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TECHNICAL PAPER

Prediction of welding responses using AI approach: adaptive neuro-fuzzy inference system and genetic programming

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Abstract

Laser welding of thin sheets has widespread application in various fields such as battery manufacturing, automobiles, aviation, electronics circuits and medical sciences. Hence, it is very essential to develop a predictive model using artificial intelligence in order to achieve high-quality weldments in an economical manner. In the present study, two advanced artificial intelligence techniques, namely adaptive neuro-fuzzy inference system (ANFIS) and multi-gene genetic programming (MGGP), were implemented to predict the welding responses such as heat-affected zone, surface roughness and welding strength during joining of thin sheets using Nd:YAG laser. The study attempts to develop an appropriate predictive model for the welding process. In the proposed methodology, 70% of the experimental data constitutes the training set whereas remaining 30% data is used as testing set. The results of this study indicated that the root-mean-square error (RMSE) of tested data set ranges between 7 and 16% for MGGP model, while RMSE for testing data set lies 18–35% for ANFIS model. The study indicates that the MGGP predicts the welding responses in a superior manner in laser welding process and can be applied for accurate prediction of performance measures.

Keywords Laser welding · Nd · YAG laser · ANFIS · MGGP · Titanium alloy · Stainless steel

1 Introduction

Stainless steel (SS-316) and titanium alloy (Ti6Al4V) are extensively used in various fields of sophisticated industries such as biomedical, electrical and electronics, chemical plant, nuclear industries, automobiles and aviation sectors. The extensive use of these materials is due to their excellent functional and structural properties, e.g., corrosion resistance, high fatigue strength, high strength-to-weight ratio and biocompatibility [1–3]. The report published by Transparency Market Research Group [4] indicated that titanium alloy has huge impact in production of medical instruments, medical implants, and aviation sectors for production of airframes, aircraft engines, etc. Similarly, the report published by Grand View Research Group [5] stated that the global stainless steel market size was valued at USD 111.4 billion in 2019 and is anticipated to witness a CAGR of 6.3% in terms of revenue from 2020 to 2027. These two materials (i.e., titanium alloy and stainless steel) are widely used and studied by researchers. In the present world, with advancement of technology, we can create and absorb lot of data. With the introduction to Industry 4.0, implementing computer intelligence in the manufacturing industry is one of the reasons in adopting artificial intelligence (AI) in manufacturing sectors. A survey has been conducted by Fortune business insights [6], HCL [7], and Bernard Marr and Co. [8] on application and influence of AI on manufacturing sectors on year 2020. The reports stated that USA and European Union have invested about USD 111 million for growth of AI in manufacturing and industrial sectors. The report states that other countries like China and Saudi Arabia have taken steps forward of implementing AI in industries. To address all this study and issues implementing AI in manufacturing

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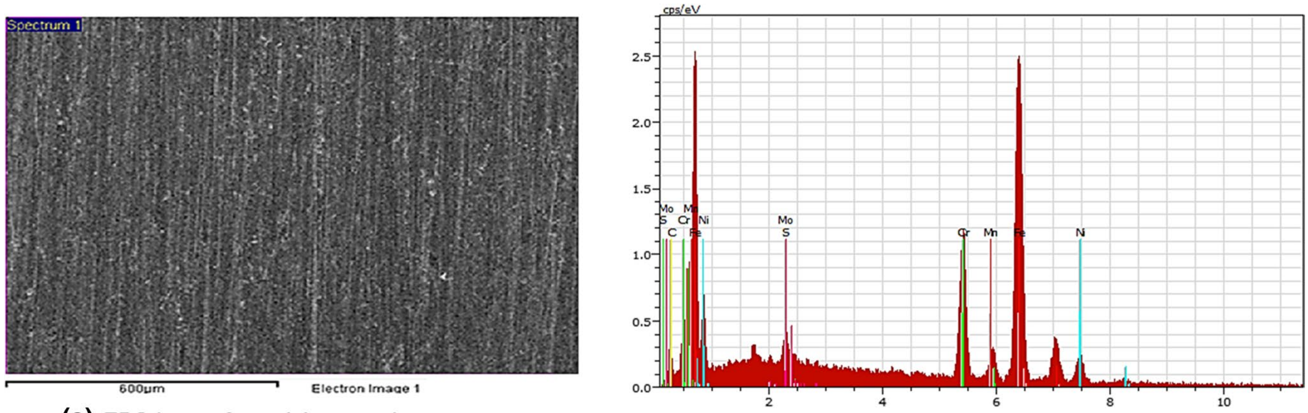
process of titanium alloy and stainless steel is an important topic and this will help industries and researchers to implement AI in manufacturing processes.

Joining of these materials is extensively studied by the researchers because of their aforementioned qualities and applications. The research is continuously carried out to attain good quality weldments of these materials [9–12]. Past literature suggests that the research work carried out by various researchers is mainly focused on joining of thick sheets of materials [13–17] and limited research work is reported on joining of thin sheet materials [18–20]. With the miniaturization of products, there is necessity to study the fabrication process of thin sheets. Laser is the best alternative for joining of thin sheets among other joining process. Laser welding process is a costlier technique for joining of materials. Hence, it is very necessary to adopt a methodology for predicting the weld quality using computational intelligence (CI) or artificial intelligence (AI) to attain high accuracy welds [21–24]. Recently, researchers focused more on development of predictive models in laser material processing using various approaches such as finite element model (FEM) [25, 26], statistical model [27, 28], numerical model [29, 30] and artificial intelligence (AI) [22–24] based models. There are various other artificial intelligence (AI) approaches such as neural network (NN) [31, 32], ANN [33], BPNN [33], support vector machine (SVR) [34], genetic programming (GP) [34–36], and multi-gene genetic programming (MGGP) [34, 37]. All these approaches are very effective and vary with different conditions and applications. Researchers have introduced different AI techniques such as support vector regression methodology, sensor data fusion by support vector regression methodology, statistical evaluation, and adaptive neuro-fuzzy approaches for predicting and forecasting processes in real-life problem to engineering problems. Shamshirband et al. [38] have implemented artificial intelligent (AI) process like support vector regression (SVR) methodology in constructing effective multisensory system. The study aimed to propose a methodology to improve tracking ability in sensory system. Olatomiwa et al. [39] have proposed adaptive neuro-fuzzy system in solar energy systems to predict the solar radiation in day time. The introduction of AI in the study provides global attention in very important applications like agricultural crop production, hydrological and ecological studies and development of solar energy systems. Orlowska and Szabat [40] have used adaptive neuro-fuzzy approach to control the vibration in electric controller using neuro-fuzzy controller in the study. The study shows the adaptability of AI to electrical and electronic systems.

Petković et al. [41] have introduced adaptive neuro-fuzzy inference system to estimate and optimize the design of lens systems. The introduction of ANFIS (adaptive neuro-fuzzy inference system) helps in providing good quality lens in digital manufacturing technology. To achieve efficiency in steam turbine, it is very necessary to detect and diagnose defects as early as possible. Salahshoor et al. [42] proposed artificial intelligence techniques such as SVM (support vector machine) and ANFIS to predict the diagnostic defects and faults in industrial steam turbine. Gupta [43] have proposed AI methodologies such as artificial neural networks (ANN) and support vector regression (SVR) to understand the effectivity of the proposed models over statistical approaches during turning operation. The study suggests the efficiency of AI methodology over statistical tools. Jahangirzadeh et al. [44] have proposed support vector regression model in construction of bridge pier. The study was performed to determine the optimum dimensions during construction of rectangular collar to minimize the cost and inaccuracy.

Less research work is available on AI-based approach in manufacturing processes. Sohrabpoor [45] have proposed adaptive neuro-fuzzy inference system (ANFIS) integrated with response surface methodology (RSM) for prediction of machining responses during laser processing of mild steel. The study suggests that the developed predictive model is quite accurate in predicting the responses. Aminian and Teimouri [46] have performed laser machining and laser weld of aluminum-based metal matrix composites. Aminian and Teimouri [46] have proposed different techniques such as response surface methodology (RSM), artificial neural network (ANN) and ANFIS for predicting the outputs for both laser processing techniques. The results of the comparative study indicate more promising results for the ANFIS process than for ANN and RSM. Zhang et al. [47] have adapted AI method like back propagation neural network (BPNN) for predicting and optimization of welding gaps in adaptive filling in laser welding of high strength steel. Subashini and Vasudevan [33] have used ANN and ANFIS approaches for developing an efficient predicting model for estimating the depth of penetration during tungsten inert gas (TIG) welding of stainless steel. ANFIS shows more accurate results as compared to ANN approach.

Sharma et al. [48] have proposed a statistical method rooted with genetic programming (GP) method for prediction of compaction strength of parts produced through powder metallurgy route. Panda et al. [35] have used a GP-based model for predicting the dimensions of parts made by additive manufacturing. Desai and Shaikh [49] used ANN and GP methodologies to determine the depth of cut in laser micro-milling process. A comparative study was performed to estimate the accuracy of the proposed developed models. It was found that both the models are quite efficient in predicting the depth of cut in laser micromilling process. Kok et al. [36] have proposed GP for estimation of surface roughness of metal matrix composite surfaces cut by abrasive water jet machining. Garg et al. [34] have proposed



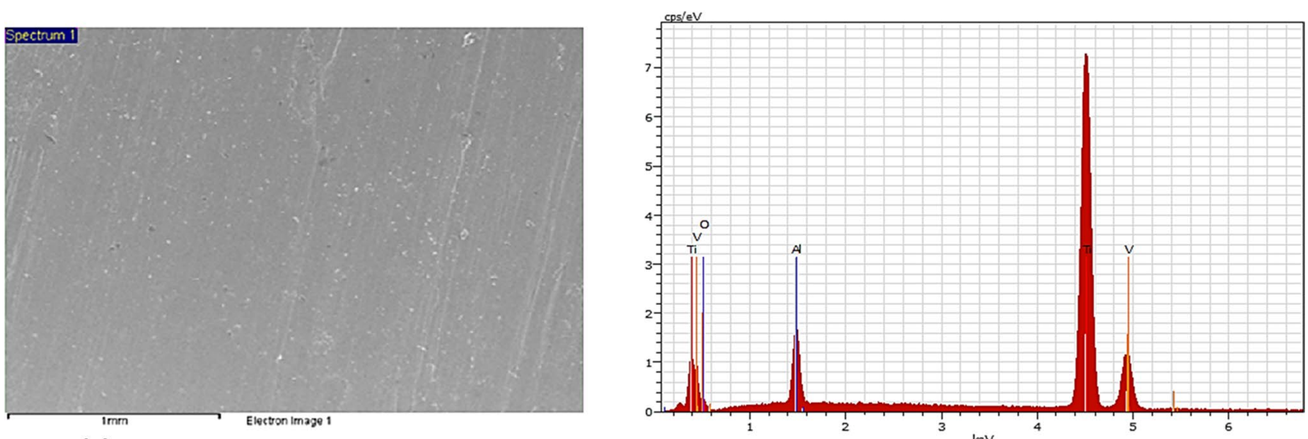
(a) EDS Image for stainless steel

(b) FESEM-EDS spectra

(c) Weight percentage of constituents present in stainless steel

Constituents	Symbol	Weight Percentage (%)
Iron	Fe	71.56
Carbon	C	2.81
Sulfur	S	0.08
Chromium	Cr	15.27
Manganese	Mn	1.28
Molybdenum	Mo	2.01
Nickel	Ni	9.84

Fig. 1 EDS spectra and constituents for stainless steel [19]



(a) EDS Image for titanium alloy

(b) FESEM-EDS spectra

(c) Weight percentage of constituents present in titanium alloy

Constituents	Symbol	Weight Percentage (%)
Titanium	Ti	92.95
Aluminum	Al	5.85
Vanadium	V	3.88
Oxygen	O	2.24

Fig. 2 EDS spectra and constituents for titanium alloy [44]

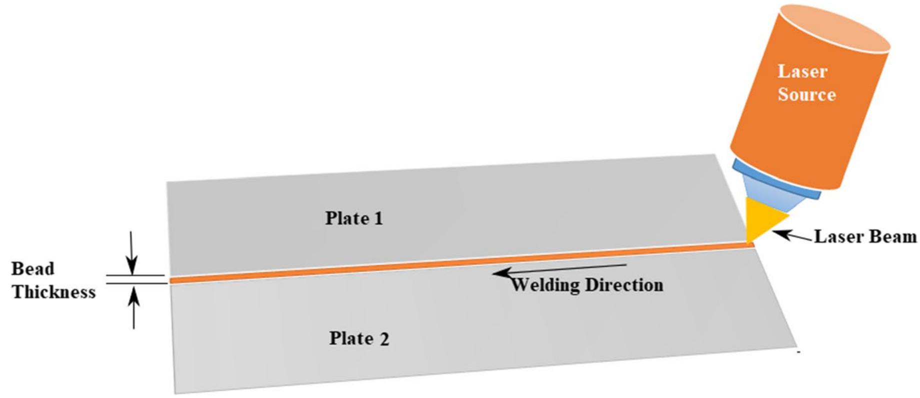


Fig. 3 Schematic layout of butt-welding process using laser

Table 1 Laser parameters

Settings	Ranges
Focal position	On the surface (fixed)
Gas flow rate (l/min)	10
Average power (W)	250
Maximum peak power (kW)	5
Offset distance (mm)	3
Shielding gas pressure (bar)	1.5 (fixed)
Pulse frequency (Hz)	2
Work piece (for laser welding)	SS 316 with SS 316 and Ti-6Al-4 V with Ti-6Al-4 V

a multi-gene genetic programming (MGGP) approach to develop a predicting model for understanding the physical behavior of performance measures in fused deposition method (FDM). To study the effectiveness of the proposed model, Garg et al. [34] compared the developed predictive models using other AI approaches such as GP, ANFIS and SVR. The study showed the efficiency of MGGP approach in predicting performance measures. Garg et al. [37] have used MGGP model for developing a functional expression between process parameters and surface characteristics in selective laser melting process (SLM). The results show the robustness of the suggested model. Chatterjee et al. [21] have proposed two different AI approaches such as MGGP and ANFIS for predicting the performance measures in laser drilling operation. The results suggest the accuracy of MGGP model as compared to ANFIS model. To establish an empirical relationship between the process parameters and process outputs during turning operation, Garg and Lam [50] have proposed a MGGP model.

Advanced engineering materials (titanium alloys and stainless steels) are extensively used engineering materials. Titanium alloys and stainless steel find their widespread applications in aerospace industry, aviation sector, turbine blade manufacturing, electronics industry, automobile industry, day to day life usable products as well as medical equipment. Laser welding of advanced engineering materials of thin sheets and their comparative studies is a quite challenging task. The excessive heat input during laser welding may lead to over burnt surface and decrease the weld quality of the weldments. Therefore, it is very necessary to determine the influence of machining parameters on stainless steel and titanium alloy under identical machining parameters. Detailed literature survey shows that previous researches were basically focused on few aspects such as effect of machining parameters on process outputs, prediction of process outputs using computational, statistical and heuristic approaches. Therefore, application of meta-heuristic methodology and artificial intelligence (AI) for predicting and optimizing the process outputs during laser material processing has been explored rarely. Implementing AI techniques in manufacturing is a big step toward improving the manufacturing quality and reduces time and cost of the process. Laser welding process is a costlier process among other available joining processes but requires high skills to handle the process. Handling this process with high skills and accuracy will provide quality jobs with minimum defects compared to other processes. Implementing computational intelligence with AI techniques will help predicting the performance measures of the machining process, as well as to minimize cost of trial and pilot runs during experimentation.

In the present study, welding of similar materials such as SS-316 with SS-316 and Ti-6Al-4 V with Ti-6Al-4 V of 0.45 mm thickness was performed using Nd:YAG laser. The study mainly focuses on adapting artificial intelligence techniques, adaptive neuro-fuzzy inference system (ANFIS) and multi-gene genetic programming (MGGP) to predict the performance measures, e.g., bead width (BW), heat-affected zone (HAZ), surface roughness (SR) and welding strength (WS) of the weldments. The two artificial intelligence techniques enable a better welding predictability, so will help critical industry practitioners using these models

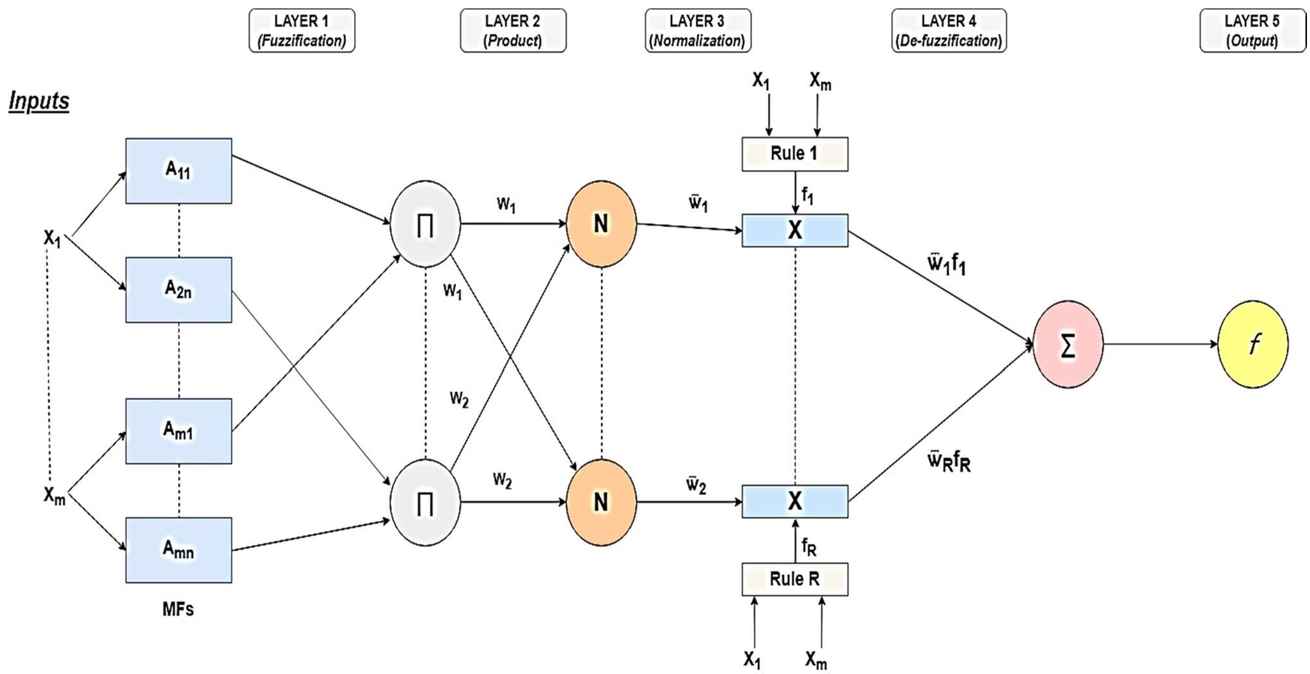


Fig. 4 ANFIS basic architecture [21]

in predicting successfully the outputs of given inputs in a reasonable manner during laser welding process. Further, the robustness of these two models allows a better manufacturing quality which in turn generates a higher safely for welded parts that are subjected to numerous cycles during their functioning period.

2 Material and methods

2.1 Materials

Selection of materials and workpieces' dimensions has been done after exhaustive literature survey and research gap. The workpieces selected for the analysis are stainless steel (SS316) and titanium alloy (Ti-6Al-4 V) having 0.45 mm thickness. The material was procured by Manahar Metals Ltd., India. In order to verify the composition and weight percentage of the workpieces, energy-dispersive X-ray spectroscopy (EDS) has been performed using (FESEM-EDS) (FEI Quanta FEG 250, USA). The weight percentage of each constituent for both workpieces SS316 and Ti-6Al-4 V is shown in Figs. 1 and 2, respectively.

2.2 Experimentation

Joining of thin sheets made of similar metals (i.e., SS316 with SS316 and Ti-6Al-4 V with Ti-6Al-4 V) of 0.45 mm thickness has been performed using Nd:YAG pulsed laser. The schematic layout of butting welding process using laser

Fig. 5 Steps involved in MGGP (pseudocode) [64]

```
BEGIN
1: Formulation of problem
2: multi gene genetic programming (MGGP) algorithm
Initiate
    2-1: Establishing parameters for the algorithm e.g. terminal and function set, number of
         generations, population size, genetic operators' rate and maximum number of genes
    2-2: Initiate initial population size for the genes
    2-3: Models are formed by combining set of genes using least square method
    2-4: Calculate performance of models based on root mean square error (RMSE)
    2-5: Apply genetic operations and form the new population
    2-6: Cross-check the model performance against the termination criterion and if not satisfied
    GOTO Step 2-5
    END;
END;
```

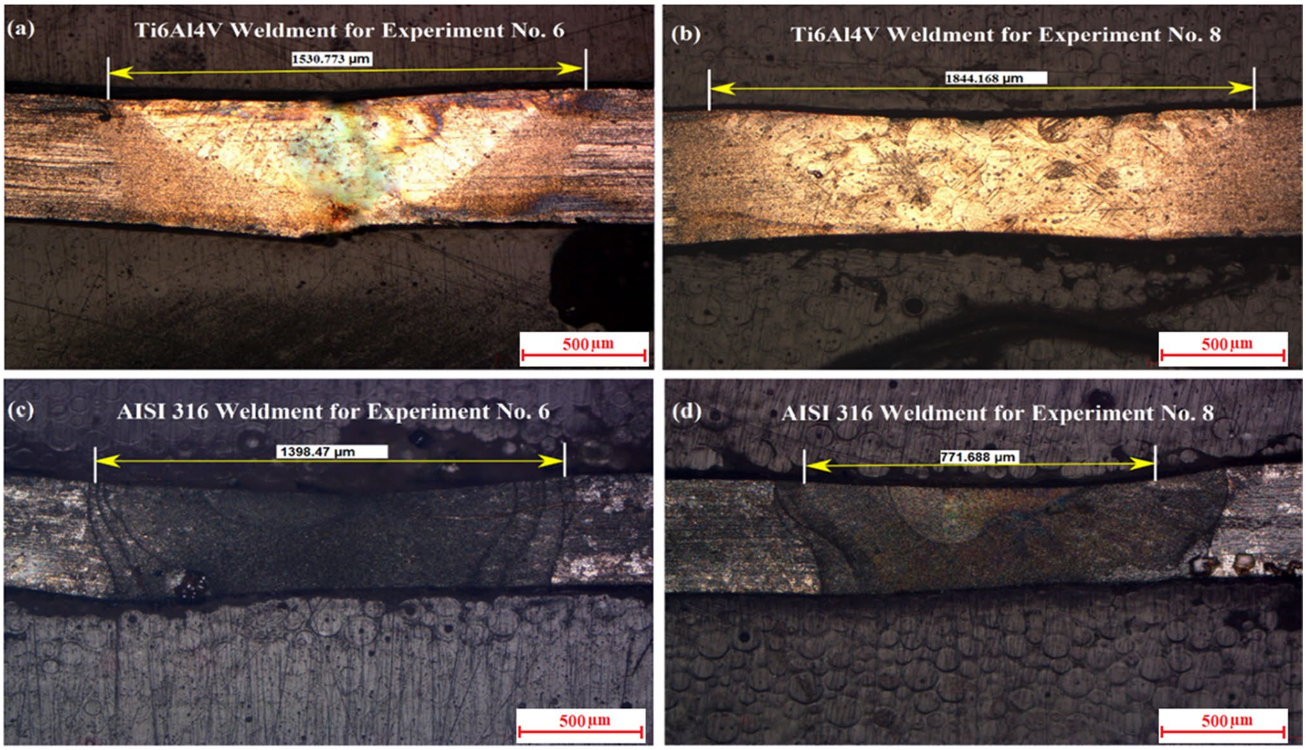


Fig. 6 Macrograph of bead width of titanium alloy and stainless steel weldments [52]

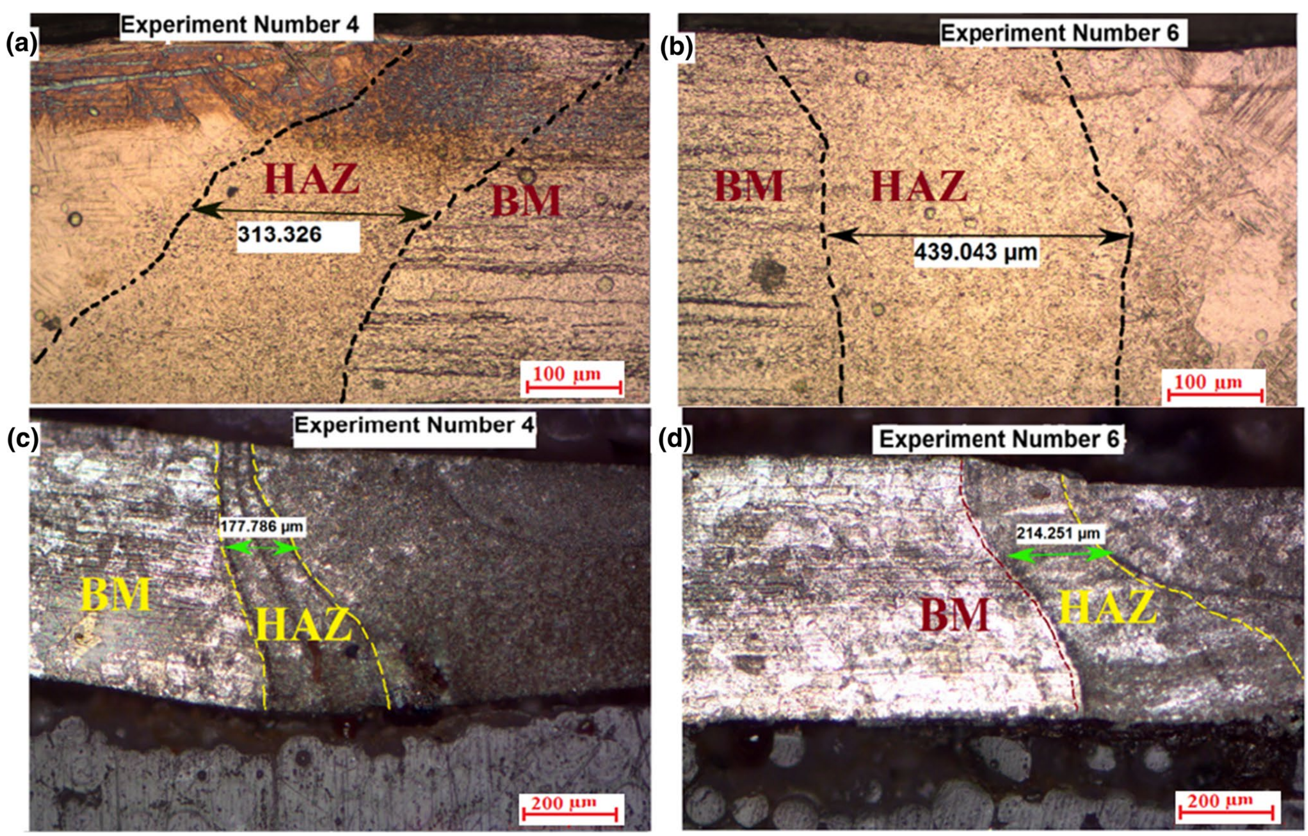


Fig. 7 Micrographs of HAZ for titanium alloy and stainless steel workpieces: **a** experiment number 4 (titanium alloy) **b** experiment number 6 (stainless steel) **c** experiment number 4 (stainless steel) **d** experiment number 6 (titanium alloy) [52]

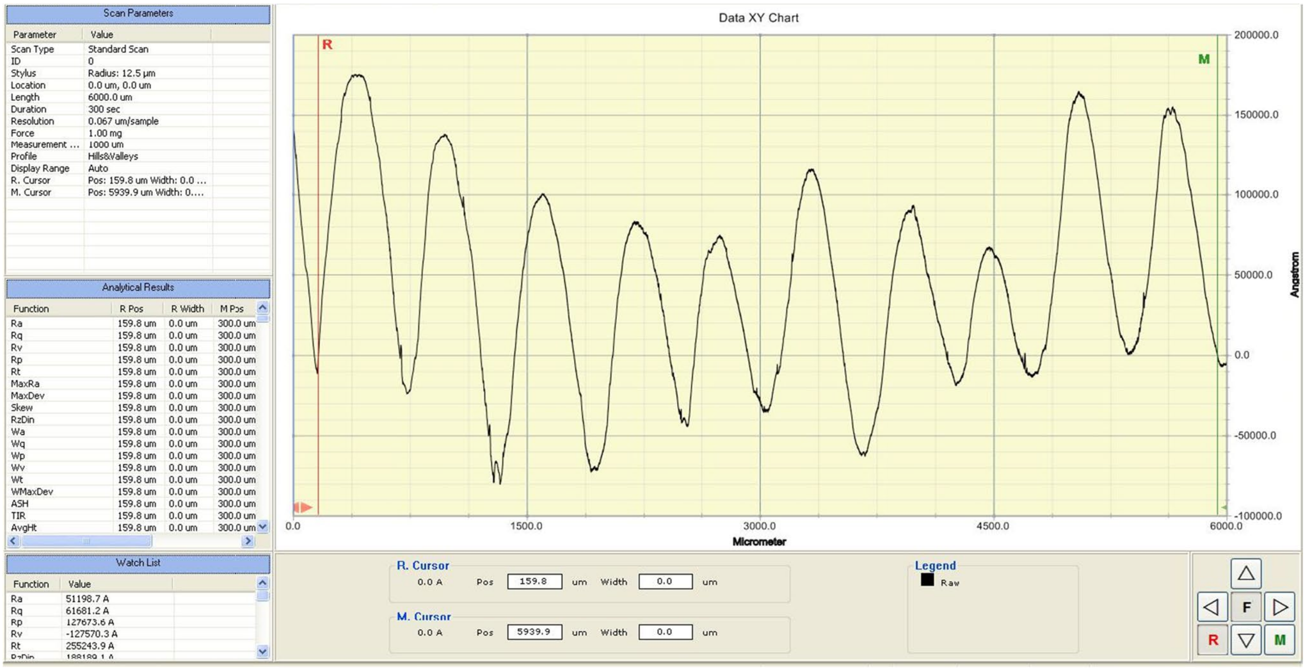


Fig. 8 Surface roughness calculation of the weldment at experiment run number 5 (for SS316)

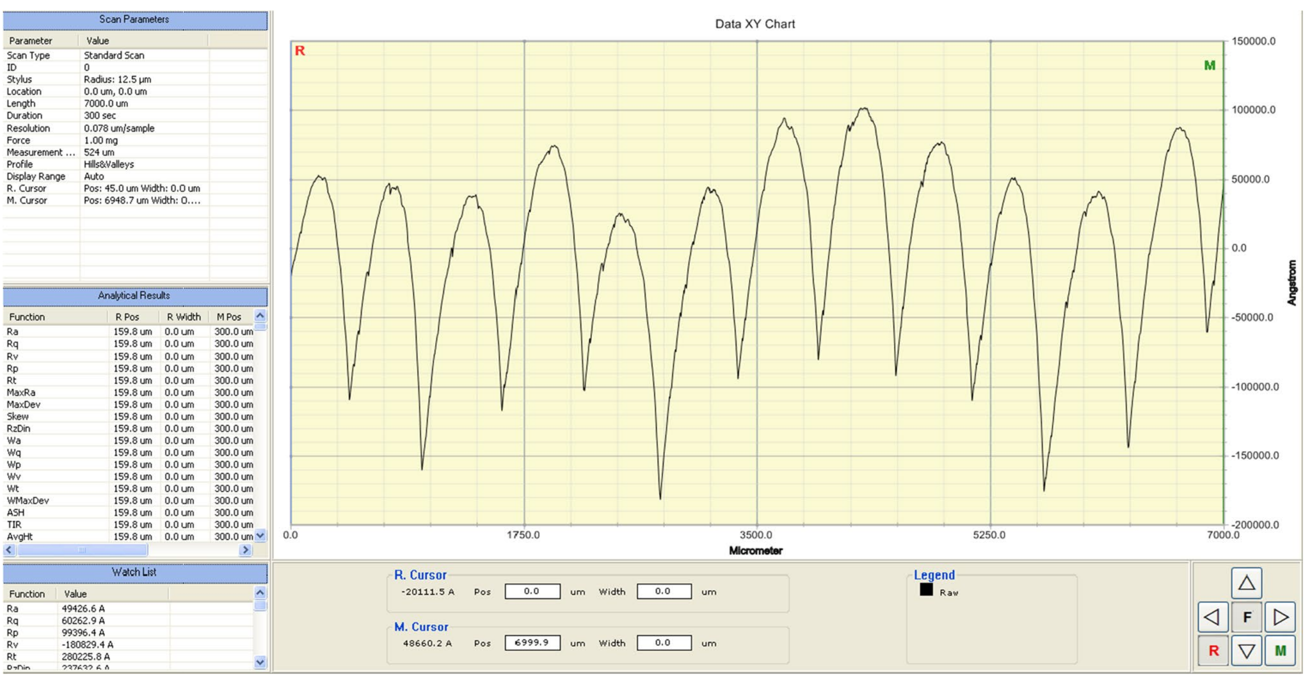


Fig. 9 Surface roughness calculation of the weldment at experiment run number 5 (for Ti-6Al-4 V)

is shown in Fig. 3. The specifications of welding setup are given in Table 1. The parameters and their ranges considered for the study were decided based on the literature survey [21, 50, 51], ranges available in the laser setup and pilot experiments. The parameters for welding setup are as follows:

- Laser current (*A*): 200 A, 230 A and 260 A
- Pulse width (*B*): 10 ms, 15 ms and 20 ms
- Welding speed (*C*): 10 mm/min, 30 mm/min and 50 mm/min

The welding of materials was performed in butt joint configuration and experiments were carried out using the design of experiments approach integrated with response surface methodology (RSM). The design matrix was decided as per face-centered central composite design (FCCCD). To perform the laser welding experiments, the three parameters such as laser current, pulse width and welding speed are varied at three different levels as explained in above section using RSM-FCCCD.

2.3 RSM

Response surface methodology (RSM) is a statistical approach embedded with mathematical technique used for strategizing, refining and optimizing procedure in a sequential way. In this process, it engages with different situation, in which a large number of input parameters possibly influence the output process or quality of product or performance measures. The output process or quality of product or performance measures are also known as response. The second-order model is widely used in response surface methodology due to its flexibility, and it can take a wide variety of functional forms (Eq. 1) [52].

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ij} X_i^2 + \sum_{i,j=1,i\neq j}^{k} \beta_{ij} X_i X_j + \varepsilon \tag{1}$$

Where Y is the corresponding response of input variables X_i; X_i^2 and X_iX_j are the square and interaction terms of factors, respectively. β_0, β_i, β_{ii} and β_{ij} are the unknown regression coefficients and ε is statistical error.

2.4 ANFIS

Adaptive neuro-fuzzy inference system (ANFIS) is a combination of two different AI methodologies known as ANN and FIS. ANN and FIS are complementary to each other. ANN has the potential of adapting knowledge from both the process such as feedback and data without involving in considerate the pattern of data sets, whereas FIS methodology has an adaptability to understand the pattern of data sets because they use linguistic terms in the form of IF-THEN rules. ANNs have an excellent learning proficiency and can adapt and learn the fuzzy decision rules. Fuzzy inference system in ANFIS offers decision-based expert knowledge to be used in ANN system. The integration of these two intelligent techniques leads to develop a hybrid artificial

Table 2 Normalized performance measures for laser welding of stainless steel workpieces

	Input parameters				Output parameters			
	Exp. No	Laser current (A)	Pulse width (B)	Scanning speed (C)	Bead width (BW)	Heat-affected zone (HAZ)	Surface roughness (SR)	Welding strength (WS)
Training Data	1	− 1.00	− 1.00	− 1.00	0.7892	0.9	0.7456	0.4179
	2	1.00	− 1.00	− 1.00	0.5037	0.6584	0.7598	0.7385
	3	− 1.00	1.00	− 1.00	0.4914	0.4237	0.1	0.6383
	4	1.00	1.00	− 1.00	0.1	0.4509	0.6283	0.5568
	5	− 1.00	− 1.00	1.00	0.9	0.8718	0.9	0.1
	6	1.00	− 1.00	1.00	0.676	0.1	0.541	0.8522
	7	− 1.00	1.00	1.00	0.5013	0.6274	0.5777	0.5499
	8	1.00	1.00	1.00	0.2502	0.3859	0.4974	0.9
	9	− 1.00	0.00	0.00	0.6562	0.6629	0.8157	0.2973
Testing data	10	1.00	0.00	0.00	0.3068	0.5467	0.7387	0.6326
	11	0.00	− 1.00	0.00	0.6932	0.5779	0.7672	0.3725
	12	0.00	1.00	0.00	0.5185	0.5541	0.5346	0.5065
	13	0.00	0.00	− 1.00	0.3821	0.8634	0.3492	0.8316
	14	0.00	0.00	1.00	0.5382	0.7072	0.5048	0.8443
	15	0.00	0.00	0.00	0.3166	0.6742	0.6043	0.5741
	16	0.00	0.00	0.00	0.4387	0.7571	0.5844	0.6368
	17	0.00	0.00	0.00	0.4519	0.6476	0.6179	0.4716
	18	0.00	0.00	0.00	0.4249	0.7842	0.6762	0.526
	19	0.00	0.00	0.00	0.4435	0.7501	0.6176	0.6075
	20	0.00	0.00	0.00	0.4112	0.7066	0.6242	0.6138

Table 3 Normalized performance measures for laser welding of titanium alloy workpieces

	Input parameters				Output parameters			
	Exp. No	Laser current (A)	Pulse width (B)	Scanning speed (C)	Bead width (BW)	Heat-affected zone (HAZ)	Surface roughness (SR)	Welding strength (WS)
Training data	1	− 1.00	− 1.00	− 1.00	0.2907	0.1	0.7536	0.5746
	2	1.00	− 1.00	− 1.00	0.2104	0.3998	0.351	0.3845
	3	− 1.00	1.00	− 1.00	0.9	0.5115	0.7849	0.4936
	4	1.00	1.00	− 1.00	0.1	0.5535	0.2682	0.8992
	5	− 1.00	− 1.00	1.00	0.5887	0.6264	0.3921	0.3932
	6	1.00	− 1.00	1.00	0.8948	0.3793	0.5359	0.1
	7	− 1.00	1.00	1.00	0.5632	0.9	0.9	0.8709
	8	1.00	1.00	1.00	0.2826	0.3946	0.8964	0.7708
	9	− 1.00	0.00	0.00	0.6364	0.8532	0.6095	0.8095
Testing data	10	1.00	0.00	0.00	0.4259	0.7345	0.4199	0.9
	11	0.00	− 1.00	0.00	0.4082	0.4218	0.1824	0.3641
	12	0.00	1.00	0.00	0.3399	0.7063	0.4828	0.8247
	13	0.00	0.00	− 1.00	0.2985	0.5234	0.3862	0.4074
	14	0.00	0.00	1.00	0.5094	0.595	0.6488	0.1852
	15	0.00	0.00	0.00	0.5621	0.7144	0.1	0.7755
	16	0.00	0.00	0.00	0.5127	0.6901	0.1819	0.6198
	17	0.00	0.00	0.00	0.5912	0.6147	0.3228	0.5803
	18	0.00	0.00	0.00	0.5056	0.6427	0.2362	0.8921
	19	0.00	0.00	0.00	0.4642	0.6331	0.2171	0.8521
	20	0.00	0.00	0.00	0.5038	0.5949	0.3095	0.7215

Table 4 Tuning parameters for MGGP

Parameters	Values
Population size	270
Timeout	10 s
Iterations	3
Tournament size	25
Maximum genes	6

intelligence (AI) network adaptive neuro-fuzzy inference system (ANFIS). The ANFIS network system consists of five different layers such as (1) fuzzification of input data, (2) product of fuzzified data, (3) normalization of fuzzified data, (4) defuzzification of fuzzified results and (5) output of responses. The ANFIS model consists of five layers and each of the layers consists of some nodes like ANN model [52, 53]. The detailed structure of ANFIS is shown in Fig. 4. The past literature has already discussed the working principle and implementation details of ANFIS [53–59]. ANFIS is widely used for predicting performance measures in machining and welding area [53–59].

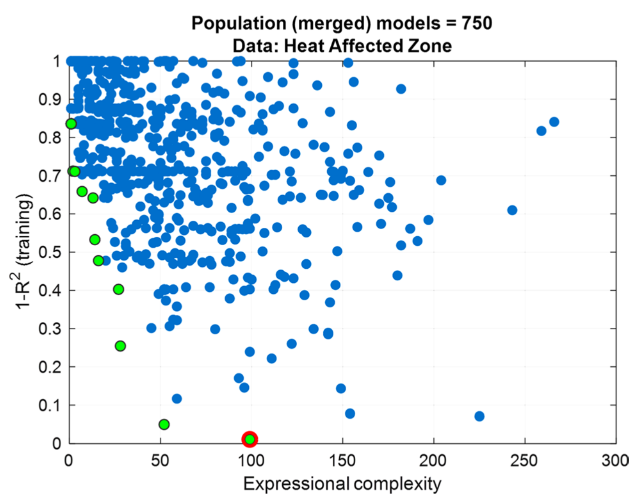


Fig. 10 Multi-gene regression for population heat-affected zone of stainless steel workpiece

2.5 MGGP

MGGP is a new and advanced version of genetic programming (GP) for predicting the responses. MGGP is effectively used as predictive tool in artificial intelligence, and in the

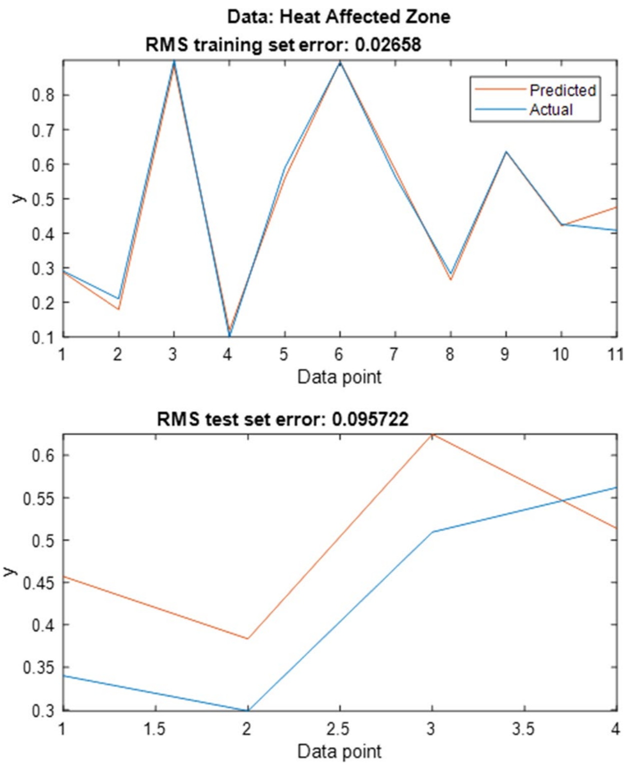


Fig. 11 Predicted vs actual data using MGGP model (training and testing) for heat-affected zone during laser welding of stainless steel

present study, MGGP is used for estimation of quality of weldments in laser welding process. GP was introduced in early 1990s by J.R. Koza [60–62] and became an effective technique of evolutionary computational algorithms, used for solving problems of any degree of complexity in all types of engineering problems [63].

MGGP is an updated and modified robust version of GP algorithm. The standard genetic programming is effectively integrated with the model structure adaptability technique and classical regression process [63]. MGGP can easily understand the import information patterns inside the multi-dimensional information domain with high speed by excluding the typical and complex mathematical procedure [63, 64]. The steps included in MGGP model are stated by the pseudocode in Fig. 5. The comprehensive descriptions and understanding on MGGP can be found in [35, 50, 63, 64].

3 Results and discussion

The weldments of stainless steel and titanium alloy are analyzed by means of optical microscope, scanning electron microscope, surface profile meter and universal testing machine to determine the performance measures such as bead width (BW) (Fig. 6) [52], heat-affected zone (HAZ) (Fig. 7) [52], surface roughness (SR) (Figs. 8 and 9) and welding strength (WS), respectively.

The normalized values of the performance measures are considered for developing prediction models using the artificial intelligence techniques known as ANFIS and MGGP. The normalization of data of performance measures is made using Eq. 2 for lower-the-better and Eq. 3 for

Table 5 Actual vs predicted performance measures of laser welding of stainless steel

Exp. No.	BW			HAZ			SR			WS			
	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	
1	0.7892	0.2907	0.3945	0.9	0.1000	0.2870	0.7456	0.7536	0.7745	0.4179	0.5746	0.4192	Training data
2	0.5037	0.2104	0.0247	0.6584	0.3998	0.1790	0.7598	0.3510	0.3585	0.7385	0.3845	0.5036	
3	0.4914	0.9000	0.7964	0.4237	0.5115	0.8828	0.1	0.7849	0.7487	0.6383	0.4936	0.5383	
4	0.1	0.1000	0.2855	0.4509	0.5535	0.1192	0.6283	0.2683	0.3328	0.5568	0.8992	0.8909	
5	0.9	0.5887	0.6665	0.8718	0.6264	0.5582	0.9	0.3921	0.4639	0.1	0.3932	0.3969	
6	0.676	0.8948	0.8525	0.1	0.3793	0.8963	0.541	0.5359	0.4924	0.8522	0.1000	0.0599	
7	0.5013	0.5632	0.4856	0.6274	0.9000	0.5821	0.5777	0.9000	0.8982	0.5499	0.8709	0.8734	
8	0.2502	0.2826	0.3246	0.3859	0.3946	0.2645	0.4974	0.8964	0.9267	0.9	0.7708	0.8047	
9	0.6562	0.6365	0.5897	0.6629	0.8532	0.6347	0.8157	0.6095	0.5547	0.2973	0.8095	0.7780	
10	0.3068	0.4259	0.3800	0.5467	0.7345	0.4220	0.7387	0.4199	0.3610	0.6326	0.9000	0.7859	Testing data
11	0.6932	0.4082	0.5008	0.5779	0.4218	0.4751	0.7672	0.1824	0.1824	0.3725	0.3641	0.5098	
12	0.5185	0.2430	0.4892	0.5541	0.3321	0.4571	0.5346	0.3265	0.3866	0.5065	0.3962	0.9417	
13	0.3821	0.2154	0.3694	0.8634	0.2639	0.3836	0.3492	0.2478	0.3803	0.8316	0.3199	0.5599	
14	0.5382	0.2754	0.5678	0.7072	0.3132	0.6249	0.5048	0.2945	0.5220	0.8443	0.3057	0.4494	
15	0.3166	0.2473	0.4848	0.6742	0.3426	0.5138	0.6043	0.2120	0.2845	0.5741	0.3515	0.7257	

Exp. No.: Experiment number, Exp. Val.: Experimental value

Table 6 Actual vs predicted performance measures of laser welding of titanium alloy

Exp. No.	BW			HAZ			SR			WS			
	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	Exp. val	ANFIS	MGGP	
1	0.2907	0.7892	0.8003	0.1	0.9000	0.8880	0.7536	0.7456	0.6167	0.5746	0.4179	0.4742	Training data
2	0.2104	0.5037	0.4955	0.3998	0.6584	0.6700	0.351	0.7598	0.7947	0.3845	0.7385	0.7298	
3	0.9	0.4914	0.4803	0.5115	0.4237	0.4245	0.7849	0.1000	0.2113	0.4936	0.6383	0.6023	
4	0.1	0.1000	0.1082	0.5535	0.4509	0.4520	0.2682	0.6283	0.5726	0.8992	0.5568	0.5902	
5	0.5887	0.9000	0.8914	0.6264	0.8718	0.8753	0.3921	0.9000	0.9171	0.3932	0.1000	0.1442	
6	0.8948	0.6760	0.6875	0.3793	0.1000	0.0979	0.5359	0.5411	0.5073	0.1	0.8522	0.8182	
7	0.5632	0.5013	0.5099	0.9	0.6274	0.6116	0.9	0.5777	0.6252	0.8709	0.5499	0.4934	
8	0.2826	0.2502	0.2387	0.3946	0.3859	0.3999	0.8964	0.4975	0.4630	0.7708	0.9000	0.9661	
9	0.6364	0.6562	0.6619	0.8532	0.6629	0.6866	0.6095	0.8157	0.7257	0.8095	0.2973	0.2812	
10	0.4259	0.3068	0.3126	0.7345	0.5467	0.5230	0.4199	0.7387	0.7613	0.9	0.6326	0.5845	Testing data
11	0.4082	0.6932	0.6817	0.4218	0.5779	0.5767	0.1824	0.7672	0.8766	0.3641	0.3725	0.3720	
12	0.3399	0.1869	0.3420	0.7063	0.2579	0.5315	0.4828	0.2808	0.6356	0.8247	0.2980	0.4934	
13	0.2985	0.2501	0.4637	0.5234	0.3018	0.6593	0.3862	0.3264	0.5362	0.4074	0.2611	0.5992	
14	0.5094	0.2835	0.5532	0.595	0.2711	0.5468	0.6488	0.3460	0.6156	0.1852	0.2647	0.6056	
15	0.5621	0.2793	0.4905	0.7144	0.2983	0.6048	0.1	0.3872	0.7435	0.7755	0.2172	0.4328	

Table 7 Root-mean-square error (RMSE) for testing data during laser welding

Performance measures	Stainless steel		Titanium alloy	
	ANFIS	MGGP	ANFIS	MGGP
Bead width	0.2063	0.0761	0.2200	0.1307
Heat-affected zone	0.3260	0.0957	0.4286	0.1348
Surface roughness	0.2131	0.1219	0.1853	0.1356
Welding strength	0.3105	0.1652	0.4561	0.1196

higher-the-better characteristics. In Eqs. 2 and 3, X_{ij} denotes j^{th} performance measure in i^{th} trial, and $X_{\min}$ and $X_{\max}$, respectively, are the maximum and minimum values of j^{th} performance measures. For laser welding process, higher-the-better characteristic is used for performance measures such as BW and WS. Lower-the-better characteristic is used for performance measures such as HAZ and SR. The performance measures are normalized (as detailed in Eqs. 2 and 3) according to their desired results such as higher-the-better and lower-the-better for BW and WS, and HAZ and SR, respectively. The normalization of performance measures helps in executing the methodology in an effective manner. It is clearly observed that normalized values of performance measures ranges between 0.1 and 0.9, which is very helpful in handling the training and testing inputs in the proposed methodology. This will be very helpful in providing uniform data sets for executing all the output values in a predictive model. The normalized values of the performance measures are listed in Tables 2 and 3.

Normalization

$$\text{Lower the Better} = \frac{x_{\max} - x_{\text{ij}}}{x_{\max} - x_{\min}} \tag{2}$$

$$\text{Higher the Better} = \frac{x_{\text{ij}} - x_{i\,\min}}{x_{\max} - x_{\min}} \tag{3}$$

3.1 Prediction of performance measures using MGGP

To predict the quality characteristics of the weldments of stainless steel and titanium alloy work pieces obtained via Nd:YAG laser welding, multi-gene genetic programming is implemented in MATLAB 2017b. The experimental data are divided into two parts namely training data and testing data. Seventy percent of experimental data (nine data) is selected for training while remaining thirty percent (six data) for testing. Trial and error methodology has been adopted to decide the parameters on MGGP. The parameters are shown in Table 4. The following tuning parameters (Table 4) are considered as per literature [21, 63, 64].

The steps of MGGP model applied to weldments are presented through Figs. 10 and 11. Figure 10 shows the multi-gene regression model for the population in proposed MGGP model. The residual plot suggests the adequacy of the proposed model based on root-mean-square error. Figure 11 compares the actual and predicted data during training and testing phase. Since root-mean-square error of 0.09572 is

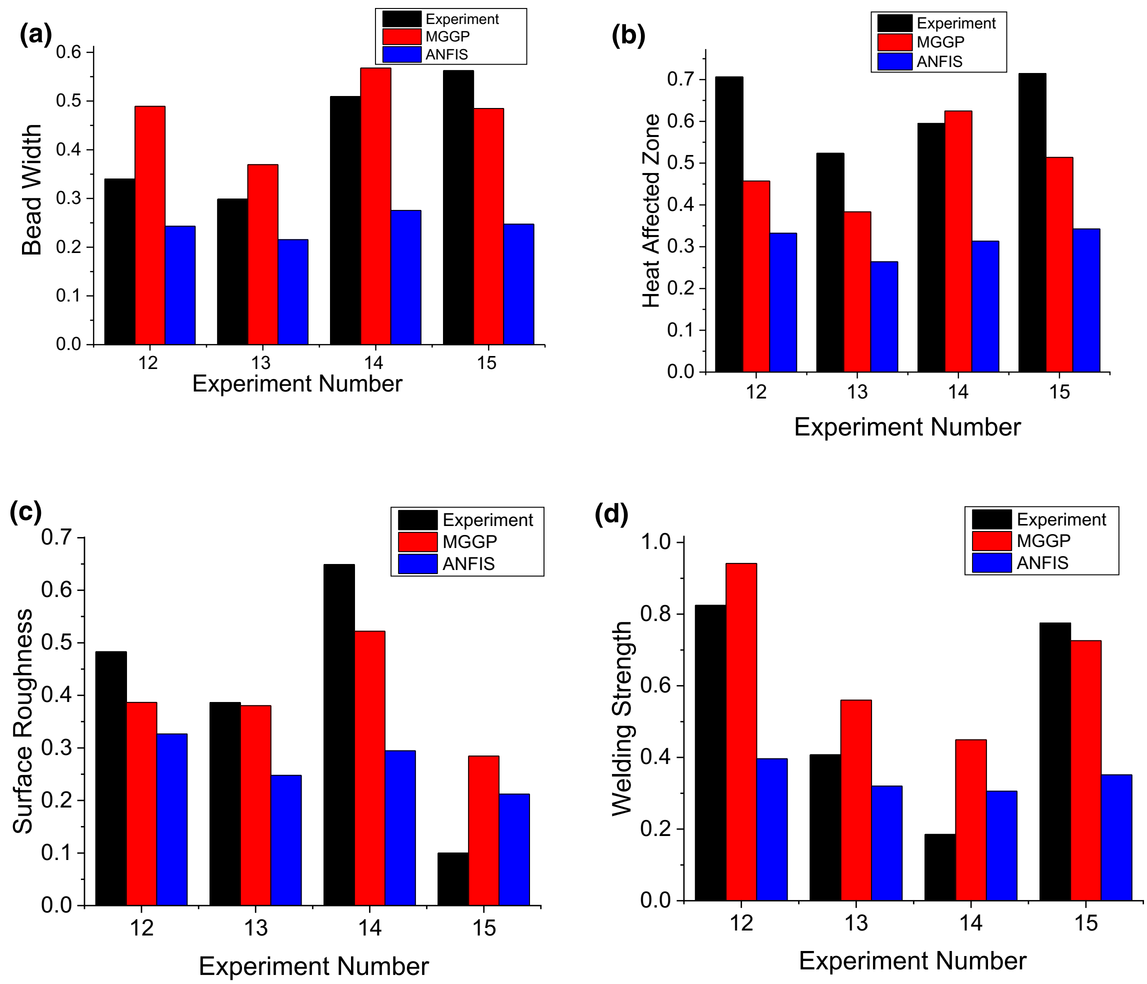


Fig. 12 Comparative graphs for experimental and predicted values for testing data using stainless steel as workpiece

obtained during testing phase, the model is considered to be adequate. Similarly, the analysis is performed for other performance measures of the weldments for both the workpieces. Tables 5 and 6 present the predicted performance measure of weldments for stainless steel and titanium alloy work pieces, respectively.

3.2 Comparison of prediction techniques

To analyze the effectiveness of both the predictive models, the predicted values obtained from MGGP and ANFIS for performance measures of weldments are compared with actual experimental values in Tables 5 and 6 for stainless steel and titanium alloy, respectively. From the study, it is observed that both the methods are quite adequate in predicting the performance measures during training phase because a maximum relative error of 6.3% and 6% is obtained for ANFIS and MGGP, respectively. These error values are well below the 10% limit indicated by the industrial partner involved in this research.

3.3 Experimental validation

To check the adequacy of the developed models, testing of each predictive model has been carried out. The unexamined experimental data have been used for testing and validation of the proposed ANFIS and MGGP models (Tables 5 and 6, respectively). The maximum relative errors of 11.2% and 9% are, respectively, obtained for ANFIS and MGGP in the testing phase. It is noted that MGGP model shows minimum root-mean-square error in comparison to ANFIS model for all the performance measures in testing phase both for stainless steel and titanium alloy workpieces (Table 7). Comparison of predicted values from ANFIS and MGGP with experimental data for testing data is made in Figs. 12 and 13 for stainless steel and titanium alloy, respectively. It is observed from the graphs that the values predicted by MGGP always match the experimental value. These results indicate that MGGP is superior over ANFIS in predicting the performance measures during laser welding.

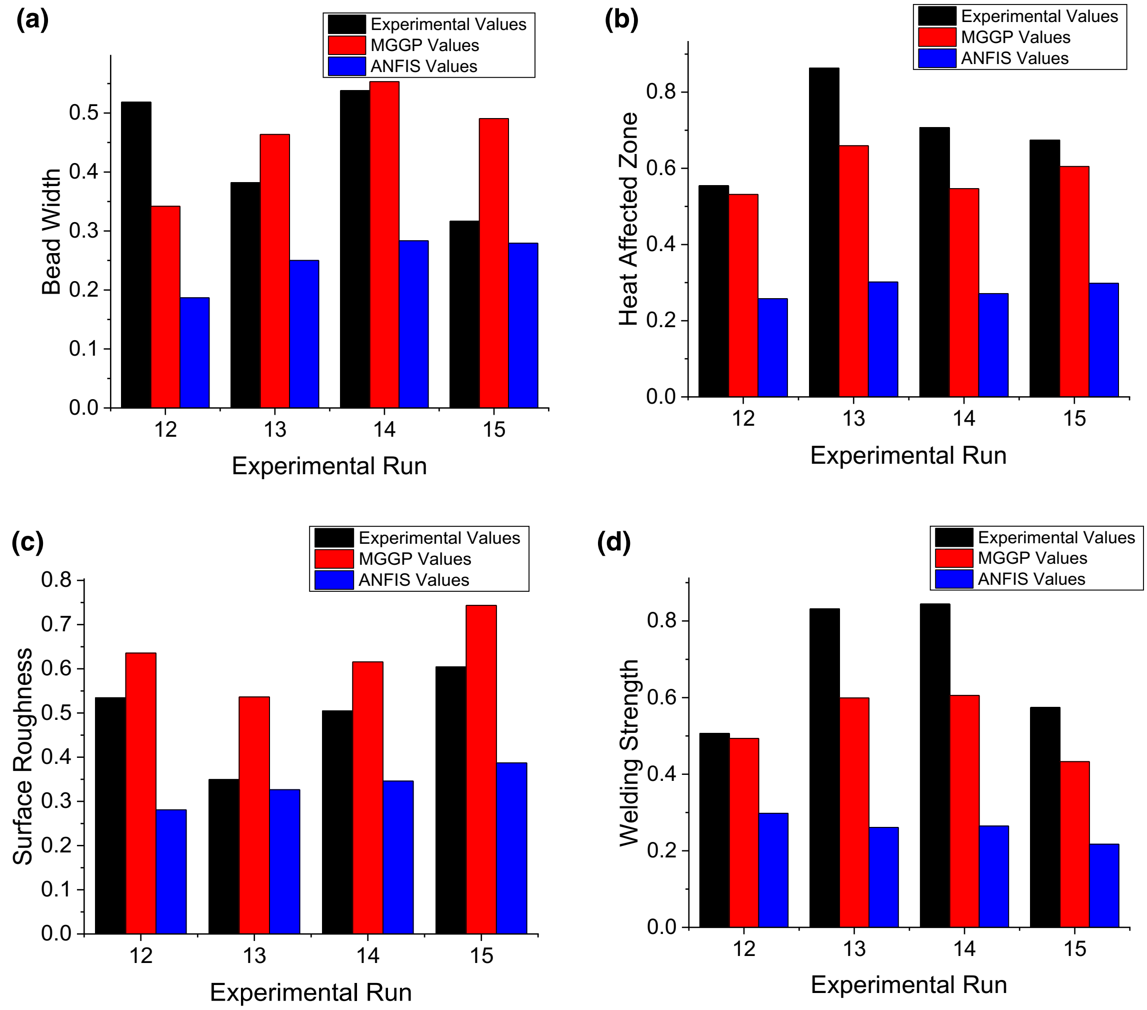


Fig. 13 Comparative graphs for experimental and predicted values for testing data using titanium alloy as workpiece

4 Conclusions

Two advanced AI techniques, namely ANFIS and MGGP, were implemented in this research to estimate the best welding responses and reduce the costly experimental verification. The following outcomes were obtained from the present study:

- A comparative study was conducted between the two techniques to analyze the adequacy of the predictive models for the prediction of performance measures of the weldments. It can be concluded that both the AI techniques are quite effective in predicting performance measures of weldments in the training phase. The root-mean-square error (RMSE) is below 10% for both the weldments.
- To determine the effectiveness of proposed AI models, it is required to correlate the findings on test data of both the models. The MGGP model shows an RMSE of only 0.1652 while the ANFIS model shows an RMSE of 0.4286 during prediction of the performance measures for both the processes and workpieces.
- The results obtained in this study indicate that MGGP is an adequate model for predicting the performance measures of laser drilling and laser welding process among competing artificial intelligence techniques. It is observed that the maximum mean relative error of 11.2% and 9% was obtained for ANFIS and MGGP, respectively, in the testing phase. From this study, it can be concluded that the MGGP model achieves a higher prediction accuracy than the ANFIS model.

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