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Research Paper

Modeling of Weld Bead Geometry Using Adaptive Neuro-Fuzzy Inference System (ANFIS) in Additive Manufacturing

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Abstract. Additive Manufacturing describes the technologies that can produce a physical model out of a computer model with a layer-by-layer production process. Additive Manufacturing technologies, as compared to traditional manufacturing methods, have the high capability of manufacturing the complex components using minimum energy and minimum consumption. These technologies have brought about the possibility to make small pieces of raw materials in the shortest possible time without the need for a mold or tool. One of the technologies used to make pieces of the layer-by-layer process is the Gas Metal Arc Welding (GMAW). One of the basic steps in this method of making parts is the prediction of bead geometry in each pass of welding. In this study, taking into account the effective parameters on the geometry of weld bead, an empirical study has been done in this field. For this purpose, three parameters of voltage, welding speed and wire feeding rate are considered as effective parameters on the welding geometry of the process. Width and height of the bead are also determined by the parameters of the geometry of the weld according to the type and application of the research as output parameters are considered. In this paper, an adaptive neuro-fuzzy inference system (ANFIS) is used to create an adaptive model between input process data and parameters of weld bead geometry. The least squares mean error is used to evaluate the model. The predicted results by the model have a good correlation with the experimental data.

Keywords: Weld bead geometry, Additive manufacturing, modeling, ANFIS, Gas Metal Arc Welding (GMAW).

1. Introduction

Rapidly growing demand for the production of flexible and high-speed components has made new techniques have been developed, among which, one can name the Gas Metal Arc Welding (GMAW), etc. The technology of manufacturing can generally be divided into categories such as forming, subtractive, and additive. Each construction method is in one of these categories or a combination of them. Rapid prototyping is considered to be the modern technology, which goes under the Additive Manufacturing category [1]. In an Additive Manufacturing technique, a piece is directly produced layer-by-layer from a 3D model file. Many geometric constraints are eliminated in this way, and the piece is made with an appropriate speed and precision without the need for a die or a tool. As shown in Fig. 1, Additive Manufacturing methods have a high variation, each depending on the type of process used, has certain capabilities. One of the methods for producing layers is the use of welding technology. The Hybrid Layered Manufacturing (HLM) is a rapid process using the created layers by GMAW [2, 3].

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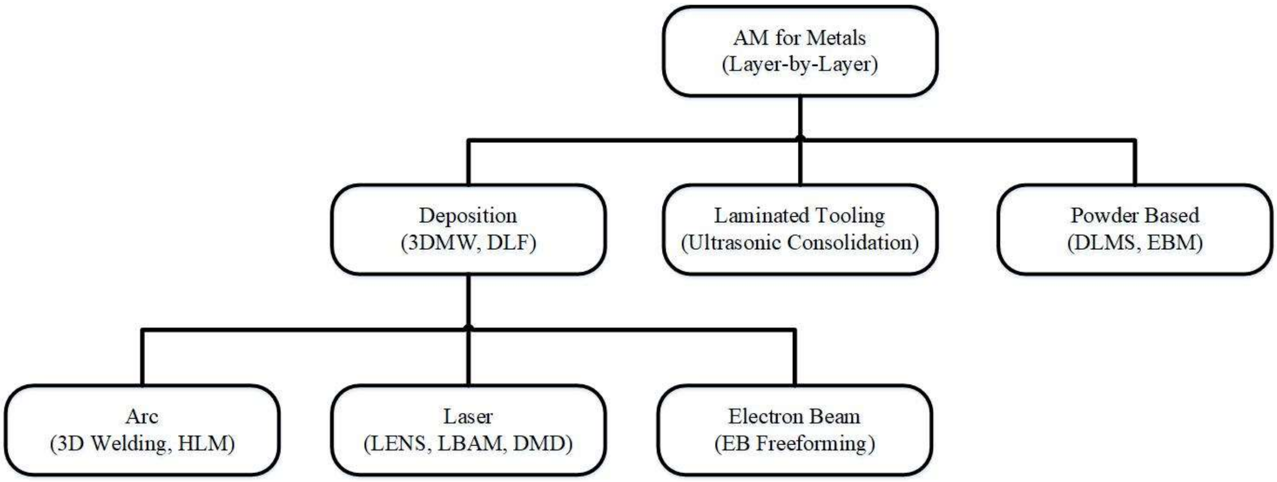


Fig. 1. Metal additive manufacturing processes.

Energy sources for depositing layers of welding may be lasers, electron beam or arc [4]. Many of the ongoing research works on metal components through Additive Manufacturing techniques have focused on the manufacturing by laser welding or by GMAW. The advantages of using laser as a source of heat can be attributed to the creation of a concentrated thermal zone and a low distortion in the produced parts, but the efficiency of this method is low. Welding method requires a complicated and expensive system to wire feeding. Recently, rapid prototyping methods based on GMAW have been considered by the researchers, due to their high efficiency, low cost, and high density. And, metallic parts produced by GMAW have significant advantages over mechanical properties, high density and weld strength [5].

Today, producing the workpieces using layer-by-layer process (rapid prototyping) in 3D space and laser as an energy source, with the help of computer design software, have attracted attention of many users. The reason is the low heat produced in the workpiece [6]. In laser methods, the materials are exited from the nozzle in the form of powder and they are melted by the laser energy and the layers are formed by the addition of the materials together and solidifying them, this deposition system builds the part, layer by layer, [7]. But in this case, the disadvantages of the laser, like the disadvantages of using a laser for humans, had a high energy cost, which resulted in the use of other methods, among which GMAW is considered as one of the best methods to produce workpieces in the form of additive layers [8]. This method has several advantages, such as high efficiency, lower cost and easier equipment. The construction of several sections with a production system with an additive layer is based on shield gas and temperature control and various control model. The predicted results by the model had a good correlation with the experimental data. The construction of several sections with a production system with an additive layer based on shield gas and temperature control and various control techniques were developed to improve the surface with some adaptive methods of modeling and controlling the process of bead geometry created by the layers [9, 10]. A workpiece production system with an additive layer and a GMAW method consists of several different parts. The welding system was studied to use in the production of workpieces with an additive layer technology and it was integrated with three-dimensional milling techniques to achieve high-quality and high-level precision to produce a hybrid method in 3D and 2½D states [11]. The thickness, the moving path, and the parameters of motor system relations and the accumulation of the layer and the width and height of the weld layer in each layer can be predicted by using 3D models. Now, regression and neural network methods can be used for prediction to develop and focus on the parameters of the layer width and the height and depth of penetration [12]. The model's ability to predict the bead geometry method and the type of process have a direct impact on the quality of the work pieces made by the Additive Manufacturing method.

In many processes, such as GMAW, the empirical research on an optimum range costs much and is time consuming. Creating a model for adjusting the relationship between the input and output parameters of the process is one of the solutions. Lee et al. [13] proposed regression analysis and Taguchi method to predict weld bead based on input parameters. In the Additive Manufacturing method by GMAW, the relationship between the welding geometry and the process input parameters must be established by a model. Therefore, in order to optimally adjust the parameters designing the welded bead geometry, the relationship between the variable process parameters and Geometry of the bead should be studied. The main reason is that the bead geometry of a weld line plays a major role in determining the surface roughness, thickness of the layer, and the dimensional accuracy of the layered workpieces. In various studies, the dependence of weld bead geometry on parameters of process has been obtained meaningfully [5]. Process parameters are based entirely on experience or they are extracted from the database. It is good to notice that the input parameters considered in this method may not produce the desired size of the bead, so producing models that provide a link between the geometry of the bead and the process variables is very important.

One of the common models for predicting the output parameters of processes is the ANFIS. ANFIS is a hybrid predictor model that uses the neural network and fuzzy logic to link the input and output data [14]. Kovacevic and Zhang [15] developed Neuro-Fuzzy Inference System for predicted weld penetration state. They illustrated the fuzzy model so effectiveness in deriving the details correlations of weld penetration and weld geometry. Zhang and Kovacevic [16] developed a neuro-fuzzy model to control the weld fusion (top-side and back-side bead widths). It is showed that the correlation among each of output and input depends on the other input. Carotopandy et al. [17] used this model to predict the geometry of the GMAW process. They studied the geometry of flat welded wire in different parts such as bead height, penetration depth and HAZ area, and compared the results of the fuzzy model with the results of the experiment. Based on their research, the fuzzy model has the proper ability to predict the weld bead geometry. Chandraskar et al. [18] used ANFIS to predict the geometry prediction in the TIG process. They used the least squares mean evaluation criterion to show that ANFIS has a higher predictive value for weld geometry as compared to the neural network. ANFIS models have a high capability to predict the parameters of the A-TIG welding geometry such as penetration depth, welded bead width and HAZ width [19]. Liu et al. [20] present a neuro-fuzzy-based human welder intelligence model to predict the 3D weld pool geometry. They showed that the proposed ANFIS model could be predicted human welder's response to 3D weld pool surfaces with acceptable accuracy. Liu and Zhang [21] present an innovative iterative local ANFIS model-based data-driven for 3-D weld pool characteristic. They used of ANFIS model to improve the accuracy of a linear model. The prepared iterative local ANFIS model shows better modeling performance. Liu et al. [22] developed a nonlinear Hammerstein model to predict the 3D weld pool surface in gas tungsten arc welding (GTAW). A dynamic Hammerstein model is used for weld pool convexity, and a neuro-fuzzy model used for couplings parameters of weld pool characteristic. They showed that nonlinear models could improve the detail of complex correlation.

In this study, the experimental field has led to the creation of this model and wire speed, table velocity and voltage are considered as effective input process parameters. According to the research requirements, the height and the width of the bead width were considered as output process parameters.

In order to achieve the desired quality in the Additive Manufacturing process by using GMAW, the relationship between process parameters and welding geometry, should be studied [12]. In the present study, due to the reliable model for prediction of welding geometry parameters used in Additive Manufacturing process using GMAW, voltage parameters, wire speed and table velocity were studied.

2. Experimental Details

GMAW is a multi-energy process involving various physical and chemical phenomena, such as physical plasma, heat and mass transfer and viscosity. As shown in Fig. 2 the GMAW is the creation of between electrodes electric arc that feeds continuously and creates a melt pool. This region is protected by an external gas (neutral or active). The heat generated by the arc melts the surface of the base metal as well as the tip of the electrode. At this stage, the electrode is welded as a filler to the piece [23]. An Additive Manufacturing with GMAW is capable of customizing workpieces without using any mold with metal materials directly with the data sent from the CAD/CAM design and fabrication system. In addition, it has met a considerable reduction in production costs and time to produce products in the market as well as energy and material savings [24]. This method is mainly used in manufacturing large workpieces made of high-cost alloys and the reason is to reduce the primary raw material [25, 26].

The purpose of the present research is to predict the geometry of the welded bead in GMAW for additive manufacturing. For this purpose, as shown in Fig. 3, the 3arc401 machine is used for welding along with the Carry MIG401 system 401. In this test, the Welding Wire is Ama18-40 with standard of Din 8559 and a diameter of 1.2 mm, made of steel.

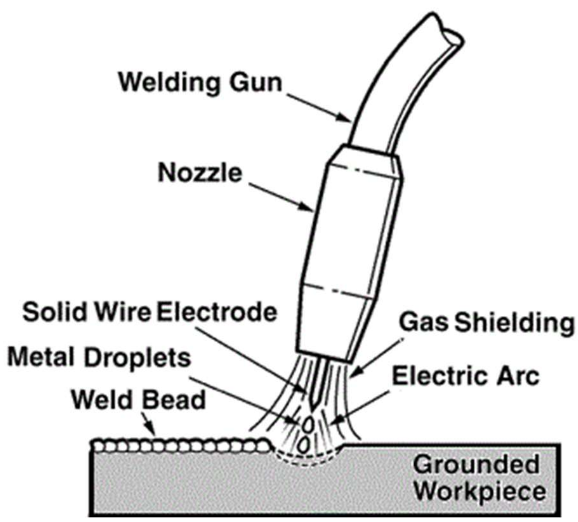


Fig. 2. Schematic of gas metal arc welding process

In this research, the wire feed rate (electrode), welding voltage and welding speed are considered as effective input parameters at the cross section of the weld bead, and bead height and bead width of the outputs are aimed. According the full factorial design of experiments, the four-level for voltage, the four-level for welding speed and the three-level for wire feed rate are considered. To measure the speed of the output wire from the nozzle, the amount of wire output at a specified time was measured and it was assigned at a time unit, and the output speed was obtained with centimeter units per minute. In order to accurately determine the welding speed in this research, there has been used an FP4M milling machine of Tabriz, which was used from the table of forward movement table in four situations. The data and intervals of each process variable are shown in Table 1.

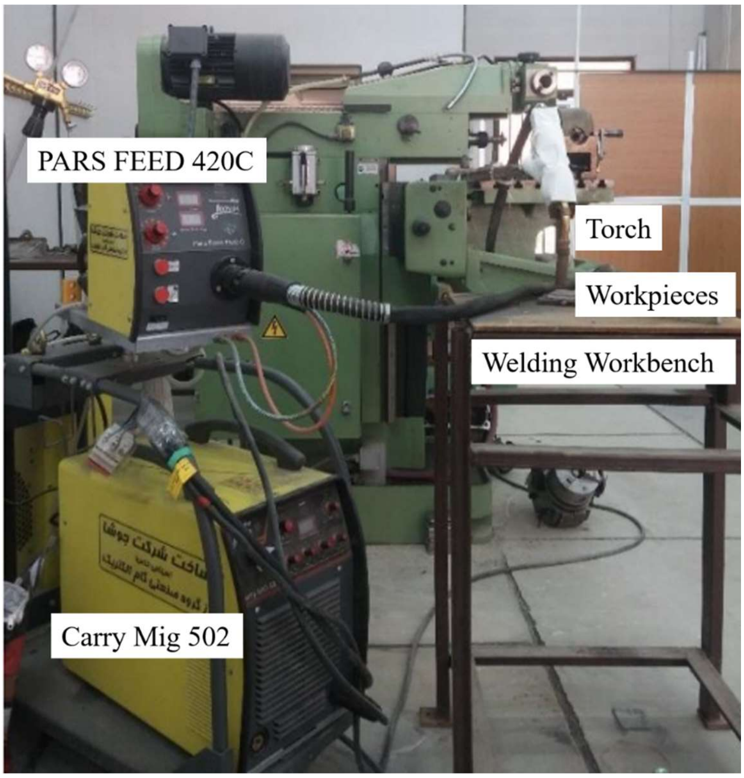


Fig. 3. Joosha welding equipment

After finishing the experiments, the workpieces are cut and after etched with diluted nitric acid. The aim is to achieve a weld cross section. A sample of etched pieces is shown in Fig. 4. Measurement of these dimensions was done using a dial caliper with a precision of 0.02 mm. The results obtained from the experimental experiments are shown in Table 2 and Fig. 5. Forty two samples of the measurements were used for training the ANFIS model and six of them, indicated by *, were applied to test the model accuracy.

Table 1. Input parameters of GMAW process.

Parameter	Voltage (V)	Wire Feed Rate ($cm/\min$)	Welding Speed ($mm/\min$)
Range	17-32	210-253	200-400

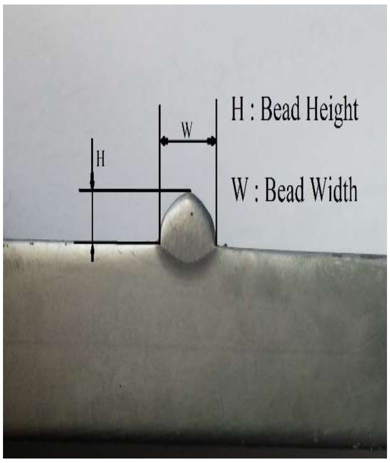


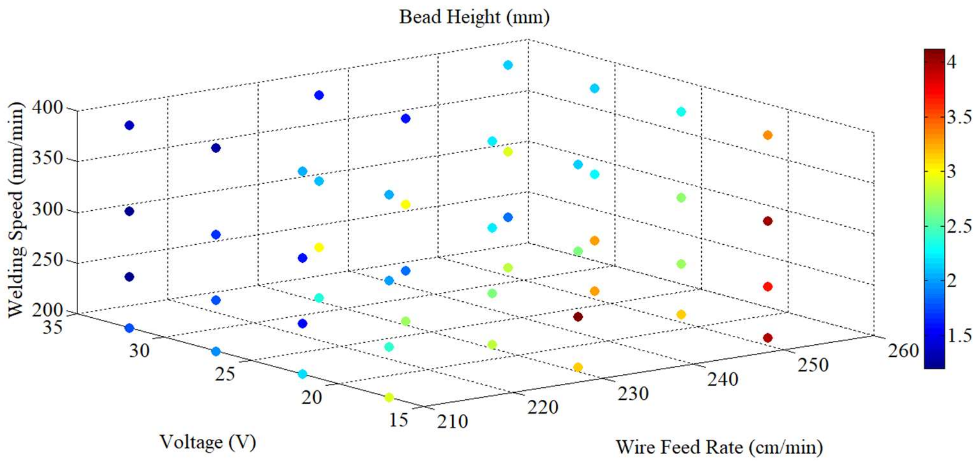
Fig. 4. Section view of weld bead

Table 2. Design of experiment matrix and results.

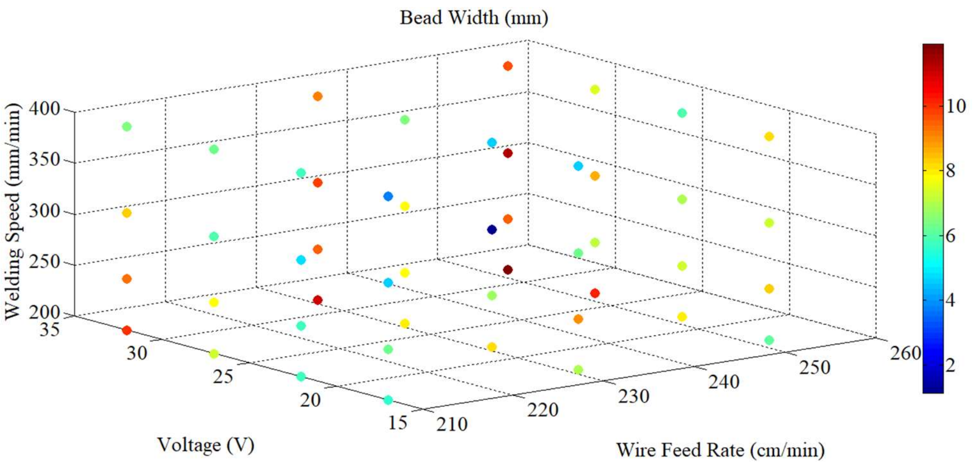
Exp. No.	Setting Parameters			Bead Geometry Parameters	
	Wire Feed Rate ($cm/\min$)	Voltage (V)	Welding Speed ($mm/\min$)	Bead height (mm)	Bead width (mm)
1	210	17	200	2.92	5.68
2	210	17	250	2.4	6.2
3	210	17	315	2	4.66
4	210	17	400	2.06	3.82
5	210	22	200	2.2	5.8
6	210	22	250	1.52	5.78
7	210	22	315	1.6	4.74
8	210	22	400	2.06	5.82
9	210	27	200	1.94	7.23
10	210	27	250	1.76	7.8
11*	210	27	315	1.68	5.92
12	210	27	400	1.28	6.2
13*	210	32	200	1.78	9.92
14*	210	32	250	1.24	9.32
15	210	32	315	1.2	8.26
16	210	32	400	1.34	6.5
17	231	17	200	3.12	7
18	231	17	250	4.12	8.92
19	231	17	315	2.62	6.22
20	231	17	400	2.14	4.56
21	231	22	200	2.82	8.1
22	231	22	250	2.64	6.8
23	231	22	315	2.22	1.14
24	231	22	400	2.22	4.6
25	231	27	200	2.74	7.9
26	231	27	250	1.86	7.74
27	231	27	315	2.98	7.78
28	231	27	400	1.58	6.52
29	231	32	200	2.36	11
30	231	32	250	2.98	9.46
31	231	32	315	2.08	9.74
32*	231	32	400	1.6	9.2
33	252	17	200	3.98	6.16
34*	252	17	250	3.7	8.24
35	252	17	315	4	7.28
36	252	17	400	3.32	8.06
37	252	22	200	3.12	7.96
38*	252	22	250	2.74	7.26
39	252	22	315	2.68	6.9
40	252	22	400	2.3	5.92
41*	252	27	200	3.26	10.12
42*	252	27	250	3.28	7.14
43	252	27	315	2.28	8.58
44	252	27	400	2.12	7.42
45	252	32	200	2.82	11.92
46	252	32	250	1.86	9.4
47	252	32	315	2.92	11.32
48	252	32	400	2.12	9.62

3. An Adaptive Neuro-Fuzzy Inference System

Fuzzy systems: Fuzzy logic is a multi-value logic and is a method of human decision-making. In classical logic, numerical variables are used in calculations, but in fuzzy logic, linguistic variables are used to achieve optimal results. Fuzzy systems have two types, Mamdani and Takagi-Sugeno-Kang (TSK), Fig. 6 shows the general structure of the Mamdani system [27].



a) Bead height according to the setting parameters.



b) Bead width according to the setting parameters.

Fig. 5. Input parameters and results.

The fuzzy inference section decides and determines the outputs according to the input and the base of the fuzzy rules. The fuzzy rules base also forms the memory of the fuzzy system, and keeps a set of if-and-then rules in the fuzzy for decision. In the Mamdani model, both if-and-then rules are fuzzy variables.

Mamdani's Fuzzy Rule: If x_1 is $A_1^l, \dots$ and A_n^l is x_n thenB_1 is y for l=1,2,…,m.

In this equation, n is the number of inputs and m is the number of fuzzy rules found in the rules base. Also, A_i^l andB_1 are respectively fuzzy sets of inputs and outputs that have fuzzy membership functions of $\mu\,(A_i^l)(x_i)\,\mu\,(B_1)(y)$. In this model, first, numerical inputs in the fuzzy part of the structure are converted to fuzzy variables with fuzzy membership functions. Then, according to fuzzy inputs, the value or membership functions of each of the rules in the fuzzy rule base are determined. Then, depending on the type of inelasticity of the inference engine, these rules are combined and the output of the inference engine is computed [27]. The output of the inference engine is also converted into a non-fuzzy variable into a numerical variable.

In the TSK system, if the rules are in the form of a fuzzy variable, then the rules are of a non-fuzzy type and is a linear combination of system inputs. Here is an example of TSK rules.

The fuzzy TSK: if x_1 is A_1^l and is A_n^l, the y^l is equal to $C_0^l + C_1^l x_1 + \dots + C_n^l x_n$ for $l = 1, 2, \dots, m$.

In this model, as in the previous model, numerical inputs are converted to fuzzy variables in the fuzzy set. Then, the weight of each of the rules is calculated according following relation:

$$w^l = \prod_{i=1}^{n} \mu_{A_i^l}(x_i) \quad , l = 1, 2, \dots, m \tag{1}$$

At the end, the output of the system is calculated as the weighted average of the system inputs according below equation [27]:

$$f(x)=\frac{\sum_{l=1}^{m} y^l w^l}{\sum_{l=1}^{m} w^l} \tag{2}$$

An ANFIS is in fact a TSK type of fuzzy system with an adaptive learning inference engine. In this system, according to the training data, a logical relationship between inputs and outputs is created by reducing the error between the training and output data of the network. The more this error reduces, the ANFIS function becomes more similar to data learning. This network has the appearance structure similar to a neural network, but the logic of decision making and its inference is based on the rules of fuzzy logic. Matching the parameters of this network, such as neural networks, can be accomplished using a learning algorithm. Fig. 7 shows the structure of an infinity network with two inputs and an output with four bases [28]. Fig. 7 shows that the network consists of five layers. In the first layer, there is a number of membership functions that convert the system's inputs, which are numerical, into fuzzy inputs. Each of these membership functions has its own determining parameters. In the following, the relations of the structure of a fuzzy neural system are given with two inputs and four fuzzy rules. In these relations, $O_{j,i}$ represents the output of i from the j layer and A_i and B_i are the membership functions of the first layer. This layer is equivalent to the fuzzy part of the fuzzy system.

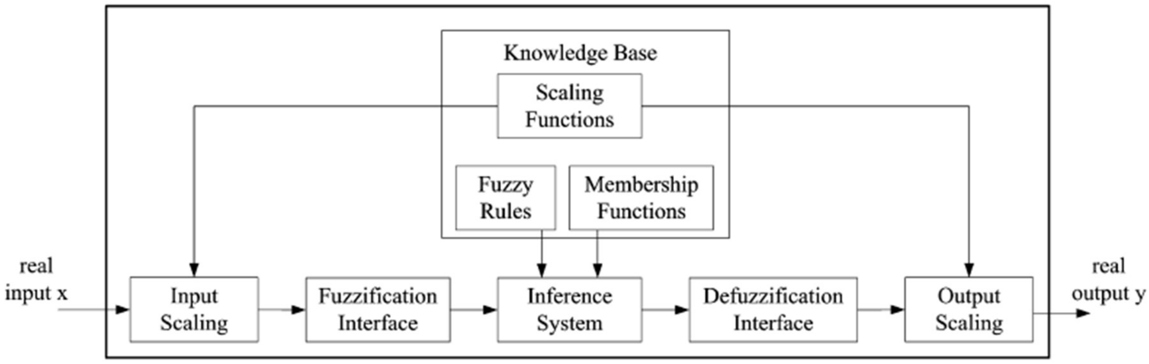


Fig. 6. Structure of Mamdani fuzzy system

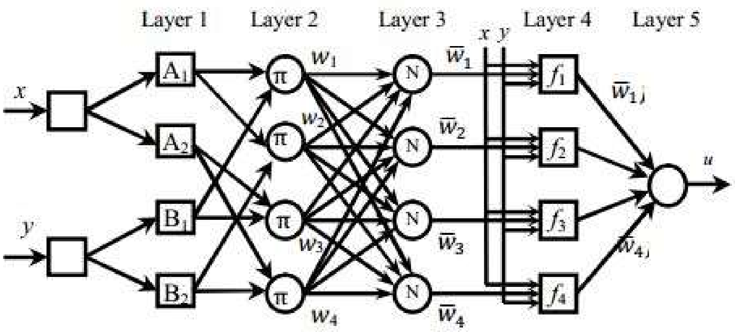


Fig. 7. Structure of ANFIS with two inputs and one output.

$$O_{1,i} = \mu_{A^i}(x), \quad i=1,2 \tag{3}$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad i=3,4 \tag{4}$$

The second layer of this network will be formed if it has fuzzy rules. In fact, if we consider the fuzzy subset as an algebraic multiplication, the multiplication of the output signals of the first layer will form the fuzzy rules [28]:

$$O_{2,i} = \mu_{A_j}(x)\mu_{B_k}(x), \ i=1,\dots,4, \quad j,k=1,2 \tag{5}$$

In the third layer, the second layer outputs are normalized to determine their effectiveness, to obtain suitable weight coefficients:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_j w_j}, \quad i=1,\dots,4 \tag{6}$$

Also, in the fourth layer, the weight coefficients obtained from the third layer in the polynomial equation of part modeling by multiplying, then the fuzzy rules determine the effect of each of the parts of the system's output.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i\right) \quad , \quad i = 1, \ldots, 4 \tag{7}$$

In the above equation, the x and y values represent the inputs of the system. Finally, in the fifth layer, with the sum of these weighted values, the output of the system is obtained as a numerical variable equal to the non-fuzzy part in the fuzzy systems:

$$O_5 = \sum_i \bar{w}_i f_i \tag{8}$$

The parameters of the second layer are called the initial parameters and the parameters of the fourth layer are called secondary parameters [28]. Typically, the root mean square error between the data output and the system output is defined as the system performance criterion, and the one that causes the error to be changed is in fact the adaptive neuro-fuzzy inference system modifiable parameters. The adjustable parameters in the adaptive fuzzy nerve system can be defined as parameters of input membership functions and output polynomial parameters, which changes the function of the system by changing these parameters. Therefore, the reduction of the magnitude of the root mean square error, by changing these parameters, can be considered as network training. This is usually done using two methods of descending gradient and hybrid algorithm. In the hybrid method, the descending gradient method is used to determine the initial parameters and the least squares error method is used to determine the secondary parameters. In the use of derivative-based methods, the probability of getting into the local minima is high. Therefore, intelligent algorithms can search for better search space to improve system performance [29-31].

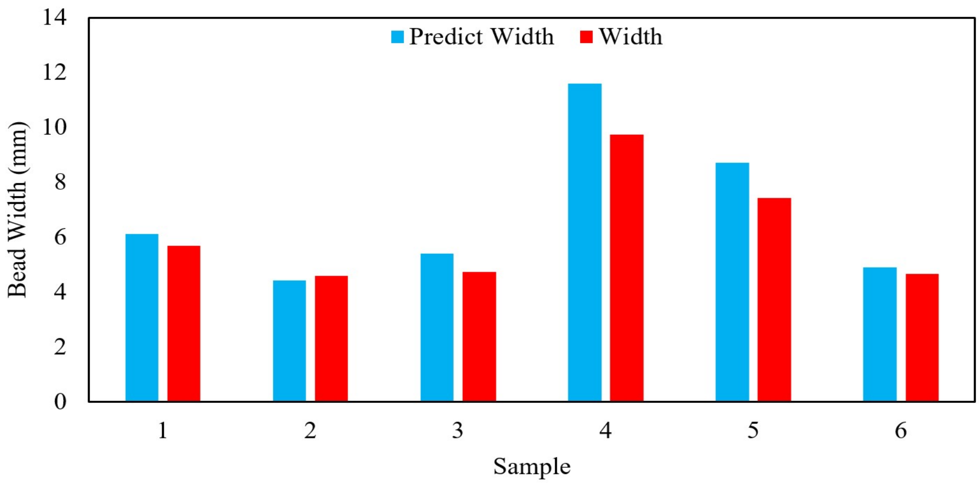
4. Results and Discussion

The results of the implemented model are discussed considering the results obtained from experimental experiments and comparing them with ANFIS results in this section. The comparison of prediction model's performance between adaptive neuro-fuzzy inference system and artificial neutral networks (ANN) were tabulated in Table 3. Table 3 shows that the neuro-fuzzy systems perform better when predicting welding geometry.

As mentioned in the introduction, in order to predict the layers created in the additive manufacturing process by using GMAW, a principled task is to predict the welding geometry of each welding step. In this study, in order to predict the width and height parameters of welding geometry, initially considering the voltage, wire speed and welding speed as process parameters of the experimental experiments required. 48 experiments were carried out taking into account 4 levels for voltage, 3 levels for wire speed and 4 levels for welding speed. From this, data from 42 experiments were used to train the ANFIS and 6 test data were used to test the obtained model.

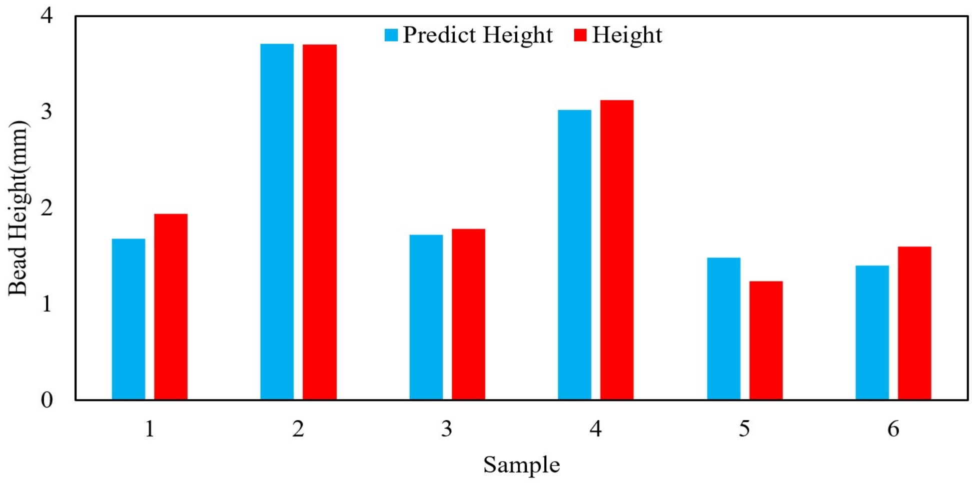
The Sugeno inference engine and the subtractive clustering method were used along with the Gaussian membership functions in order to implement the model. The number of replicates was 50 repetitions to reach the answer. The model was created. After implementation of the model, the square error indexes of the mean square error and the Root-mean-square deviation (RMSE) were used to estimate the accuracy of the model, which are defined and used in accordance with eq. (9) and eq. (10), respectively.

$$MSE = \frac{\sum_{i=1}^{N}\left(y_i - \widehat{y}_i\right)^2}{N} \tag{9}$$



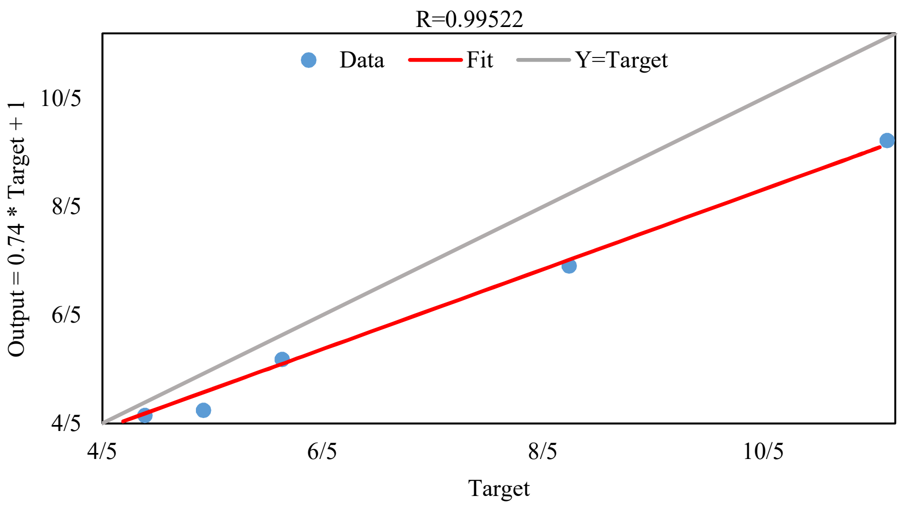
a) Width of weld bead

Fig. 8. Performance of model in predicting height and width of the weld beads in test samples

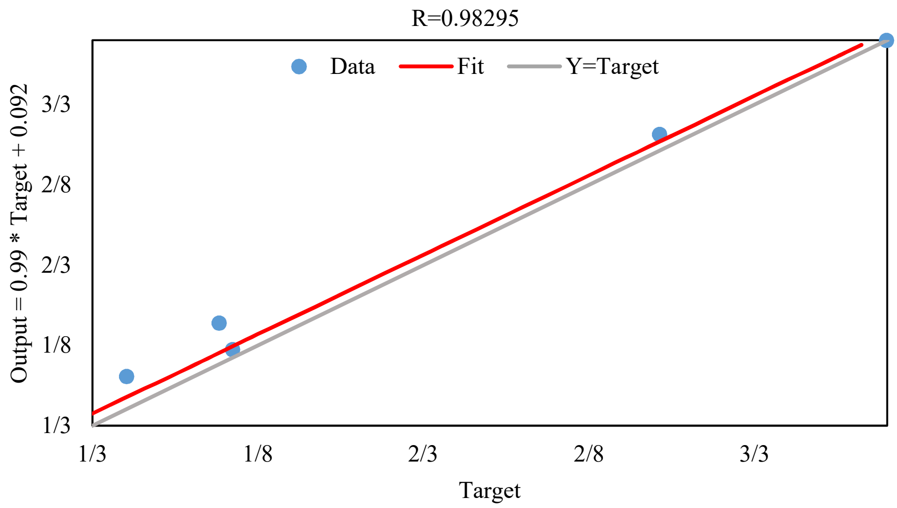


b) Height of weld bead

Fig. 8. Continued



a) Width of weld bead



b) Height of weld bead

Fig. 9. Correlation coefficient for test samples

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - \widehat{y}_i\right)^2}{N}} \tag{10}$$

Table 3. Comparison of prediction model's performance.

Model	Details	Correlation Coefficient R (Width of bead)	Correlation Coefficient R (Height of bead)
ANFIS	TSK type	0.99522	0.98295
ANN	Feed-Forward Back propagation (3-10-10-2)	0.95581	0.93024

In this equations, y_i is the calculated output and $\hat{y}_i$ is the predicted output by the model. The mean error of the mean squared error in the data of the prediction test of bead height was 0.995 and the root mean square error was 0.9846. The model implemented in the prediction of the width of the bead of the mean squared error in the test data is 0.0299 and the root mean squared error is 17.229. As shown in Fig. 8, the designed model has high accuracy and, given the close proximity of this criterion at the test stage, this model has high generalizability. Also in Fig. 9, the correlation coefficient is used to predict the width and height of the bead. Comparison of the data obtained from the experiment and the network output data suggests that the ANFIS has a high accuracy in the approximation of the geometry of the bead.

5. Conclusion

In the present study, the modeling of the weld bead geometry in terms of parameters of the GMAW, voltage, welding speed and wire feed rate using an ANFIS, as one of the powerful tools for modeling, was described. The accuracy of the model was measured by standard statistical measures. Regarding the obtained values for the correlation coefficient in the training and experiment stages for both weld bead width and weld bead height, the designed model had high accuracy and, given the close proximity of this criterion in the training and experiment stages, this model can be highly generalized. The results of this modeling can be used to predict and control the thickness of the layers in the additive manufacturing process using the GMAW.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and publication of this article.

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