215	6.2	0.8	0.45	763	821.9000
14	215	6.2	0.7	0.34	753	841.9000
15	215	6.2	1	0.34	749	794.6000
16	215	6.2	1.5	0.45	702	772.1000
17	220	3	1.5	0.34	700	801.9090
18	221	4	0.7	0.55	688.5	824.0000
19	221	4.5	0.7	0.43	691	758.3900
20	221	6.2	1	0.45	712	780.2900

Table 4: Normalized data

N°	Welding current [A]	Welding speed [mm/s]	Heat input Q [kJ/mm]	Carbon equivalent (CE)	Yield strength [MPa]	Tensile strength [MPa]
1	0.1000	0.8877	0.1000	0.9000	0.6744	0.6263
2	0.1000	0.3462	0.3182	0.1000	0.8631	0.4512
3	0.1000	0.9000	0.1727	0.5190	0.7721	0.8177
4	0.2333	0.3462	0.3909	0.1000	0.6675	0.4550
5	0.2333	0.3462	0.3182	0.9000	0.3598	0.6234
6	0.2333	0.1000	0.6818	0.1000	0.3872	0.2455
7	0.3222	0.8877	0.1073	0.5190	0.6060	0.8005
8	0.3222	0.3462	0.4636	0.5190	0.2504	0.7191
9	0.4111	0.1000	0.6818	0.9000	0.2935	0.2148
10	0.4556	0.4692	0.9000	0.5190	0.3619	0.4062
11	0.5000	0.5111	0.1000	0.1000	0.8521	0.8005
12	0.6333	0.8877	0.1000	0.9000	0.9000	0.6742
13	0.6333	0.8877	0.1727	0.5190	0.6812	0.7086
14	0.6333	0.8877	0.1000	0.1000	0.6128	0.9000
15	0.6333	0.8877	0.3182	0.1000	0.5855	0.4474
16	0.6333	0.8877	0.6818	0.5190	0.2641	0.2321
17	0.8556	0.1000	0.6818	0.1000	0.2504	0.5172
18	0.9000	0.3462	0.1000	0.9000	0.1718	0.7287
19	0.9000	0.4692	0.1000	0.4429	0.1889	0.1000
20	0.9000	0.8877	0.3182	0.5190	0.3325	0.3096

The parameters used to set up the algorithm are shown in Table 5, and the control parameters are the absolute error and relative error given by Equation 3.

$$e = \frac{X' - X}{X} \quad \text{or} \quad e(\%) = \frac{X' - X}{X} * 100 \tag{3}$$

where X is any given experimental data and X' is the corresponding predicted value.

Table 5 : Algorithm parameters

Number of experiments	**Training data**	**Validation data**	**Test data**	**Activation function**	**Evaluation function**
20	11	6	3	Levenberg–Marquardt at backpropagation	Mean square Error

To avoid overfitting, only 55% of the data are chosen for the training phase. 30% of the data are used for the validation phase of the algorithm and 15% are used for testing.

The neural network algorithm

The neural network algorithm works like the human brain. The artificial neural network (ANN) consists of interconnected artificial neurons that can be used in data fitting, prediction, or optimization, among other applications (Afzal et al., 2021), (Bejani et al., 2021). Input data is processed using weights on every neuron and a bias. An activation function is then used to find the best fit. The principle of the neural network is shown in Figure 2 (Abiodun et al., 2018), (Wu et al., 2021) and (Mohammadizadeh et al., 2023).

The built-in MATLAB function for the neural network can be accessed using the path MATLAB R2017b >> APPS >> Neural Net Fitting. The goal is to find the network with the best combination of coefficients to obtain the best fit from the experimental data.

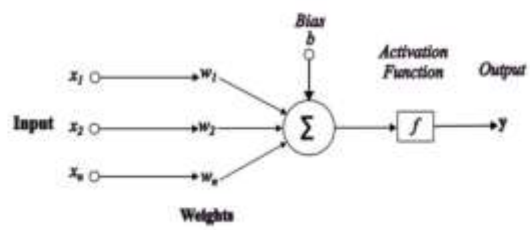

Fig. 2 Artificial Neural network principle

III. RESULTS AND DISCUSSION

In this paper, an artificial intelligence (AI) algorithm was designed to determine the mechanical properties of high-strength steels, particularly in weld joints created through dissimilar gas metal arc welding of S700MC and S960QC steels. To achieve the said objective two approaches were used namely Yield and Tensile strength prediction without filler properties in the input and yield and tensile strength prediction with filler properties in the input.

Model without the filler wire's properties as input

Yield strength's results

The distribution of the absolute error obtained when determining the yield strength is shown in Figure 3. The error is well distributed around zero and ranges from -0.2037 to 0.1689. Considering the relative errors in absolute value, the average of relative errors is 0.0790. The data from the test phase appear to have a smaller absolute error compared to the data from the training and validation phases used to set the algorithm. This shows the ability of the algorithm to produce good results for unobserved data.

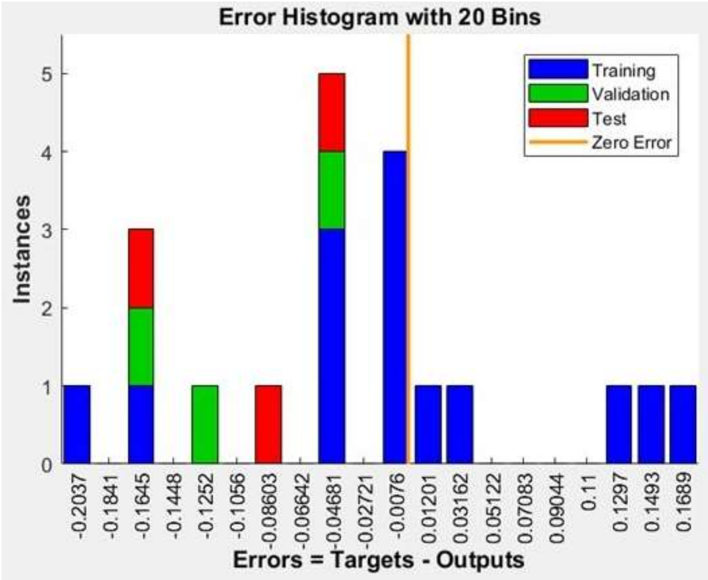

Fig.3. Histogram error for the yield strength without the carbon equivalent of filler wire as input

Figure 4 shows the regression of the predicted data against the experimental data. It represents the regression of the training data, the validation data, and the test data. The regression of all the data is also shown, along with the corresponding regression coefficient. The regression of the training data shows an approximation of the experimental data by the data predicted by the algorithm, with a regression coefficient R = 0.9456. The values of the regression coefficients for the validation and test phases are 0.9243 and 0.9758 respectively. The regression of all the data shows some points not on the regression line and an overall regression coefficient of 0.9503.

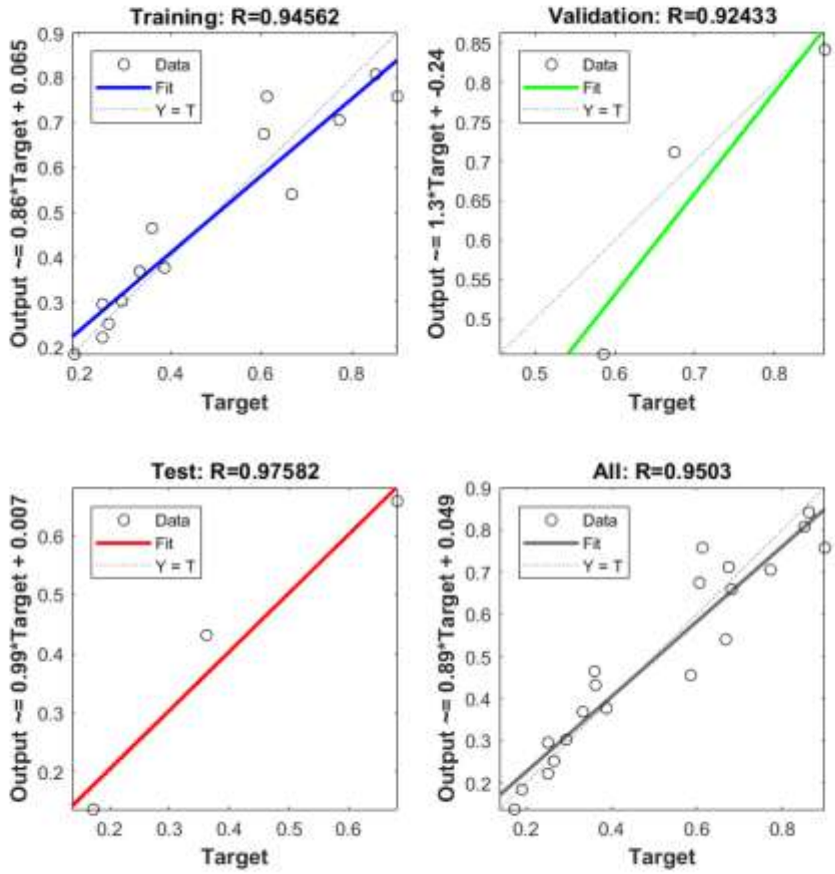

Fig. 4. Regression for the yield strength without the carbon equivalent of filler wire as input

Table 6 shows the relative errors for all the data used. The normalized yield strength data and the values predicted by the algorithm are shown. These data are used to determine the corresponding relative error and to deduce the predicted value of the yield strength in MPa, given the actual experimental values of the yield strength in MPa. The relative error is calculated from Equation 3. Therefore, knowing the experimental data and the distribution of the relative error enables us to deduce the predicted value using Equation 4 (Pradhan et al., 2022).

$$X' = X(\mathrm{e} + 1) \tag{4}$$

From Table 6, the approximation produces a relative error distributed between 0.0031 and 0.1684 for all datasets used. Considering the relative errors in absolute value, the average of relative errors is 0.0790. As a result, the algorithm approximates the yield strength with a maximum error of 16.8411%.

Table 6: Predicted values of yield strength without filler wire as an input parameter

N°	Experimental Yield Strength normalized	Predicted Yield Strength Normalized	Relative error	Experimental Yield Strength [MPa]	Predicted Yield Strength [MPa]
1	0.6744	0.6381	-0.0538	762.0000	720.9568
2	0.8631	1.0054	0.1649	789.6009	919.7347
3	0.7721	0.7503	-0.0283	776.3888	754.3236
4	0.6675	0.6505	-0.0255	761.0988	741.6032
5	0.3598	0.4302	0.1957	716.0898	856.0934
6	0.3872	0.3988	0.0300	720.0655	741.6256
7	0.6060	0.5545	-0.0850	752.0456	688.1276
8	0.2504	0.2671	0.0666	700.0655	746.5954
9	0.2935	0.2944	0.0032	706.3567	708.5546
10	0.3619	0.3719	0.0277	716.3456	736.1387
11	0.8521	0.7644	-0.1029	788.0565	706.9067
12	0.9000	0.9375	0.0417	795.0566	828.1665
13	0.6812	0.6370	-0.0649	763.0755	713.5156
14	0.6128	0.5953	-0.0286	753.0566	731.4967
15	0.5855	0.6159	0.0520	749.0655	787.9565
16	0.2641	0.3086	0.1684	702.0980	820.2243
17	0.2504	0.2179	-0.1297	700.0908	609.2032
18	0.1718	0.1536	-0.1061	688.5980	615.4723
19	0.1889	0.1667	-0.1176	691.0545	609.7634
20	0.3325	0.3028	-0.0894	712.0566	648.3745

Tensile strength results

The prediction of the tensile strength produced a distribution of absolute errors, as shown in Figure 5. The absolute error is well distributed around. The error lies between -0.1458 and 0.1245. The maximum absolute value of the error is 0.1458 which corresponds to the test dataset.

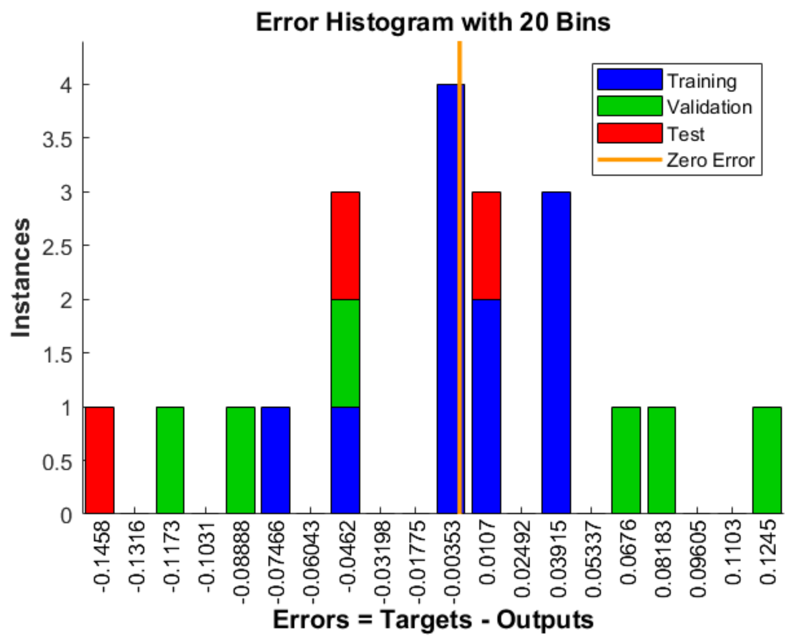

Fig. 5. Histogram error for the tensile strength without filler wire 's properties

The regression of the predicted data against the experimental data is shown in Figure 6. For the training phase, the regression coefficient R = 0.9922. For the validation and test phases, the regression coefficients are respectively 0.9008 and -0.7976. The regression of all samples shows no particularly isolated point and an overall regression coefficient of 0.9448 Table 7 shows the relative errors of the datasets used. The normalized tensile strength data and the values predicted by the algorithm are shown. These data are used to determine the corresponding relative error and to deduce the predicted value of the tensile strength in MPa, given the actual experimental values of the tensile strength in MPa. It is shown that this tensile strength prediction can be an issue in terms of the weldability of such high-strength and ultra-high-strength steel. The dependency of filler wire with and new criterion of carbon equivalent is inevitable in the improved prediction of the algorithm. It is important to notice the risk of hydrogen-induced cracking in the heat-affected zone of the welded joints. In that case, the process may need to be preheated.

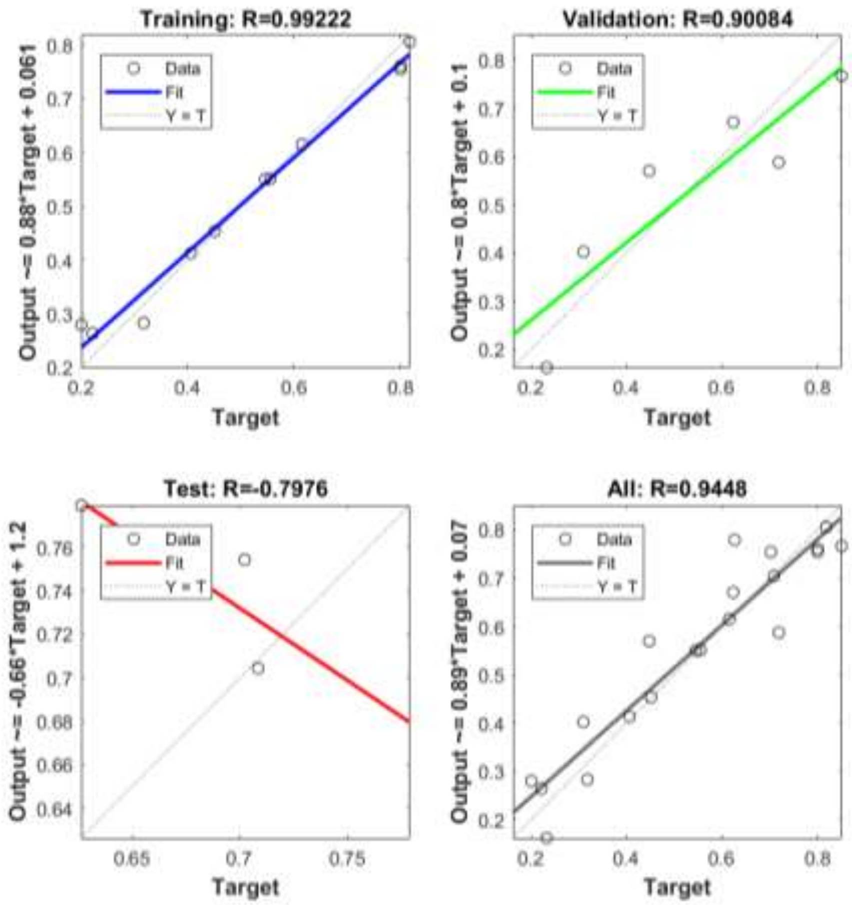

Fig. 6. Regression for the yield strength without the carbon equivalent of filler wire as input

The relative error is determined using Equation 3, and the predicted tensile strength values are determined from the experimental values using Equation 4. The relative error obtained ranges from 0.0005 to 0,1667. Considering the relative errors in absolute value, the average of the relative errors is 0.0653.

Table 7: Predicted values of tensile strength without filler wire as an input parameter

N°	Experimental Tensile Strength normalized	Predicted Tensile Strength Normalized	Relative error	Experimental Tensile Strength [MPa]	Predicted Tensile Strength [MPa]
1	0.6263	0.5690	-0.0914	813.3766	738.9387
2	0.4512	0.4514	0.0006	795.0676	795.4465
3	0.8177	0.6813	-0.1668	833.3676	694.3267
4	0.4550	0.4929	0.0832	795.6554	861.5976
5	0.6234	0.6182	-0.0084	813.0566	806.1768

6	0.2455	0.2214	-0.0980	773.5655	697.6965
7	0.8005	0.7863	-0.0177	831.5576	816.7966
8	0.7191	0.7178	-0.0018	823.0676	821.4898
9	0.2148	0.2077	-0.0332	770.3677	744.7775
10	0.4062	0.4046	-0.0039	790.3566	787.2489
11	0.8005	0.7089	-0.1144	831.5234	736.3778
12	0.6742	0.6676	-0.0097	818.3342	810.3787
13	0.7086	0.6968	-0.0166	821.9664	808.2357
14	0.9000	0.8939	-0.0067	841.9565	836.2365
15	0.4474	0.4941	0.1046	794.6655	877.6987
16	0.2321	0.2725	0.1742	772.1655	906.6189
17	0.5172	0.4600	-0.1106	801.9765	713.2078
18	0.7287	0.7759	0.0648	824.0980	877.4167
19	0.1000	0.0972	-0.0283	758.3654	736.8876
20	0.3096	0.3627	0.1717	780.5662	914.1878

A model with the filler wire's properties as input

Yield strength's results

Figure 7 shows a well-distributed absolute error around zero when determining the yield strength. For these datasets, the absolute errors are between -0.1339 and 0.2515. Figure 8 allows us to better appreciate the neural network algorithm's approximation of the yield stress values, with some values proving not fully on the regression line. However, the regression coefficient of 0.9669 allows us to conclude that the algorithm obtained sufficiently captures the information on the yield strength of the weld joint. The regression of the training data shows a regression coefficient of 0.9650. The regression coefficients obtained for the validation and test phases are respectively 0.9949 and 0.9764.

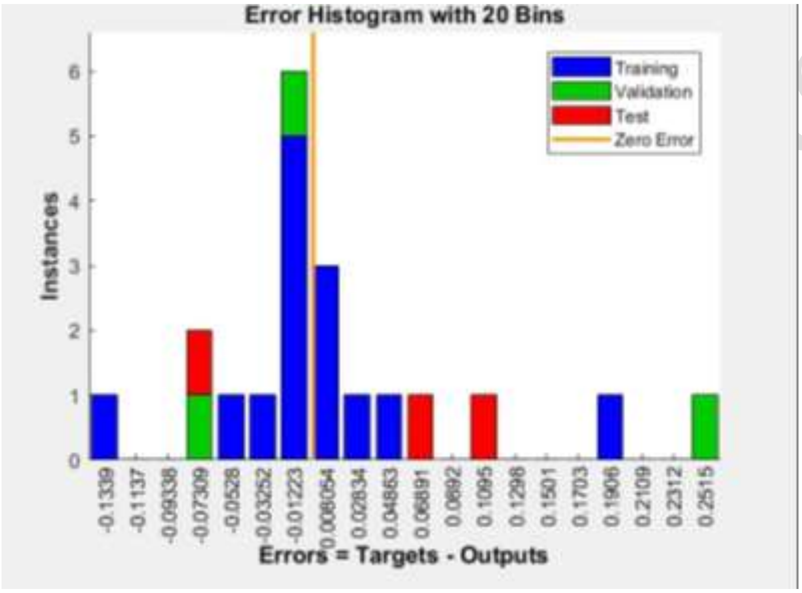

Fig. 7. Histogram error for the yield strength with the carbon equivalent of filler wire as input

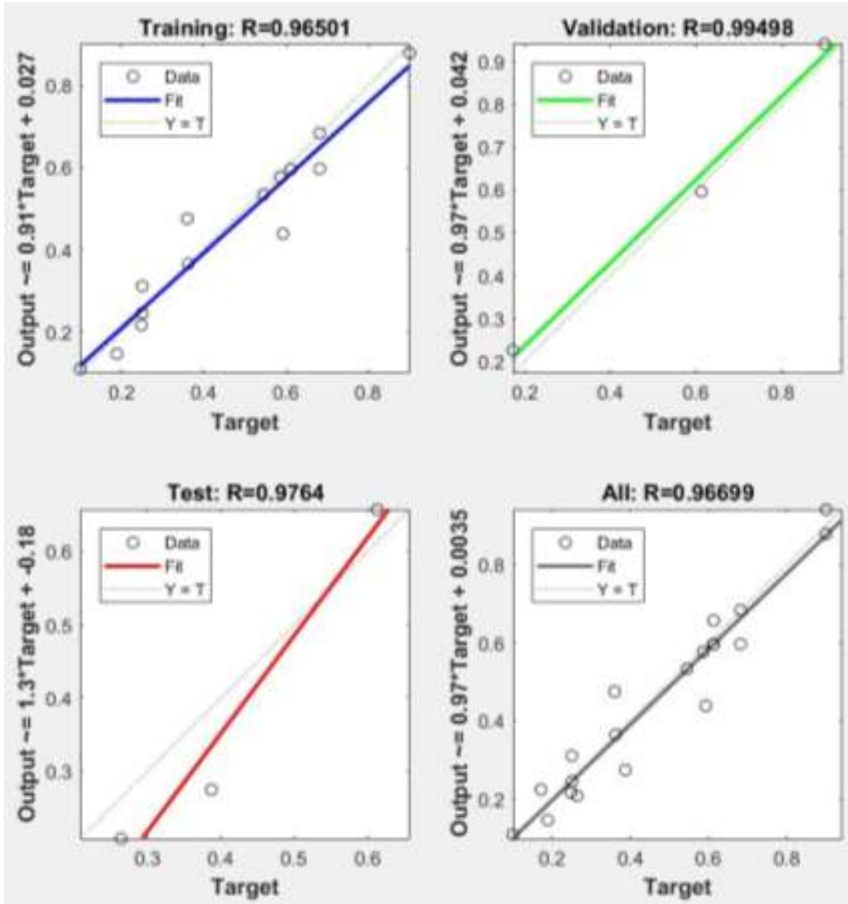

Fig. 8. Regression for the yield strength with the carbon equivalent of filler wire as input

Table 8 shows the relative errors of all the data studied and the approximate values of the yield strength. The output data, consisting of the values obtained experimentally, are normalized and presented, as well as the approximate values obtained by the algorithm. The relative errors obtained for this set of data allow us to deduce the predicted values of the yield strength. The relative errors are distributed between 0.0058 and 0.0773 in absolute value. Given the low relative error, the approximation for these data is considered satisfactory. When considering the relative errors in absolute value, the average of relative errors is 0.0399, which is much better as compared to the model without the carbon equivalent of filler wire as input.

Table 8: Predicted values of yield strength with filler wire as input parameter

N°	Experimental Yield Strength normalized	Predicted Yield Strength Normalized	Relative error	Experimental Yield Strength [MPa]	Predicted Yield Strength [MPa]
1	0.6744	0.6381	0.0058	762.0345	766.4452
2	0.8631	1.0054	0.0255	789.6565	809.7670
3	0.7721	0.7503	0.0219	776.3565	793.2567
4	0.6675	0.6505	0.0176	761.0565	774.7838
5	0.3598	0.4302	-0.0673	716.0565	667.7789
6	0.3872	0.3988	-0.0267	720.0567	700.7099
7	0.6060	0.5545	-0.0774	752.0565	693.8287
8	0.2504	0.2671	0.0970	700.0565	767.9389
9	0.2935	0.2944	0.0221	706.3565	721.8998
10	0.3619	0.3719	-0.0596	716.3565	673.6479
11	0.8521	0.7644	-0.0743	788.0567	729.4793
12	0.9000	0.9375	-0.0170	795.0908	781.4698
13	0.6812	0.6370	-0.0276	763.0783	741.9903
14	0.6128	0.5953	0.0302	753.0234	775.7897
15	0.5855	0.6159	0.0045	749.0357	752.3893
16	0.2641	0.3086	-0.0124	702.0546	693.2898
17	0.2504	0.2179	-0.0661	700.0467	653.7289
18	0.1718	0.1536	0.0245	688.5765	705.3789
19	0.1889	0.1667	0.0769	691.0786	744.1687
20	0.3325	0.3028	0.0446	712.0686	743.7576

Figure 9 shows the error distribution when determining the tensile strength. The errors are well distributed around zero and range from -0.1822 and 0.1051. Figure 10 shows the approximation between the results obtained by the algorithm used and the experimental results. The overall regression coefficient is 0.9797. The regression obtained with the training data is 0.9981, which justifies the fact that the absolute errors illustrated by the error histogram are closer to zero for the training data. The regression coefficients for the validation and test phases are 0.9689 and 0.9982 respectively. The prediction values of yield strength with filler wire as an input parameter led to good weld behaviours. The optimum mechanical properties are because of the evaluation of the carbon equivalent of different materials used. Modern materials (high-strength or ultra-high-strength steels) made using complex alloying elements in their composition have exhibited unprecedented weldability. It is important to recommend that welders have a general idea about the hardenability of the different welded-based materials and filler wire (Alhassan et al., 2021).

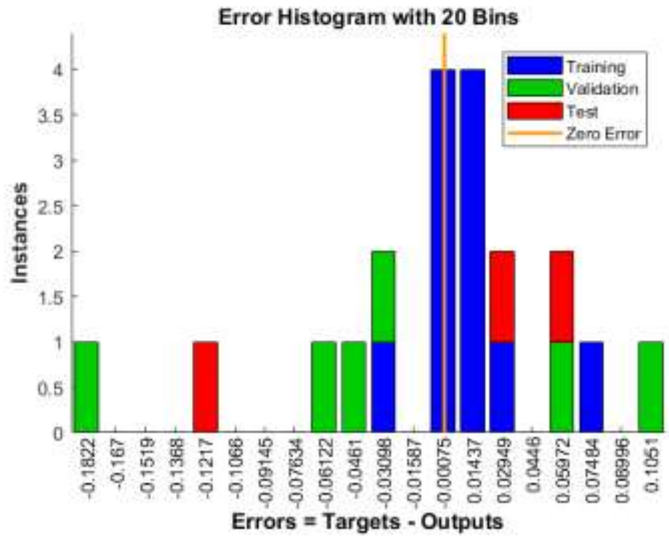

Fig. 9. Histogram of the tensile strength for the carbon equivalent of the filler wire

Figure 10 shows the approximation between the results obtained by the algorithm used and the experimental results. The overall regression coefficient is 0.9797. The regression obtained with the training data is 0.9981, which justifies the fact that the absolute errors illustrated by the error histogram are closer to zero for the training data. The regression coefficients for the validation and test phases are 0.9689 and 0.9982 respectively.

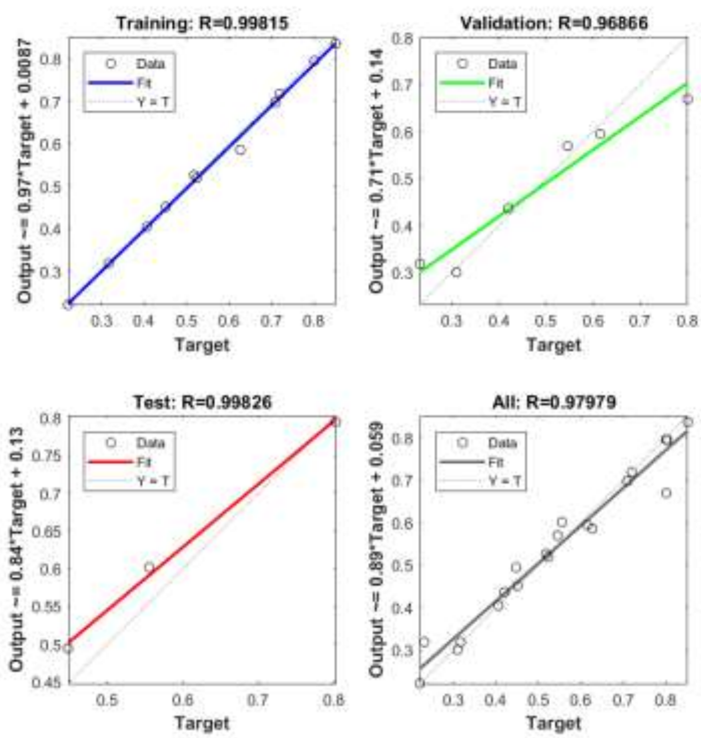

Fig. 10 : Regression for the tensile strength with the carbon equivalent of filler wire as input

Table 9 shows the relative errors of and approximated values for the tensile strength. The relative error is distributed between 0.0000 and 0.1104 in absolute value. When considering the relative errors in absolute value, the average of relative errors is 0.02909275, which is much better as compared to the model without the carbon equivalent of filler wire as input. That is why the research results of (Alhassan et al., 2021), evaluated the impact of carbon equivalent on the weldability of metal. It is just a positive aspect in terms of tensile strength evaluation. The carbon equivalent avoids a weld defect and optimizes the mechanical properties of the welded joint.

Table 9: Predicted values of tensile strength with filler wire's carbon equivalent as an input parameter

N°	Experimental Tensile Strength normalized	Predicted Tensile Strength Normalized	Relative error	Experimental Tensile Strength [MPa]	Predicted Tensile Strength [MPa]
1	0.6263	0.6558	0.0471	813.3000	851.5990
2	0.4512	0.4512	0.0000	795.0000	795.0290
3	0.8177	0.8421	0.0298	833.3089	858.1409
4	0.4550	0.4550	0.0000	795.4787	795.4123
5	0.6234	0.6235	0.0000	813.0789	813.0123
6	0.2455	0.2488	0.0138	773.5898	784.1832
7	0.8005	0.8005	0.0000	831.5898	831.4823
8	0.7191	0.7191	0.0000	823.0888	823.0145
9	0.2148	0.2148	0.0000	770.3898	770.2954
10	0.4062	0.4062	0.0000	790.3870	790.3076
11	0.8005	0.8005	0.0000	831.8995	831.5498
12	0.6742	0.7341	0.0890	818.3989	891.1089
13	0.7086	0.7759	0.0949	821.9900	899.9189
14	0.9000	0.8006	-0.1104	841.9988	748.9489
15	0.4474	0.4473	-0.0001	794.6800	794.5400
16	0.2321	0.2253	-0.0292	772.1800	749.5778
17	0.5172	0.4958	-0.0414	801.9900	768.6878
18	0.7287	0.7464	0.0243	824.0900	843.9978
19	0.1000	0.1000	0.0000	758.3900	758.3087
20	0.3096	0.2781	-0.1018	780.2890	700.8189

Conclusion

This study was carried out using two approaches. In the first approach, where only gas-metal arc welding parameters were used as input data, the algorithm showed promising results for predicting yield strength and tensile strength of welded joints. However, some data points exhibited greater absolute errors, possibly due to factors such as variations in welding conditions or material properties not fully captured by the input parameters. In the second approach, where the carbon equivalent of the filler wire was added as an input variable, the prediction performance improved for both yield strength and tensile strength. The regression coefficients went from 0.9503 to 0.9669 and from 0.9448 to 0.9797 for the yield strength and tensile strength respectively. The average of the absolute values of relative errors decreased from 0.0790 to 0.0399 and from 0.0653 to 0.0290. These results suggest an enhanced predictive capability with the inclusion of filler wire properties. These findings highlight the importance of considering additional factors, such as filler wire characteristics, in accurately predicting the mechanical properties of weld joints. Despite some outliers in prediction errors, the overall performance of the algorithm seems promising, particularly with the refinement achieved by incorporating the carbon equivalent of the filler wire. Future studies could be conducted to develop a neural network, which leads to a prediction of the mechanical properties and microstructural constituents of the welded joints of dissimilar high-strength steel.

References

Alhassan, M., Bashiru, Y., (2021)."Carbon Equivalent Fundamentals in Evaluating the Weldability of Microalloy and Low Alloy Steels", *World Journal of Engineering and Technology*, 9, 782-792, https://doi.org/10.4236/wjet.2021.94054.

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., Arshad, H. (2018). "State-of-the-art in artificial neural network applications: A survey", *Heliyon*, 4, p. e00938, https://doi.org/10.1016/j.heliyon.2018.e00938.

Ajith Raj R., Anand, M. (2018)."Modeling and Prediction of Mechanical Strength in Electron Beam Welded Dissimilar Metal Joints of Stainless Steel 304 and Copper Using Grey Relation Analysis", *International Journal of Engineering and Technology (UAE)*, 7, 198-201, https://doi.org/10.14419/ijet.v7i3.6.14969.

Ansaripour, N., Heidari, A., Eftekhari, S.A. (2020). "Multi-objective optimization of residual stresses and distortion in submerged arc welding process using genetic algorithm and harmony search". *Proceeding Institute of Mechanical Engineering Journal*, 234, 862–871, https://doi.org/10.1177/0954406219885977

Afzal, A., Bhutto, J.K., Alrobaian, A., Kaladgi, A.R., Khan, S.A. (2021). "Modelling and Computational Experiment to Obtain Optimized Neural Network for Battery Thermal Management Data", *Energies*, 14, 7370, https://doi.org/10.3390/en14217370.

Azizi, A., Vatankhah Barenji, A., Barenji, R., Hashemipour, M. (2016). "Modelling Mechanical Properties of FSW Thick Pure Copper Plates and Optimizing It Utilizing Artificial Intelligence Techniques", *International Journal of Sensor Networks and Data Communications*, https://doi.org/10.4172/2090-4886.1000142.

Banik, S.D., Kumar, S., Singh, P.K., Bhattacharya, S., Mahapatra, M.M. (2021). "Distortion and residual stresses in thick plate weld joint of austenitic stainless steel: Experiments and analysis". *Journal of Materials Processing Technology*, 289, 6944, https://doi.org/10.1016/j.jmatprotec.2020.116944.

Bayock, N., Kah, P., Salminen, A., Belinga, M., Yang, X. (2020). "Feasibility study of welding dissimilar Advanced and Ultra High Strength Steels", *Reviews on Advanced Materials Sciences*, 59, 54-66, January 2020, https://doi.org/10.1515/rams-2020-0006.

Bayock, N., Kah, P., Mvola, B., Layus, P. (2019). " Effect of Heat Input and Undermatched Filler Wire on the Microstructure and Mechanical Properties of Dissimilar S700MC/S960QC High-Strength Steels", *Metals*, 9, 1-19, https://doi.org/10.3390/met9080883.

Bejani, M.M., Ghatee, M. (2021), "A systematic review on overfitting control in shallow and deep neural networks", Artificial Intelligence

Review, 54, 6391–6438, https://doi.org/10.1007/s10462-021-09975-1.
Chaki, S. (2019). "Neural networks based prediction modeling of hybrid laser beam welding process parameters with sensitivity analysis. *Applied Sciences*, 1, 1285, https://doi.org/10.1007/s42452-019-1264-z.
De Filippis, L., Serio, L., Facchini, F., Mummolo, G., Antonio Domenico, L. (2016). "Prediction of the Vickers Micro hardness and Ultimate Tensile Strength of AA5754 H111 Friction Stir Welding Butt Joints Using Artificial Neural Network", *Materials*, 9, 915, https://doi.org/10.3390/ma9110915.
Elatharasan, G., S. Kumar, (2013). "An Experimental Analysis and Optimization of Process Parameter on Friction Stir Welding of AA 6061-T6 Aluminium Alloy using RSM", *Procedia Engineering*, 64, 1227-1234, https://doi.org/10.1016/j.proeng.2013.09.202.
Farrokh, K., Elyas, G., Masoud, M., Rahimian, M. (2018), "Analytical Solutions for the Flexural Behaviour of Metal Beams Strengthened with Prestressed Unbonded CFRP Plates", *Civil Engineering Infrastructures Journal*, 51, 101 –118, https://doi.org/10.7508/ceij.2018.01.006.
Gyasi, E. A., Kah, P., Wu, H., Kesse M. A. (2017). "Modelling of an artificial intelligence system to predict structural integrity in robotic GMAW of UHSS fillet welded joints", *International Journal of Advanced Manufacturing Technology*, 93,1139-1155, https://doi.org/10.1007/s00170-017-0554-0.
Gupta, S., Pandey, K., Kumar, R. (2016). "Artificial intelligence-based modelling and multi-objective optimization of friction stir welding of dissimilar AA5083-O and AA6063-T6 aluminum alloys", *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, 232, https://doi.org/10.1177/1464420715627293.
Kesse, M.A., Buah, E., Handroos, H., Ayetor, G.K. (2020). "Development of an Artificial Intelligence Powered TIG Welding Algorithm for the Prediction of Bead Geometry for TIG Welding Processes using Hybrid Deep Learning". *Metals*, 10, 451, https://doi.org/10.3390/met10040451.
Kim, T.-W., Ju, W.-H., Jeon, S.-H., Kim, Y.-C. (2022). "A Study on Mechanical Properties of Austenitic Stainless Steel Welds Using ArcTig Welding", 40, 343–351, https://doi.org/10.5781/JWJ.2022.40.4.7.
Kim, D.-Y., Lee, H., Yu, J., Park, J.-K. 2024. "Application of Convolutional Neural Networks for Classifying Penetration Conditions in GMAW Processes Using STFT of Welding Data", *Applied Sciences*, 14, 4883, https://doi.org/10.3390/app14114883.
Merayo, D., Rodriguez-Prieto, A., Camacho, A.M. (2020). "Prediction of Mechanical Properties by Artificial Neural Networks to Characterizes the Plastic Behaviour of Aluminium Alloys". *Materials*, 13, 5227, https://doi.org/10.3390/ma13225227.
Mishra, A. (2020). "Artificial Intelligence Algorithms for the Analysis of Mechanical Property of Friction Stir Welded Joints by using Python Programming", *Welding Technology Review*, 92, 6, https://doi.org/10.26628/wtr.v92i6.1120.
Mishra, A., Pathak, T. (2020). " Estimation of Grain Size Distribution of Friction Stir Welded Joint by using Machine Learning Approach", *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, 10, 99-110, https://doi.org/10.14201/ADCAIJ202110199110.
Mohammadizadeh, M.R., Esfandnia, F., Khatibinia, M. (2023), "Prediction of Shear Strength of Reinforced Concrete Deep Beams Using Neuro-Fuzzy Inference System and Meta-Heuristic Algorithms", *Civil Engineering Infrastructures Journal*, 56(1): 137-157, https://doi.org/10.22059/CEIJ.2022.334953.1803.
Odebiyi, O. S., Adedayo, S. M., Tunji, L. A., Onuorah, M. O. (2019). "A review of weldability of carbon steel in arc-based welding processes", *Cogent Engineering*, 6, 1609180, https://doi.org/0.1080/23311916.2019.1609180.

Palanivel, R., Laubscher, R. F. Dinaharan, I. (2017). "An investigation into the effect of friction welding parameters on tensile strength of titanium tubes by utilizing an empirical relationship", *Measurement*, 98, 77-91, https://doi.org/10.1016/j.measurement.2016.11.035.

Park, S., Kim, C., Kang, N. (2024). "Artificial Neural Network-Based Modelling for Yield Strength Prediction of Austenitic Stainless-Steel Welds", *Applied Sciences*, 14, 4224, https://doi.org/10.3390/app14104224.

Payares-Asprino, C. (2021). "Prediction of Mechanical Properties as a Function of Welding Variables in Robotic Gas Metal Arc Welding of Duplex Stainless Steels SAF 2205 Welds Through Artificial Neural Networks", *Advances in Materials Science*, 21, 75-90, https://doi.org /10.2478/adms-2021-0019.

Penttilä, S., Kah, P. J., Ratava, Eskelinen, H. (2019). "Artificial Neural Network Controlled GMAW System: Penetration and Quality Assurance in a Multi-Pass Butt Weld Application", *International Journal of Advanced Manufacturing Technology*, 105, 3369-3385, https://doi.org/10.1007/s00170-019-04424-4.

Pradhan, R., Joshi, A.P., Sunny, M.R., Sarkar, A. (2022). "Machine learning models for determination of weld bead shape parameters for gas metal arc welded T-joints-A comparative study", *Computer science*, 02, 11-27, https://doi.org/10.48550/arXiv.2206.02794.

Rajamanickam, R., Giridharan, P., Senthil, K. B. (2017). " Predicting the tensile strength of friction stir welded dissimilar aluminum alloy using ANN", *International Journal of Civil Engineering and Technology*, 8, 345-353, https://doi.org/10.1016/j.protcy.2014.08.036.

Rubio-Ramirez, C., Giarollo, D.F., Mazzaferro, J.E., Mazzaferro, C.P. (2020). "Prediction of angular distortion due GMAW process of thin-sheets Hardox 450®steel by numerical model and artificial neural network", *Journal of Manufacturing and Processing*, 68, 1202–1213. https://doi.org/10.1016/j.jmapro.2021.06.045.

Singh, J., Singh, G. (2022). "Effects of variation in welding current during SMAW process on A36 mild steel". *International Journal of Research and Applied Sciences Engineering and Technology*, 10, 259–264, https://doi.org/10.22214/ijraset.2022.46148.

Tran, N.-H., Van Hung, B., Hoang, V.-T. (2023). "Development of an Artificial Intelligence-Based System for Predicting Weld Bead Geometry", *Applied Sciences*, 13, 4232, https://doi.org/10.3390/app13074232.

Uhrlandt, D. (2016). " Diagnostics of metal inert gas and metal active gas welding processes", *Journal of Physics D: Applied Physics*, 49, 313001, https://doi.org/10.1088/0022-3727/49/31/313001.

Wang, Y., Wu, X., Li, X., Xie, Z., Liu, R., Liu, W., Zhang, Y., Xu, Y., Liu, C. (2020). "Prediction and Analysis of Tensile Properties of Austenitic Stainless Steel Using Artificial Neural Network", *Metals*, 10, 234, https://doi.org/10.3390/met10020234.

Winiczenko, R. (2016). "Effect of friction welding parameters on the tensile strength and microstructural properties of dissimilar AISI 1020-ASTM A536 joints", *International Journal of Advanced Manufacturing Technology*, 84, 941-955, https://doi.org/10.1007/s00170-015-7751-5.

Wu, C., Wang, C., Lee, C., Kim, J.W. (2021)." An algorithm for prediction of bending deformation induced by multi-seam welding of a steel-pipe structure". *Journal of Mechanical Science and Technology*, 35, 707–716, https://doi.org/10.1007/s12206-021-0131-1.