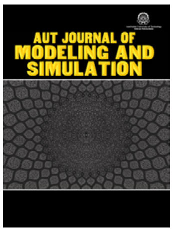

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Application of the Extreme Learning Machine for Modeling the Bead Geometry in Gas Metal Arc Welding Process

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ABSTRACT: Gas metal arc welding (GMAW) is a widespread process used for rapid prototyping of metallic parts. In this process, in order to obtain a desired welding geometry, it is very important to predict the weld bead geometry based on the input process parameters, which are voltage, wire feed rate, welding speed and welding nozzle angle. For this purpose, a global model of the welding geometry must be defined based on these parameters. Due to the non-linear and coupled multivariable relationship between the process parameters and the weld bead geometry, it is not possible to define this model in form of an explicit mathematical expression, and therefore application of supervised learning algorithms can be investigated as an efficient alternative in this problem. In this paper, application of the extreme learning machine (ELM) and support vector machine (SVM), as two efficient and powerful machine learning algorithms for predictive modelling of this process has been investigated and error analysis of the proposed models suggest that the output parameters of this process can be predicted by the ELM algorithm with higher precision and generalization capability.

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1. Introduction

Rapid Prototyping (RP) is a method of construction used to quickly fabricate a scale model of a physical part or assembly using three-dimensional computer aided design with rearranging of the layers. Rapid prototyping technology is as such gaining a lot of importance because it helps designers to carry forward their ideas and implement them in their design to fabricate three-dimensional models of products. Laser welding and Gas Metal Arc Welding (GMAW) are methods of fabricating metal parts which are considered in many of the conducted researches studying the incremental manufacturing methods. Although laser generates a concentrated thermal area with a little alteration in the fabricated parts, it is not much considered due to low efficiency. Also, laser welding requires a complex and costly system to feed wire. Lately, this method of welding has been replaced by the Rapid Prototyping methods which the Gas Metal Arc Welding (GMAW) is much more considered by the scholars. The reason behind popularity of RP methods is their high efficiency, low cost, as well as high density. Furthermore, metal parts which have been fabricated by a Gas Metal Arc Welding (GMAW) method ensure the better mechanical specifications such as high density and welding strength [1]. Budget is a considerable issue in the large industries, and reducing the costs entirely rests on the determination of the welding features in the practices done with Gas Metal Arc Welding and the association between the prevailing parameters and means to realize the perfect state. On the other hand, attaining the needs is determined by the regular tests and spending money. Thus, modeling the industrial systems through the mathematical relations to realize an optimal point between the input and output parameters are of importance. Nowadays, in the modern industries with automatic engineering machines, welding robots, which are programmed by the Artificial Neural Network (ANN) and Fuzzy Logic, are employed to improve the production time. Such rapid prototyping methods as Gas Metal Arc Welding can benefit from robots since they are efficient in completing the work through the desired method and they can be controlled by immediate data sent by the automatic production system. Zhang et al. [2] in 2003 used Gas Metal Arc Welding (GMAW) to develop an incremental manufacturing method with a melted metal sheet. Layering parts and material transfer control mechanisms employed in the applied system. To increase the quality of surface and dimensional precision of parts, in their study in 2006, Song and Park [3] established an integrated application in the field of three-dimensional welding and milling. In their study in 2010, Karunakaran et al. [4], tried to establish a new method of manufacturing metal parts in which the hybrid layer technology was considered to combine the cooperative applying GMAW and

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CNC machining for layering sedimentation and machining. In general, the fundamental idea of RP is an incremental layer production process which enables the designers and engineers to produce parts with complex three-dimensional geometry. weld bead plays an imperative role in the incremental methods of geometry in which the surface fineness, thickness of the layer, and the dimensional accuracy of the produced piece are of important; consequently, adjustment and input parameters should be sensibly premeditated and in the end the suitable model should be designed to provide the best relationship between input parameters of the process, as well as the output process. Modeling methods have been established to stop the repetitive tests and to advance laboratory conditions so that, in recent years, such approaches as factorial design, linear regression, second order regression, Taguchi method and artificial network have been applied to join the desired parts and modeling the input and output parameters. To optimize the geometry of the weld bead, Kim et al. [5] in 2002, used the neural network method to inspect and determine the variables of Gas Metal Arc Welding process. Using regression model and SA algorithm on experimental data for the development of mathematical models, Kolahan et al. [6] implemented modeling and optimizing the GMAW process in 2010. The developed models using the SA algorithm are optimized and the computational results obtained from this method reveal the efficiency of this method in determining the welding parameters, so that the weld bead geometry is created with the desired size. Bing effective in developing mathematical models for parameters of weld bead geometry in Gas Metal Arc Welding, precise multiple linear regression is one of the best techniques. Furthermore, to optimize the process parameters by the identical experimental data, many efforts were made to model the process using BPNN. Also, to improve the process parameter, BPNN was used to generate the genetic algorithm (GA). Using wavelengths and neural network methods, Huang and Kovacevic [7] in 2011, optimized and modeled welding in laser welding technique in which neural network with optimal training provided a suitable model for optimizing the welding of wild bead geometry in Gas Metal Arc Welding. In another study conducted in 2016 by Moghaddamet al. [8] multivariate modeling and optimization technique for Gas Metal Arc Welding on the API-X42 alloy was examined, and modeling and optimization with PSO method were proposed when experimental tryouts with the BPNN neural network performed. Thus, the impact of the heat-affected region was declined to the minimum ratio. Using Gas Metal Arc Welding, Panchagnula et al. [9] developed thin-walled parts with an incremental construction. Thin wall parts are pieces made up of a welding pass, and it is not easy to generate since the welding beads laid on each other due, thin wall parts are complex in terms of the geometry. To build such components, the researchers used a five-axis CNC.

Using an incremental construction based on electric arc welding with Gas Metal Arc Welding, Xiong et al. [10] conducted a research in which thin-walled parts was studied. The scholars, in this research, constructed angled walls by precise adjusting the welding parameters which enabled them to construct walls with angles more than 45 degrees. Absolutely driven based on experience or extracted from the databases, the data, in this process, could result in undesired outputs, or the desired sizes of the weld beads could be totally distorted. Thus, the best job was to create and use a model providing reasonable connections between input and output parameters. The findings of the present study reveal that a model can be created by running various empirical tests which provide a reliable basis to develop and test the different models. In this research, the velocity of the wire, the speed of the table, the voltage and the angle of the nozzle of the welding are considered as effective parameters of the input process and according to the research requirements, such parameters as the height of the weld bead and its width are considered as output parameters of the process. ELM was also used to provide a relationship between the input and output parameters of the process. The second section in this paper briefly discusses the GMAW process. The experimental details are discussed in Section three and the ELM and SVM algorithms are addressed in section four and five, respectively. The results and conclusions are embedded in section six.

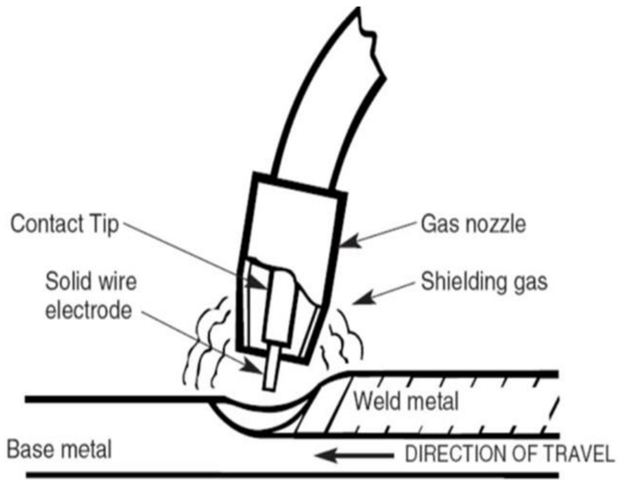

Fig. 1. Schematic diagram of Gas Metal Arc Welding

2. The GMAW Process

Gas Metal Arc Welding is a multi-energy process that involves various physical and chemical phenomena, such as physical plasma, flow of heat and fluidity of metal transfer. Gas Metal Arc Welding (Fig. 1) consists of creating an electric arc between the electrode that is continuously fed and generates a melt pool which is secured by a neutral or active foreign gas. The Tip of the electrode melts and dissolves the surface of the base metal which is done through the heat generated by the arc. At this stage of welding, the electrode works as filler which is transferred to the welded piece [18]. Using Gas Metal Arc Welding as an incremental build-up provides the ability to fabricate the customizing parts with metal supplies directly with the data sent from the computer-aided design (Cad\Cam) and construction system without using the mold. Moreover, it results in a substantial reduction in production costs and time of the products in the market, as well as energy and material savings [11]. Since the waste of raw material in this method is noticeably low, it is mainly used to fabricate large parts made of costly alloys [12, 13].

3. Experimental Details

The present investigation aims to calculate the geometry of the welded beads in Gas Metal Arc Welding for augmentation applications. To do this, as Fig. 2 shows, the 3arc401welding machine, and Carry MIG 401 wire feed system are used to test. The Ama40-18m steel welding wire with 1.2 mm diameter and Din 8559:Sg2 standard was selected to conduct the test in this experiment.

In this survey, the feeding speed of the wire (electrode), the welding voltage, the welding speed and the angle of the welding nozzle are considered as operative input factors at the cross section of the welded bead, and some other factors as bead's height and width are likewise taken into account. The three-speed welding speed parameter, the three-wire feeding speed and the angle of the welding nozzle are also taken into account as the three-level voltage factors. The output of the wire at a definite time was considered to calculate the speed of the output wire discharged from the nozzle. The outcomes of the calculations were measured in accordance with time unite and the output speed based on the centimeters on minute (cm/min). FP4M model milling machine, made in Tabriz, was used in order to precise determination of the welding speed. And, out of various forward movement conditions of the table, four conditions were selected and identifies for the test. Table 1 provides the data and interval variables of each process.

Done with the experiments, the parts are cut from one point, polished and etched using diluted nitric acid. This is to clear up the welding bead segment. The weld bead geometry on a sample of etched pieces is shown in Fig. 3. The dimensions are measured via a dial gaged caliper with a precision of 0.02mm. The results of the experimental tests are listed in Table 2.

Automated Gas Metal Arc Welding systems benefit from several inputs which can be used to run and control the system to yield a desired output. Various analyzing methods of existing parameters can be used to study the modeling the behavior of the several welding processes done by Gas Metal Arc Welding. The best example of this are linear regression, surface response method, artificial neural network and Taguchi method which all can be applied to investigate the input parameters in different situations to optimize the geometry of the weld bead in order to obtain the best geometric state [14-19]. Robotics Development and automation in the process of Gas Metal Arc Welding changed the welding process and it is considered as a breakthrough. This method is beneficial in terms of developing the manufacturing parts such as increasing the production capacity, improving precipitate strength, and declining total price of obtaining.

4. Extreme learning machines

One type of feedforward neural networks are extreme learning machines which are utilized for classification, regression, clustering, sparse approximation, compression and feature learning and they consist of a single layer or multiple layers of hidden nodes, where there is no need to tune the parameters of hidden nodes. One can assign these hidden nodes in a random manner or alternatively these nodes can inherit from their ancestors and remain constant. The output weights of hidden nodes are learned in a single step in most cases which usually results in learning a linear model.

Fig. 2. Gas Metal Arc Welding machine

Table 1. Gas Metal Arc Welding Parameters

Welding Parameters	Units	Range
Voltage	V	17-27
Wire feed rate	cm\min	210-253
Welding speed	mm\min	200-400
Welding nozzle angle	degree	105-90-75

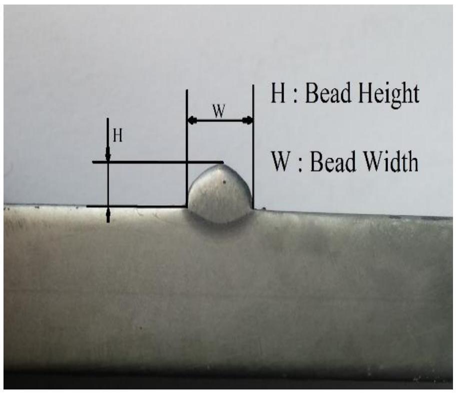

Fig. 3. The weld bead geometry on the etched part

Table 2. Experimental Results

Exp. No	Voltage (V)	Wire feed rate (F) (cm/min)	Welding speed (S) (cm/min)	Welding nozzle angle	BW	BH
1	17	210	200	90	5.4	3
2	22	210	200	90	7.68	2.64
3	27	210	200	90	10.04	3.41
4	17	231	200	90	6.2	3.7
5	22	231	200	90	8.62	3.44
6	27	231	200	90	11.2	2.46
7	17	252	200	90	7.24	3.92
8	22	252	200	90	9.2	3.76
9	27	252	200	90	11.8	3.2
10	17	210	250	90	7.4	3.6
11	22	210	250	90	5.9	2.8
12	27	210	250	90	8.1	2.56
13	17	231	250	90	4.6	4.08
14	22	231	250	90	6.12	2.9
15	27	231	250	90	8.9	2.32
16	17	252	250	90	8.7	2.06
17	22	252	250	90	6.36	3.18
18	27	252	250	90	9.9	3.54
19	17	210	315	90	3.5	3.6
20	22	210	315	90	5.7	2.46
21	27	210	315	90	7.26	1.48
22	17	231	315	90	3.92	3.5
23	22	231	315	90	5.62	2.58
24	27	231	315	90	9.1	2.6
25	17	252	315	90	6.5	3.41
26	22	252	315	90	6.96	2.7
27	27	252	315	90	7.84	2.44
28	17	210	200	75	4.46	3.3
29	22	210	200	75	6.84	3.12
30	27	210	200	75	9.2	2.04
31	17	231	200	75	4.5	4.8
32	22	231	200	75	7.74	3.14
33	27	231	200	75	10.96	2.56
34	17	252	200	75	5.78	6.46
35	22	252	200	75	8.64	3.4
36	27	252	200	75	11.18	2.8
37	17	210	250	75	4.52	3.02
38	22	210	250	75	6.04	2.2
39	27	210	250	75	7.86	2
40	17	231	250	75	4.34	3.8
41	22	231	250	75	7.16	2.76
42	27	231	250	75	9.1	2.54
43	17	252	250	75	4.22	2.9
44	22	252	250	75	5.9	2.1
45	27	252	250	75	7.68	1.88
46	17	210	315	75	3.92	2.64
47	22	210	315	75	5.54	2.32
48	27	210	315	75	6.92	1.7
49	17	231	315	75	3.92	3
50	22	231	315	75	6.06	2.54
51	27	231	315	75	7.02	2.24
52	17	252	315	75	3.9	4
53	22	252	315	75	5.84	3

54	27	252	315	75	7.44	2.46
55	17	210	200	105	5.9	2.9
56	22	210	200	105	7.66	2.62
57	27	210	200	105	9.46	1.96
58	17	231	200	105	5.26	3.62
59	22	231	200	105	8.36	2.86
60	27	231	200	105	11.58	2.88
61	17	252	200	105	5.62	3.92
62	22	252	200	105	9.5	3.32
63	27	252	200	105	11.52	3.24
64	17	210	250	105	4.7	3.1
65	22	210	250	105	6.22	2.54
66	27	210	250	105	8.28	2.18
67	17	231	250	105	4.92	3.52
68	22	231	250	105	7.48	2.86
69	27	231	250	105	9.22	2.44
70	17	252	250	105	4.7	4.28
71	22	252	250	105	7.14	2.84
72	27	252	250	105	9.66	2.54
73	17	210	315	105	3.82	2.76
74	22	210	315	105	6.36	2.38
75	27	210	315	105	7.78	2.24
76	17	231	315	105	4.6	3.1
77	22	231	315	105	6.76	2.72
78	27	231	315	105	8.94	2.18
79	17	252	315	105	5.18	3.8
80	22	252	315	105	6.86	3.04
81	27	252	315	105	9.7	2.74

The ELM model is widely used as a solution in estimation problems in a wide variety of fields in a lot of places or among a lot of people. There is no need to tune the parameters in ELM model so this model is not hard to use, only predefined network architecture should be tuned. This prevents many complexities that are a big challenge for gradient-based algorithms, e.g. earning rate, learning epochs, and local minima. In the ELM approach, training phase usually takes a few seconds or at most minutes in large complex applications. Conventional neural nets are not able to do so in this short time span. The ELM model is a perfect computational algorithm candidate for predicting atmospheric and meteorological variables including solar energy, air temperature and rainfall that generally have large and complex datasets to deal with [20].

ELM is simply a single hidden-layer feedforward neural network [21-23]. Unlike conventional gradient-based learning algorithms that obtain a solution by many iterations, the ELM randomly chooses the input weights and biases and subsequently determines the output weights through simple matrix computations given arbitrary distinct samples $\{(x_i,t_i)\}_{i=1}^{N}$, where $x_i \in R^n$ with $x_i=[x_{i1},x_{i2},\ldots,x_{in}]^T$ and $t_i \in R^m$ with $t_i=[t_{i1},t_{i2},\ldots,t_{im}]^T$, ELM with K hidden nodes and activation function $g(.)$ can be mathematically modeled like Eq. (1) [24]:

$$f(x_j;w,b,\beta)=\sum_{i=1}^{K}\beta_i g(w_i.x_j+b_i),\ j=1,\ldots,N \tag{1}$$

Where $w_i=[w_{i1},w_{i2},\ldots,w_{in}]^T$ is the weight vector connecting the i the hidden node and the input nodes and $\beta_i=[\beta_{i1},\beta_{i2},\ldots,\beta_{im}]^T$ is the weight vector connecting the i the hidden node and the output nodes, and b_i is the threshold of the i the hidden node. The standard ELM with K hidden nodes and activation function $g(.)$ can approximate the N samples with zero error, meaning that

$$\sum_{i=1}^{K}\beta_i g(w_i.x_j+b_i)=t_j \qquad j=1,\ldots,N. \tag{2}$$

N equations above can be rewritten as $H\beta=T$ where H is the hidden-layer output matrix of the ELM

$$H=\begin{bmatrix} g(w_1.x_1+b_1) & \cdots & g(w_K.x_1+b_K) \\ \vdots & \ddots & \vdots \\ g(w_1.x_N+b_1) & \cdots & g(w_K.x_N+b_K) \end{bmatrix}_{N\times K} \tag{3}$$

$\hat{a}=[\beta_1,\beta_2,\ldots,\beta_K]^T$ Denotes the matrix of output weights, and $T=[t_1,t_2,\ldots,t_m]^T$ denotes the matrix of targets. By using continuous probability distributions input weights and hidden layer biases are initialized randomly and, in fact, they are not necessarily tuned. Once random values are assigned to these parameters in the beginning of learning, it is possible for the hidden-layer output matrix H to remain constant. Find specific parameters $\hat{w}_i,\hat{b}_i$ and $\hat{\beta}$, such that $\|H(\hat{w}_1,\ldots,\hat{w}_k,\hat{b}_1,\ldots,\hat{b}_k)\hat{\beta}-T\| = \min \| H(w_1,\ldots,w_k,b_1,\ldots,b_k) - \|$ which is similar to the cost function minimization procedure of the conventional gradient-based learning algorithms used in back-propagation (BP) learning.

$$C_{BP}=\sum_{j=1}^{N}\left[\sum_{i=1}^{k}\beta_i g\left(w_i.x_j+b_i\right)-t_j\right]^2 \tag{4}$$

If we assume that the input weights and hidden-layer biases are randomly chosen and constant, training an SLFN is similar to solve a least-squares problem of linear system. The least-squares solution which has the smallest norm among linear system above is $\hat{\beta}=H^{+}T$ where H^{+} is the Moore–Penrose generalized inverse of matrix H. One popular method to obtain H^{+} is the singular value decomposition (SVD) method.

5. Support vector machines

Support vector machines (SVMs) are classified as supervised learning algorithms which are in the family of algorithms that analyze data and recognize patterns, widely used in classification and regression tasks. The ancestor of the support vector machines is Generalized Portrait algorithm developed in 1960s [25]. SVM itself is a generalization of this algorithm. Cortes and Vapnik [26] proposed the present form of the SVMs at the AT&T Bell Laboratories in 1990s. The main advantage of the SVMs are structural risk minimization and minimization of empirical risk, which results in a better generalization capability in many practical applications compared to Neural Networks [27].

The purpose of SVM-based classification is to find a hyper-plane which maximizes the margin between training samples of two classes in the dataset, as depicted in Fig. 4. Eq. (5) describes this classifier in mathematical form, in which w and b are the weights and bias vector, respectively. Maximization of the margin between the two classes is performed via minimization of the risk function R(w) expressed in Eq. (6), subjected to the constraints of Eq. (7), for the N samples of the (xi, yi) in the training dataset.

$$f\left(x\right)=sign\left(w^T x+b\right) \tag{5}$$

$$R(w)=\frac{1}{2}w^T w=\frac{1}{2}\|w\|^2 \tag{6}$$

$$y_i\left(w^T x_i+b\right)\geq 1,\ \ i=1,\ldots,N \tag{7}$$

Support vectors are the closest samples to the hyper-plane

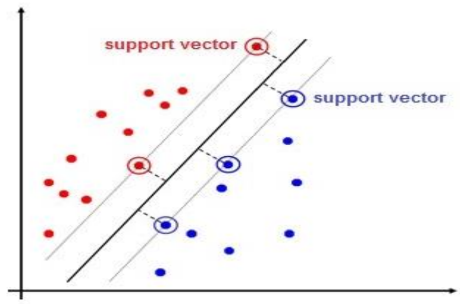

Fig. 4. SVM-based maximum margin classification

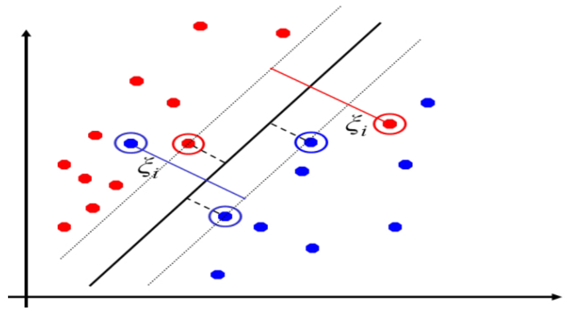

Fig. 5. SVM classification in case of samples which are not linearly separable

(Fig. 4). The support vectors lay on a hyper-plane satisfying the condition of

$$y_{sp}\left(w^T x_{sp}+b\right)=1 \tag{8}$$

When the samples of two classes in the training dataset are not linearly separable, another approach should be used. A factor must be added to the risk function in Eq. (6) because there is an inevitable error, remember in this case there are always some samples which lay outside the permitted borders. The optimization problem transforms to risk minimization of Eq. (9) subjected to the constraints of Eq. (10). In Eq. (9), $\hat{\imath}_{i}$ is the distance between the support vectors' hyper-plane and the samples which lay outside it, as depicted in Fig. 5. The parameter C, is the regularization factor and it trades off the relative importance of maximizing the margin and training error- i.e., the structural and empirical risks.

$$\mathrm{R}(w)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{N}\xi_i \tag{9}$$

$$y_i\left(w^T x_i+b\right)\geq 1-\xi_i,\qquad i=1,\ldots,N \tag{10}$$

Although this method is useful, it does not necessarily lead to acceptable classification accuracy, especially when the feature space is in such a way that the border between two classes is non-linear. In this condition, the original feature space can be mapped to some higher-dimensional feature space where the training set is separable, through a nonlinear function known as the kernel function, as depicted in Fig. 6

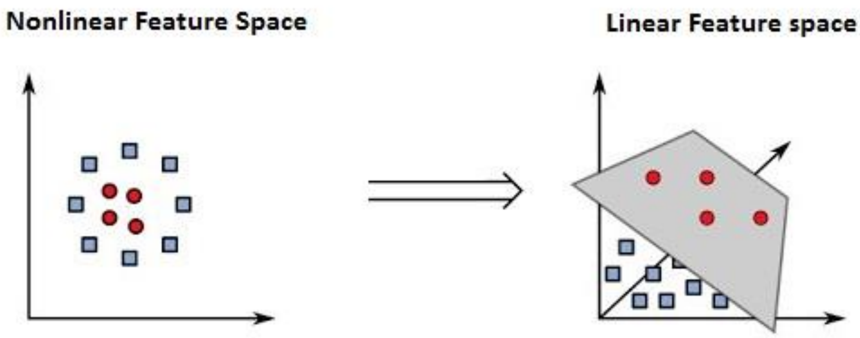

Fig. 6. Nonlinear input space mapped with a kernel function to a linear feature space

Table 3. Error analysis of the ELM and SVM models for the test data

Output	Method	RMSE	R^2
Bead Width	ELM	0.3242	0.9786
	SVM	0.3589	0.9738
Bead Height	ELM	0.1962	0.8606
	SVM	0.222	0.8215

[28].

In this case, SVM-based classifier system can be can be described as

$$f\left(x\right)=sign\left(w^T\phi\left(x\right)+b\right) \tag{11}$$

in which w and b are obtained by minimizing the risk function R(w) in Eq. (5) subjected to the constraints of

$$y_i\left(w^T\phi(x_i)+b\right)\geq 1-\xi_i, \tag{12}$$

for the N samples in the training database.

The problem of regression can be expressed as approximating a function based on a limited number of observations, in cases which have not been observed. A margin of tolerance is usually considered for approximating a function in practical applications. For example, if the function to be approximated is expressed in Euro's, the permitted margin of tolerance will be 0.01 in order to consider the Eurocent. Given a limited number of observations from the function f(x) with the permitted margin of tolerance å and a limited number of its values, SVM-based classification between f(x) + å and f(x) - å can be regarded as approximating f(x) in the permitted margin of tolerance [29]. Therefore, the formulation of support vector machines can be generalized for the purpose of regression as

$$y=f\left(x\right)=\sum\nolimits_{i=1}^{m}w_i\phi_i\left(x\right)+b_i=w^T\phi\left(x\right)+b \tag{13}$$

The goal is to calculate the values of w and b, based on a set of available training data, so that the difference between the original function and the estimated function is minimized.

To train the models, 65 samples were uses from weld bead geometry database, shown in table 5001. The model accuracy is evaluated by using the remaining 16 samples, highlighted in bold. All input and output values are normalized between -1 and 1 before testing and training, the normalization is based on Eq. (14).

$$\mathrm{un}=\frac{2{*}\mathrm{u}-\left(\mathrm{MX}+\mathrm{MN}\right)}{\left(\mathrm{MX}-\mathrm{MN}\right)} \tag{14}$$

In this equation, u denotes input or output, un is the corresponding normalized value and by MX and MN denote the maximum or minimum value of the input and output in the whole dataset respectively.

Implementation of the extreme learning machine models were implemented by a free-source Matlab implementation provided by [30]. SVM models were also implemented using SVM-KM toolbox [31]. The predicted training and test outputs were achieved using trained models and the training and test input samples. Then these outputs are scaled back to the original range using Eq. (15).

$$\hat{\mathrm{y}}=\mathrm{y}_\mathrm{n}{*}\left(\frac{\mathrm{MX}-\mathrm{MN}}{2}\right)+\left(\frac{\mathrm{MX}+\mathrm{MN}}{2}\right) \tag{15}$$

Where, the normalized and final predicted values of the output are denoted by $\mathrm{y_n}$ and $\hat{\mathrm{y}}$ respectively.

To assess the models precision, in the last stage, the root means square error (RMSE) and the coefficient of

Table 4. The ELM and SVM parameters

Output	Parameter	Value
Bead Width	ELM kernel parameter	700
	ELM Regularization coefficient	100
	SVM kernel parameter	50
	SVM regularization factor (C)	100
	SVM insensitivity parameter (ε)	10-9
Bead Height	ELM kernel parameter	330
	ELM Regularization coefficient	1000000
	SVM kernel parameter	8
	SVM regularization factor (C)	10000
	SVM insensitivity parameter (ε)	10-9

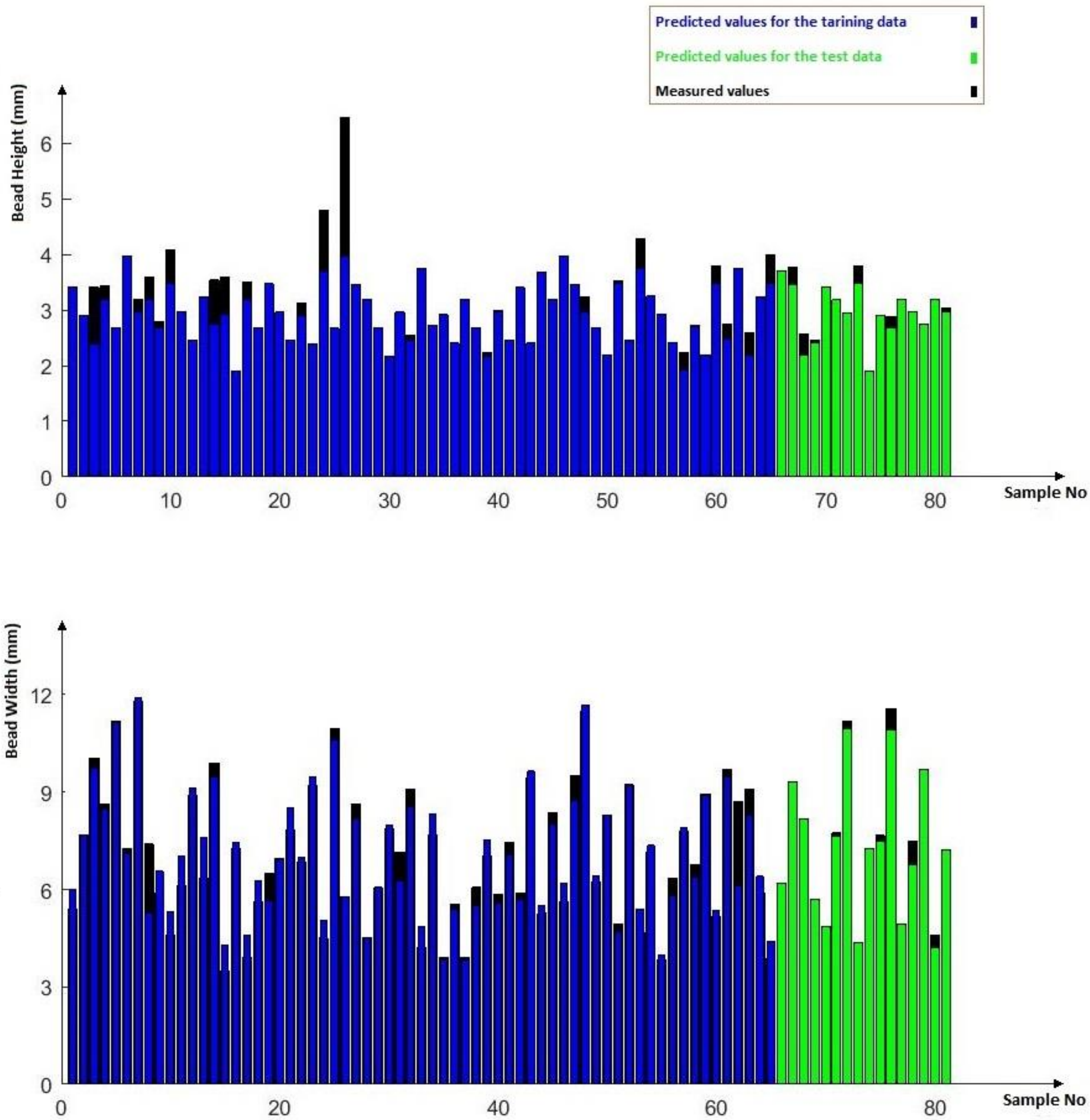

Fig. 7. The predicted values of bead width and bead height and the corresponding targets

determination (R^2) statistical indices, defined as Eq. (16) and Eq. (17) were calculated.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(t_i - y_i\right)^2}{N}} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(t_i - y_i\right)^2}{\sum_{i=1}^{N}\left(t_i - M\right)^2} \tag{17}$$

In these equations, N denotes the number of samples, t_i and y_i denote the targets and the predicted outputs, respectively, and M denotes the mean value of the targets, calculated as

$$M = \frac{\sum_{i=1}^{N} t_i}{N} \tag{18}$$

The computed values of RMSE and R^2 for the test data are shown in Table 3. The ELM and SVM kernel and model parameters are also listed in Table 4.

In conclusion, ELM-based modeling benefits from a higher degree of accuracy and superior capability for generalization compared to SVM method. The predicted outputs alongside with the targets are shown in Fig. 7, which obviously depicts the accuracy of the ELM models.

6. Conclusion

Modeling and prediction of weld bead geometry is an important issue in GMAW process. In this paper, application of the extreme learning machine (ELM) for modeling and prediction of the weld bead geometry in Gas Metal Arc welding process based on the input parameters of voltage, wire feed rate, welding speed and Welding nozzle angle has been proposed. The ELM kernel and model parameters are calculated and the coefficient of determination (R^2) is obtained as 0.97 and 0.86 for the weld bead width and height respectively in case of the test dataset. Prediction results also prove higher degree of accuracy of the ELM method over the SVM approach. Based on the ELM models, the input parameters can be tuned so as to attain desired weld geometry in this welding process with acceptable precision.

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