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Artificial neural network modeling studies to predict the friction welding process parameters of Incoloy 800H joints

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A B S T R A C T

The present study focuses on friction welding process parameter optimization using a hybrid technique of ANN and different optimization algorithms. This optimization techniques are not only for the effective process modelling, but also to illustrate the correlation between the input and output responses of the friction welding of Incoloy 800H. In addition the focus is also to obtain optimal strength and hardness of joints with minimum burn off length. ANN based approaches could model this welding process of INCOLOY 800H in both forward and reverse directions efficiently, which are required for the automation of the same. Five different training algorithms were used to train ANN for both forward and reverse mapping and ANN tuned force approach was used for optimization. The paper makes a robust comparison of the performances of the five algorithms employing standard statistical indices. The results showed that GANN with 4-9-3 for forward and 4-7-3 for reverse mapping arrangement could outperform the other four approaches in most of the cases but not in all. Experiments on tensile strength (TS), microhardness (H) and burn off length (BOL) of the joints were performed with optimised parameter. It is concluded that this ANN model with genetic algorithm may provide good ability to predict the friction welding process parameters to weld Incoloy 800H.

1. Introduction

The Incoloy alloy 800H has resistance to high temperature corrosion and so it is used in many applications involving long term exposure to elevated temperatures in corrosive atmospheres. Incoloy 800H is mainly used as super heater tubes in power generation units and high temperature boiler tubes in nuclear power plants [1]. Friction welding is a solid state joint process that produces coalescence of materials under compressive force contact of work pieces rotating or moving relative to one another to produce heat and to plastically displace material from the faying surfaces. Friction welding has gained popularity because of several advantages; one among them is to weld alloys that cannot be welded otherwise.

Recently, in the field of joining materials, computer aided artificial neural network (ANN) modelling has gained increased importance. Artificial neural network (ANN) is effectively used for modelling of manufacturing processes such as metal cutting, forming, etc. Neural network model is more accurate than those of linear and curvilinear multiple regression model. Several attempts were made to carry out input output modelling of various welding processes in forward direction using statistical regression analysis, but those related to reverse mapping had not received much attention, till date. However, the regression analysis was carried out response wise but it did not provide the complete information of the process. These problems could be solved using neural network based approaches.

R. Damodaram et al. [2] studied mechanical and metallurgical behaviour of continuous drive friction welded 718 superalloys. They observed sufficient mechanical properties obtained through friction welding. Also there is an occurrence of dynamic recrystallization of weld zones which caused hardening effect. A. Ambroziak [3] investigated friction welding of similar material welding Incoloy MA 956/Incoloy MA 956 and dissimilar material

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Table 1
Base material chemical composition (wt%).

C	Si	Mn	Cr	Mo	Ni	Al	Cu	Nb	Ti	Fe
0.06	0.29	0.93	20.14	0.08	30.28	0.58	0.18	0.03	0.56	45.1

Table 2
Friction welding parameters.

Parameter	Unit	Notation	Factor levels				
			−2	−1	0	1	2
Heating pressure	MPa	HP	60	75	90	105	120
Heating time	Sec	HT	4	5	6	7	8
Upsetting pressure	MPa	UP	135	150	165	180	195
Upsetting time	Sec	UT	5	6	7	8	9

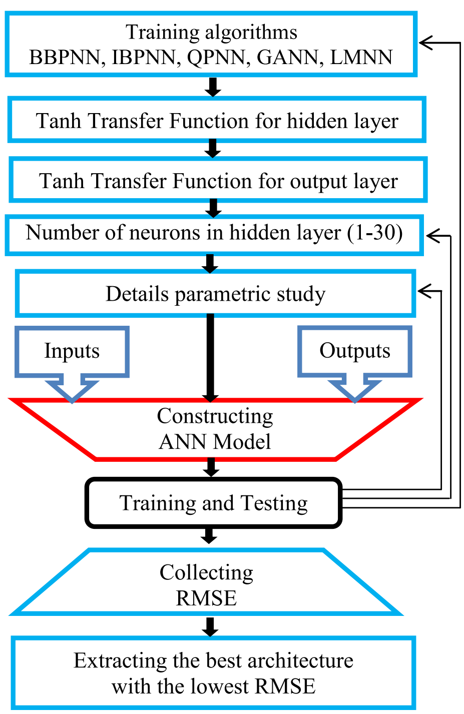


Fig. 1. Flow chart for develop ANN model.

welding Incoloy MA 956/austenitic steel. The sound quality joints were obtained. They concluded that prolonged friction time and large upsetting pressure will result in uniform weld metal zones. Z.W. Huang et al. [4] carried out characterization work of dissimilar material weldments of alloy 720Li and IN718. The inertia friction welding was used for joining of these Nickel based superalloys. They observed changes in phase distribution and grain structure on either side of the weld line but the weldments were found to be free of cracks and micropores. Song, K.H. and Nakata, K. [5] performed friction stir welding of Inconel 718. They studied mechanical and microstructural characteristics of weldments before and after post weld heat treatments. They observed improvements in mechanical properties in the weldments as compared to base material. After post weld heat treatments the tensile strength and hardness enhanced by 40–50% compared to weldments.

Paventhan et al. [6] have done the optimization of friction welding process parameters for joining carbon steel and stainless steel. They developed an empirical relationship to predict the tensile strength of friction welded AISI 1040 grade medium carbon steel and AISI 304 austenitic stainless steel, incorporating the process parameters namely friction force, forging force, friction time and forging time, which have great influence on strength of the joints. Response surface methodology was applied to optimize the friction welding process parameters to attain maximum tensile strength of the joint. A new welding method was developed for fully automatic pipelines girth welding using a new friction welding machine. The proposed new welding procedure is called Friex and it is a new variant of the well-known friction welding process. An intermediate ring is rotated in between the pipes to be welded to generate the heat necessary to realize the weld [7]. The optimum welding process parameters in friction welding of AISI 904 L super austenitic stainless steel with the help of regression analysis and evolutionary algorithms such as genetic algorithm and simulated annealing have been studied. They found that optimized parameter was obtained for a maximum fatigue life and minimum welding time [8]. A new approach for the optimization of friction welding parameters on carbon-stainless steel metal with multiple response (tensile strength and shrinkage) based on orthogonal array with grey relational analysis was presented. Experimental results showed that the responses in friction welding process could be improved effectively through this approach [9].

The input, output relationships of the butt welding of SS304 plates in both forward and reverse directions using BPNN and GANN was investigated, and the latter was found to perform

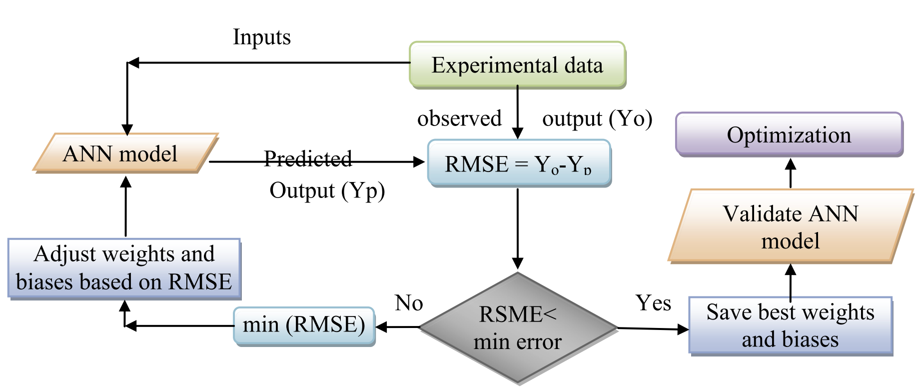


Fig. 2. Flow chart for optimization.

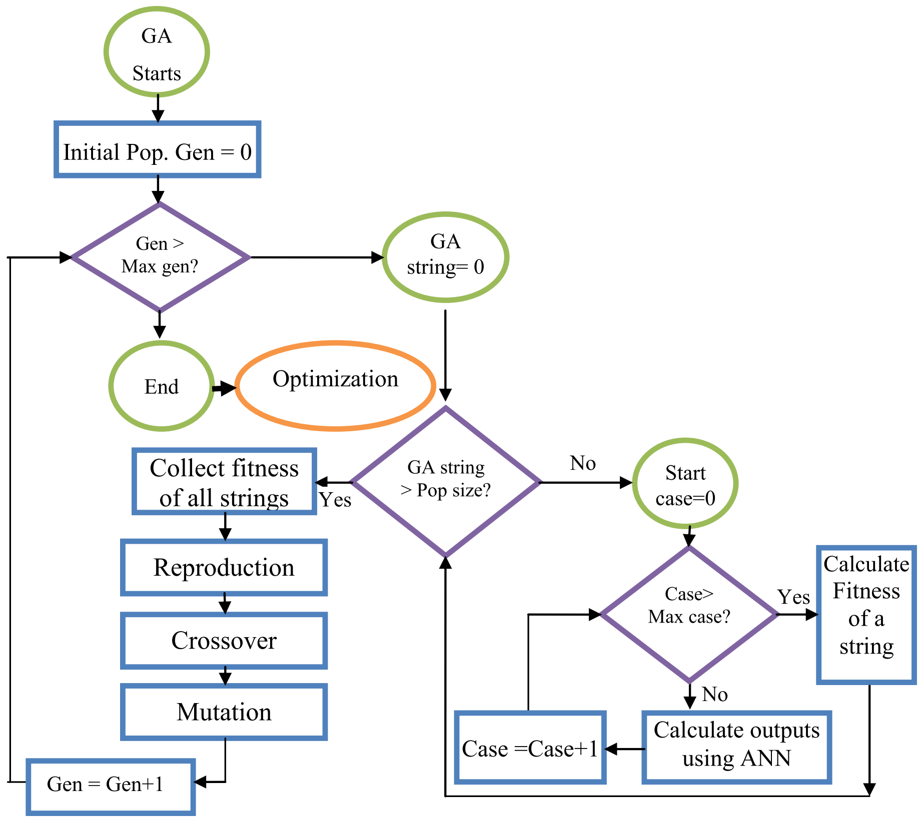


Fig. 3. A schematic view of GA-ANN system [23].

better than the former [10]. A proposed back propagation network (BPN) model to predict weld bead geometry (bead width and penetration) and tensile strength in laser welding of austenitic stainless steels [11]. The BPNN, genetic algorithm tuned neural network (GANN) and radial basis function neural network (RBFNN) for the modelling of bead on plate welding process using electron beam welding process was successfully used [12–14]. A comparison of back bead prediction (width and depth) of the GMAW process using multiple regression analysis (MRA) and ANN analysis was carried out [15]. The possibility of the use of neural networks for the calculation of the mechanical properties of friction stir welded (FSW) aluminium plates incorporating process parameters such as rotational speed and welding speed have been studied [16]. The welding parameters were optimized in terms of ratios of penetration to fuse zone width and penetration to HAZ width for CO_2 laser welding of medium carbon steel using a back propagation neural network (BPNN) [17]. ANN to correlate the collected data to the process parameters (laser power, speed and material thickness) to weld austenitic stainless steel butt joints by CO_2 laser welding irradiation was used [18]. In order to select the optimum network parameters a 24 factorial design was used. Evaluation of ANN for monitoring and control of the plasma arc welding process was carried out [19]. A comparison between back propagation and counter propagation networks in the modelling of the TIG welding process was made [20]. Both BPN and learning vector quantization neural networks to predict the laser welding (LW) parameters for butt joints were used [21]. The neural networks (NNs) can be used to develop knowledge based systems of the processes in the form of some quantitative models [22].

Based on the above literature it is very clear that only a very few work was done on the friction welding parameter optimization of Incoloy 800H. The present study makes an attempt to use a hybrid technique of ANN modelling and optimization not only for the effective process modelling, input output correlation of the friction welding of Incoloy 800H in both forward and reverse direction which might be required for its automation but also to obtain optimal strength and hardness of joints with minimum burn off length.

2. Experimental data collection

Incoloy 800H in the form of bars of diameter 12 mm and length 100 mm was used. The samples were received in cylindrical rod of 1000 mm length. They were cut into 100 mm length by abrasive cutting machine. Later they were cleaned with acetone to ensure clean faying surface and the chemical composition of the as received base material is shown in Table 1. The tensile strength of the base metal is 683 MPa.

The friction welding machine employed in this present study is a KUKA continuous drive friction. Table 2 shows the friction welding parameters used in this study.

There are two stages of continuous drive friction welding – a. Heating stage b. Upsetting stage. In the heating stage, the faying surfaces are kept in contact and one part is rotated and pressure is applied on the non-rotating part. This pressure is known as 'heating pressure'. The time for which this pressure is applied is 'heating time'. In the upsetting stage, the rotation is stopped by braking and pressure is increased. In this stage, due to higher pressure the forging of parts takes place. This pressure is taken as 'upsetting pressure'. The time for which it is applied is given as 'upsetting time'. The hot weld metal consolidated in this stage. Before the experiments, the range of parameters was decided through various mechanical tests. In the range which was used for experiments, good mechanical properties were obtained. Hence that range of process parameters was finalized.

Before welding, each faying surface was cleaned with acetone to ensure cleanliness of the surfaces. The central composite design of experiment was done based on the machine capacity and various process parameters. The tensile strength of the welded joints was conducted as per ASTM A370 standard. The microhardness values were collected using Vickers microhardness testing machine using a load of 500 g and dwell time is 20 s. Hardness was measured at the Weld, the hardness measures are the average values of three readings. Fracture accurse 4–6 mm away from the weld interface during tensile testing. The experimental values are presented in the Appendix 1.

3. Methods of analysis

Software tool: Commercially available Neural Power, professional version 2.5 was employed in this study (CPCX Software). The

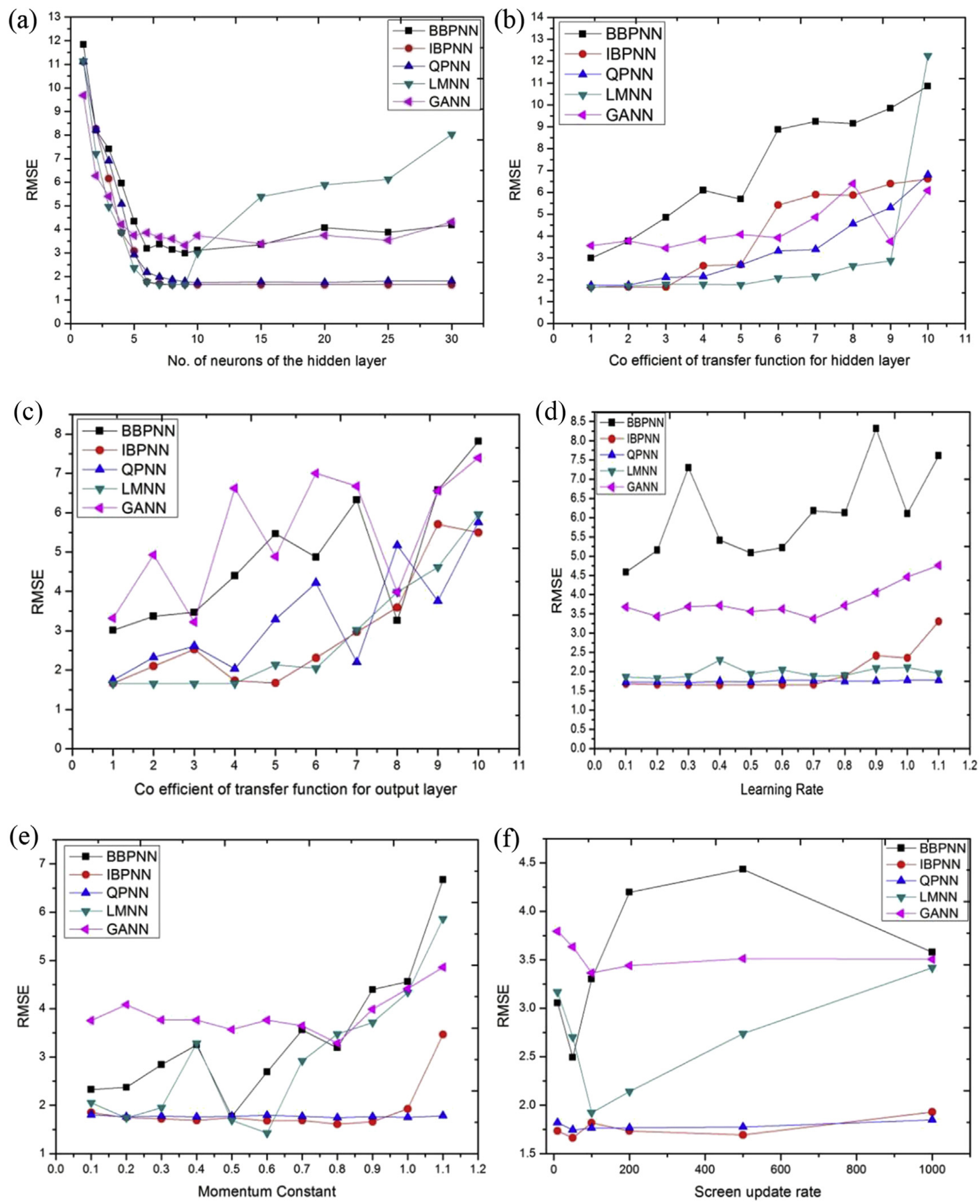


Fig. 4. Parametric study conducted of five algorithms for forward mapping (a–j).

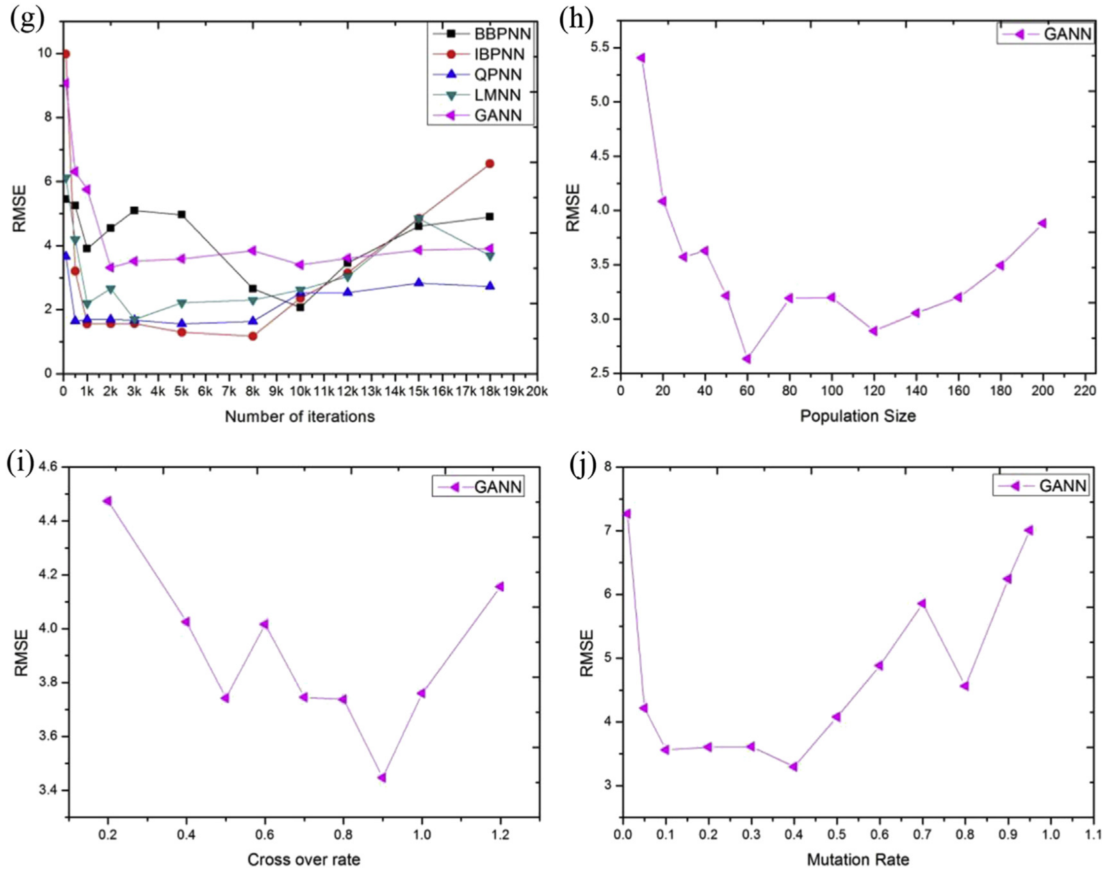


Fig. 4. (*continued*).

models were developed to establish input output correlations of the friction welding of Incoloy 800H using artificial neural networks and the developed ANN model was further used for optimization of friction welding parameters using ANN force approach as discussed below:

Friction welding process was modelled in both the forward and reverse directions using five ANN based algorithms namely batch back propagation neural network (BBPNN), incremental back propagation neural network (IBPNN), quick propagation neural network (QPNN), levenberg marquardt algorithm tuned neural network (LMNN) and genetic algorithm tuned neural network (GANN) to predict the output(s) or response(s) for a given set of input parameters. Four input parameters, namely heating pressure (HP), heating time (HT), upsetting pressure (UP) and upsetting time (UT) were considered for the forward model. Three responses, namely tensile strength (TS), microhardness (H) and burn off length (BOL) were predicted as outputs of the forward model. Three desired responses were fed as inputs to the model and the outputs were obtained in terms of the process parameters to be set to achieve the desired set of responses. The mapping of the process in reverse direction might be required for its automation. The main objectives of ANN are to develop methods and models from experiment and examples for solving problems, usually solved by the conventional techniques. ANN is a quite efficient learning tool for the generalization of deformation behaviour characteristics, and a computing tool with a high precision for the constitutive relationships between inputs and outputs by simulating the working process of biological neurons with network structures. Generally it consists of an input layer, output layer and mostly used one hidden layer. To train the network transfer or activation function is used.

In the present study, the parameters for learning were decided by detail parametric studies and 'tanh' activation function was used for both hidden and output layer. The 31 responses obtained from the experiment were divided into three sets of 21, 5 and 5 for training, testing and validation respectively which were done by the option available in the software. The flow chart for training the ANN model is shown in Fig. 1. The statistical measures used in this study are described below:

$$\text{Coefficient of determination (DC)} = 1 - \frac{\sum_{i=1}^{n}(P_i - E)^2}{\sum_{i=1}^{n}(E_i - \overline{E})^2} \tag{1}$$

$$\text{Corelation co efficient (R)} = \frac{\sum_{i=1}^{n}(E_i - \overline{E})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n}(E_i - \overline{E})^2 \sum_{i=1}^{n}(P_i - \overline{P})^2}} \tag{2}$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - E_i)^2} \tag{3}$$

Average absolute percentage deviation (AAPD)

$$= \left\{ \frac{\left[\sum_{i=1}^{n} \left(\frac{|P_i - E_i|}{P_i} \right) \right]}{n} \right\} \times 100 \quad (4)$$

here E_i = experimental value, P_i = predicted value, $\overline{E}$ = mean value of E_i, $\overline{P}$ = mean value of P_i

A numbers of artificial neurons combined through weights, which is also described as coefficients and adjustable factors are present in an ANN model, so ANN is considered as a system with parameters. The weighed sum of the inputs constitutes the activation of the neuron. The activation signal is passed through transfer function to produce a single output of the neuron. Coefficients optimization in training continues until prediction errors is minimized, and the system gets accuracy with specified level. New input data or information can be given to the network when it is trained and tested.

Nowadays, several metaheuristic algorithms have been proposed to solve the optimization problem. Such search algorithms include genetic algorithm (GA), ant colony optimization (ACO), and particle swarm optimization (PSO). Since the MLP neural network was used for modelling and optimization, the optimization procedure in this research is called a neural network based multi objective optimization. The best developed model by ANN is used to optimization of process parameters of the friction welding of Incoloy 800H using ANN tuned force approach. The flow chart for optimization is shown in Fig. 2.

3.1. Genetic algorithm

In the present work we used an evolution of Genetic Algorithms (GA). The flow chart for genetic algorithm is shown in Fig. 3.

Fig. 3 shows a schematic view of a GA-ANN system in which Genetic Algorithm (GA) was used to evolve an optimal neural network system through the batch mode of training. The ANN parameters used in this model are transfer function, connecting weights and bias values which were optimized using a GA. The

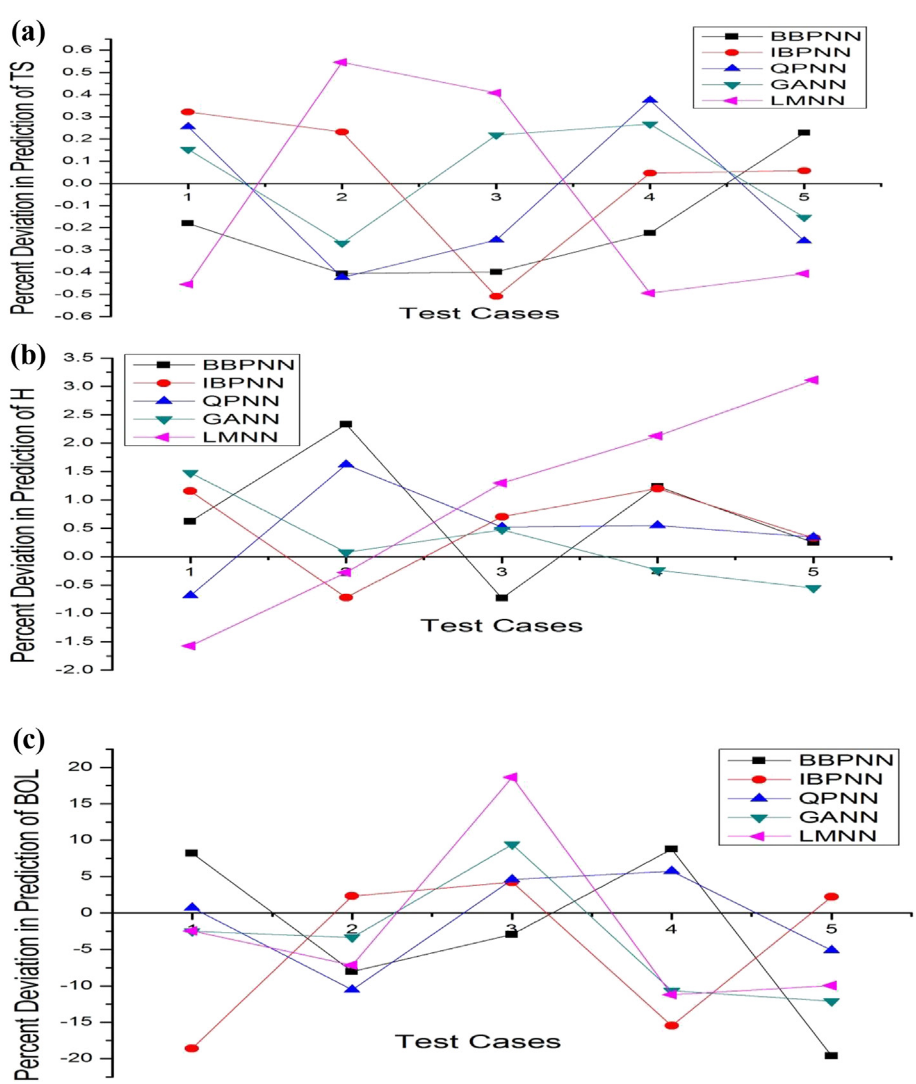


Fig. 5. Comparisons of different approaches in terms of percent deviation in predictions of various responses using all five ANN based forward models (a–c).

statistical index root mean square error (RMSE) was used to calculate the fitness of the GA string. The GA tried to evolve an optimized ANN system through a number of generations using fitness information calculated by detailed parametric studies. Interested reader may refer to [23] for the details description of the GA-ANN system.

4. Results and discussion

At first, the input output models were developed as discussed earlier and the test cases were passed through it to check the adequacy of the model. All five algorithms were used to train the neural networks. In order to determine the optimum parameters, a detailed parametric study was conducted. A series of topologies were examined in which the number of neurons was varied from 1 to 30 and likewise all other parameters such as coefficient of transfer function for hidden and output layer, learning rate, momentum constant, screen update rate, maximum number of iterations, population size, cross over rate and mutation rate were examined as shown in the Figs. 4 and 6. The root mean square error (RMSE) was used as the error function. Decision on the optimum topology was based on the minimum error of testing. Each topology was repeated five times to avoid random correlation due to the random initialization of the weights. Also, the coefficient of

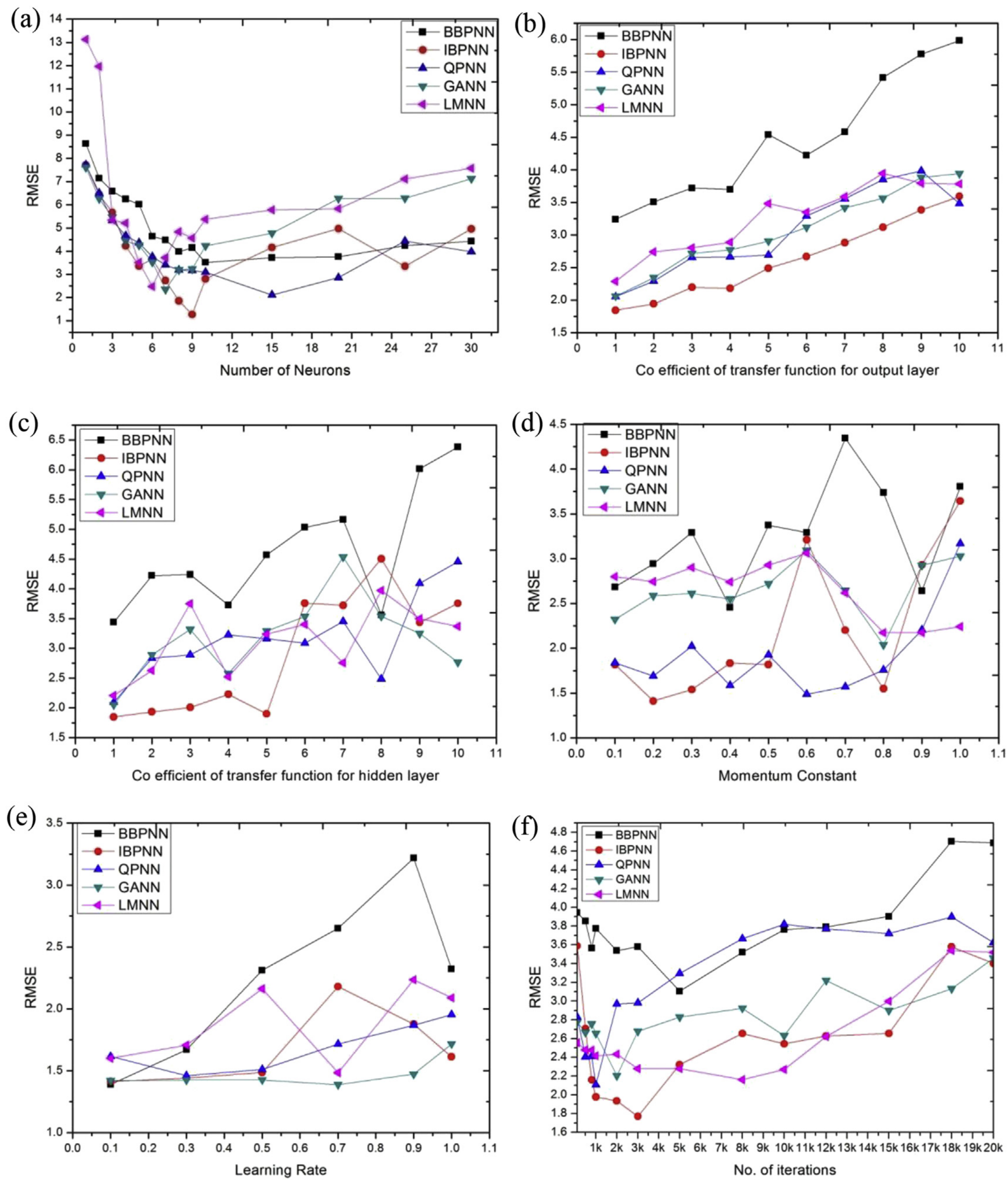


Fig. 6. Parametric study conducted for five algorithms for reverse mapping (a–j).

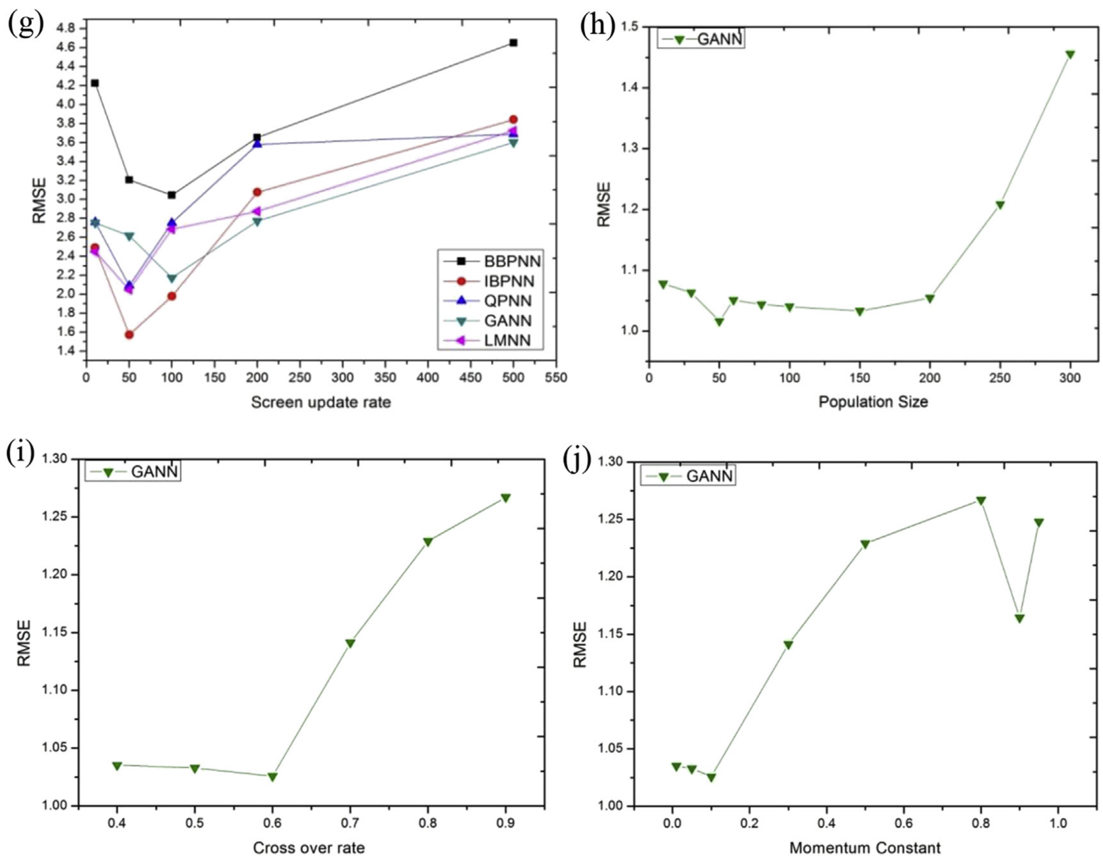


Fig. 6. (*continued*).

determination (DC) and co-relation coefficient (R) were used as a measure of the predictive ability of the network and average absolute percentage deviation (AAPD) was used on test cases for comparisons of different approaches.

4.1. Results of forward mapping

A detailed parametric study was carried out to obtain optimal set of parameters for the developed BBPNN, IBPNN, QPNN, LMNN and GANN models. The details parametric studies for all five forward models are shown in Fig. 4.

The parametric studies of the five models were carried out to determine the set of optimal parameters corresponding to the best fitness. From Fig. 4(a) it is observed that the optimal number of neurons in the hidden layer is 9 in case of GANN corresponding to lowest RMSE. Likewise from Fig. 4 it can be found that the coefficient of transfer function for hidden and output layer, learning rate, momentum constant, screen update rate and maximum number of iterations were found to be equal to 1, 0.7, 0.8, 100 and 2000 respectively for the developed GANN network. The optimum values of GA parameters such as population size cross over rate and mutation rate are found to be 60, 0.9 and 0.4 respectively. All optimized parameters obtained for all five models are presented in Table 3.

Statistical measures such as root mean square error (RMSE), correlation coefficient (R) and determination coefficient (DC) of five learning algorithms are shown in Table 4.

Table 3
Optimized parameters for all five ANN based forward models.

Sl. no.	Parameters	Symbol	BBPNN	IBPNN	QPNN	GANN	LMNN
1.	Number of neurons of the hidden layer	Hn	9	10	10	9	7
2.	Coefficient of transfer functions						
	For hidden layer	a_h	1	1	1	1	1
	For output layer	a_o	1	1	1	1	1
3.	Learning rate	λ_l	0.1	0.6	0.3	0.7	0.2
4.	Momentum constant	A	0.5	0.8	0.8	0.8	0.6
5.	Screen update rate	B	50	50	50	100	100
6.	Maximum number of iterations	Z	10,000	1000	5000	2000	3000
7.	Population size	P	–	–	–	60	–
8.	Cross over rate	λ_c	–	–	–	0.9	–
9.	Mutation rate	λ_m	–	–	–	0.4	–

Table 4
Statistical measures of all five learning algorithms for ANN model.

Learning algorithm	The best model	Training data			Testing data		
		Avg. RMSE	Avg. R	Avg. DC	Avg. RMSE	Avg. R	Avg. DC
BBP	4-9-3	2.5947	0.9240	0.8552	1.8370	0.9764	0.9143
IBP	4-10-3	1.4720	0.9535	0.9102	1.5339	0.9878	0.9764
QP	4-10-3	1.9799	0.9535	0.9103	1.5141	0.9857	0.9713
GA	4-9-3	0.9628	0.9678	0.9235	1.2148	0.9978	0.9899
LM	4-7-3	1.5012	0.9378	0.9072	2.6498	0.9546	0.9273

Table 5
Average absolute percent deviation in predictions of different responses using all five ANN based forward models.

Sl. no.	Output or response	Average absolute % deviation using BBPNN model	Average absolute % deviation using IBPNN model	Average absolute % deviation using QPNN model	Average absolute % deviation using LMNN model	Average absolute % deviation using GANN model
1.	Tensile strength	0.287778	0.232194	0.313545	0.461916	0.211904
2.	Hardness	1.034111	0.822267	0.744285	1.678174	0.659194
3.	Burn off length	9.510947	8.579526	5.344329	9.875222	7.600937

The RMSE value for both training and testing data is lowest in case of GA learning algorithm. The R and DC value are highest for GA algorithm in both cases. The DC shows the level of model fitness. If value of DC is closer to 1, the model is considered as a better design and fits to the actual data. Hence GA algorithm model is better than other four learning algorithms.

The performance of the developed model was checked by passing the test cases through it. The percent deviation in prediction of different output parameters are shown in Fig. 5.

Percentage deviation is another important index to evaluate the ANN output error between the actual and the predicted output. Table 5 displays the average absolute percent deviation in predictions of different responses as obtained by these approaches.

From Table 5 it is seen that the average absolute percentage deviation for tensile strength and hardness is lowest by using GANN model and that of burn length is lowest in the case of QPNN model.

4.1.1. Summary

The RMSE value is low for GANN in both training and testing set as compared to other four learning algorithms. All the developed five approaches could predict the responses reasonably well (within 10%). However, the performance of GANN is found to be slightly better than that of other ANN based approaches for two responses out of three. It might happen because their performances are generally found to be data dependent. Moreover, the results of GANN are seen to be comparable with those of IBPNN and QPNN. Therefore, either the GANN or IBPNN or QPNN is recommended for the forward mapping of this process.

4.2. Results of reverse mapping

Reverse mapping of this welding process was also carried out using five ANN based approaches to predict the required process parameters in order to obtain a desired set of outputs or responses. The detail parametric studies of all five learning algorithms were carried out to obtain the optimum values of learning parameters of different ANN algorithms as shown in Fig. 6.

The appropriate number of neurons in hidden layer, coefficient of transfer functions, learning rate, number of iterations and GA parameters like population size, cross over rate and momentum constant were obtained through a systematic parametric study, as shown in Fig. 6. The optimum parameters values were obtained same way as explained in the forward mapping and presented in the Table 6.

Table 6
Optimized parameters for all five ANN based reverse models.

Sr. no.	Parameters	Symbol	BBPNN	IBPNN	QPNN	GANN	LMNN
1.	Number of neurons of the hidden layer	Hn	10	8	15	7	6
2.	Coefficient of transfer functions						
	For hidden layer	a_h	1	1	1	1	1
	For output layer	a_o	1	1	1	1	1
3.	Learning rate	Λ	0.1	0.1	0.3	0.7	0.8
4.	Momentum constant	Α	0.4	0.2	0.6	0.8	0.8
5.	Screen update rate	Β	100	50	50	100	50
6.	Number of iterations	Ζ	5000	3000	1000	2000	8000
7.	Population size	Ρ	–	–	–	50	–
8.	Cross over rate	λ_c	–	–	–	0.6	–
9.	Mutation rate	λ_m	–	–	–	0.1	–

The performance of the developed model was tested on five test cases. The test cases were passed through the optimized ANN networks to check its performance for predicting the process parameters. The values of percent deviation in predictions of the process parameters are shown in Fig. 7. The average absolute percent deviation in predictions of different responses as obtained by these approaches is tabulated in Table 7. The minimum value of average absolute percentage deviation in prediction of HP, HT, UP and UT had turned out to be equal to 2.38, 4.38, 1.25 and 3.29 respectively.

4.2.1. Summary

The performance of the GANN was found to be better than that of the other algorithms in most of the cases but not in all. The GANN gave better results for three responses out of four. This indicates that the performances of these approaches are data dependent. Although GANN, QPNN and LMNN based approaches could tackle the problem of reverse mapping of this process, GANN is recommended finally based on its performance in terms of accuracy in predictions.

4.2.2. Comparisons

Form the above study; it is observed that ANN based approaches could model the input output relationships of this process accurately in both forward and reverse directions. In order to capture the information of the process completely, all the outputs were to be modelled simultaneously, which could be done using the ANN based approaches. It is important to mention that in order to automate any process, its input output relationships are to be known accurately in both the forward and reverse directions ANN based approaches have the potential to serve this purpose. As the GANN could perform better than other four ANN based approaches in case of both forward and reverse mappings, it is finally recommended for the input output modelling of this process.

4.3. Genetic algorithm tuned neural network

From the above study it is found that GANN could perform better than other four ANN based approaches in case of both forward and reverse mappings. The developed GANN model consisted of an input layer with four neurons corresponding to the four input parameters, a hidden layer and an output layer with three neurons

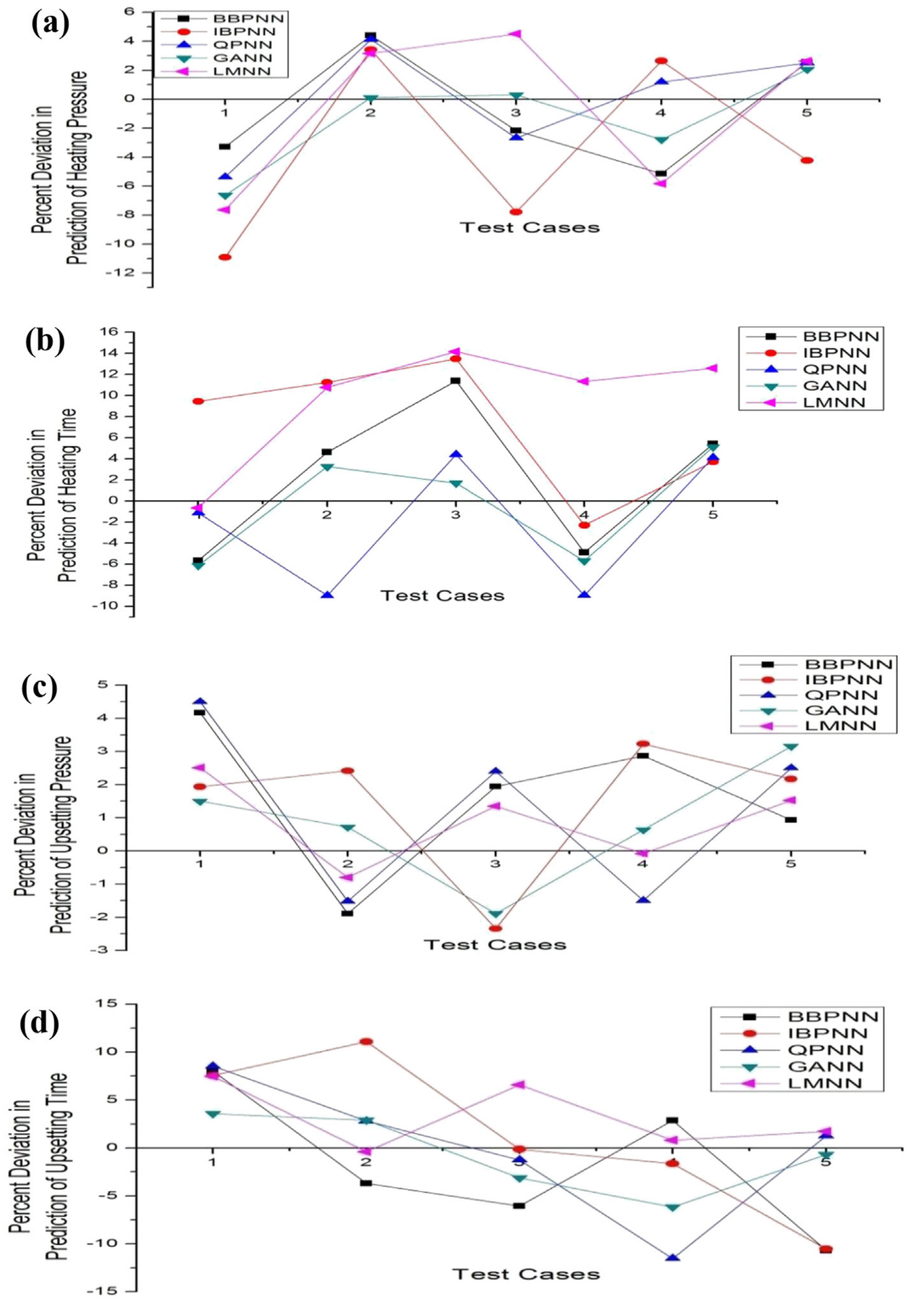


Fig. 7. Comparisons of different approaches in terms of percent deviation in predictions of various responses using all five ANN based reverse models (a–d).

Table 7
Average absolute percent deviation in predictions of different responses using all five ANN based reverse models.

Sr. no.	Output or response	Average absolute % deviation using BBPNN model	Average absolute % deviation using IBPNN model	Average absolute % deviation using QPNN model	Average absolute % deviation using LMNN model	Average absolute % deviation using GANN model
1.	Heating pressure	3.51022	5.79672	3.172929	4.75234	2.377549
2.	Heating time	6.402291	8.038938	5.524038	9.907685	4.38187
3.	Upsetting pressure	2.357951	2.418343	2.482829	1.254168	1.578344
4.	Upsetting time	6.266713	6.197504	5.071739	3.404746	3.291999

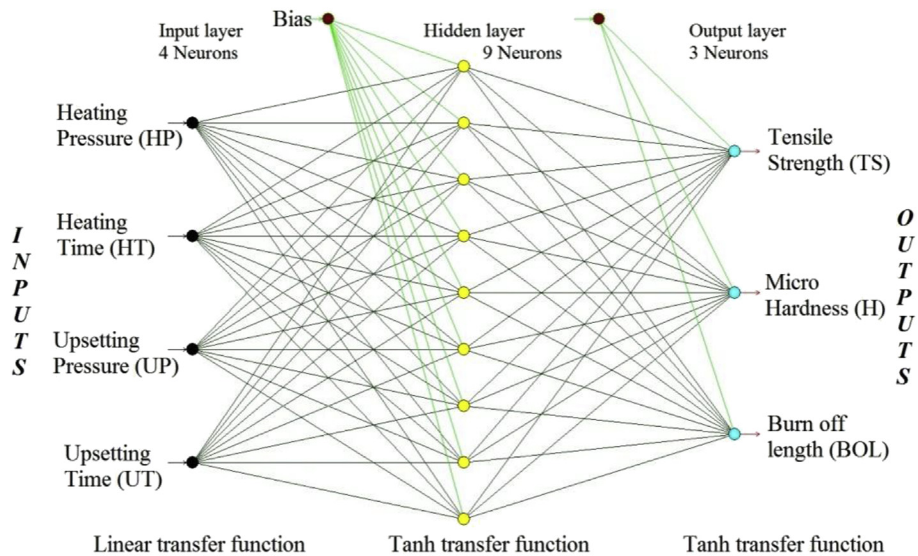


Fig. 8. A schematic view of GANN.

corresponding to the three outputs. The hidden layer contained 9 neurons, as it was decided through a detailed parametric study. The initial values of connecting weights between the input and hidden layers and those between the hidden and output layers were generated at random. The schematic view of the GANN is shown in Fig. 8.

From Fig. 8 it can be observed that there are four neurons in input layer corresponding to four input parameters, three neurons in output layer corresponding to three outputs and nine neurons for hidden layer. Linear transfer function for input layer and Tanh transfer function for both hidden and output layer. The experimentally calculated values and GANN predicted values are shown in Table 8. The averages RMSE of training, testing and validation data are 0.9628, 1.2148 and 1.2196 respectively. The scatter plot and 5% error bar of GANN predicted Tensile strength, Microhardness and Burn off length versus experimentally observed for all data set are sown in Fig. 9.

Table 8
Observed and GANN predicted responses.

Sl. no.	Observed (TS)	Predicted (TS)	Observed (H)	Predicted (H)	Observed (BOL)	Predicted (BOL)
Unit	MPa	MPa	VHN	VHN	mm	mm
Training set						
1	703.78	703.7619	182	182.0001	5.2	5.12302
2	753.6	752.54	186	185.06	4.5	4.5223
3	768.08	768.0796	191	191.4	4.7	4.599961
4	796.08	796.0819	185	182.13	5.8	5.8103
5	748.2	748.1998	197	197.5601	6.7	6.60658
6	766.58	766.5802	180	179.9998	3.5	3.478
7	814.7	814.4558	176	176.0444	3.9	3.8834
8	703.14	703.3622	180	179.9997	7.3	7.293826
9	782.44	782.4409	176	176.0466	5.2	5.23424
10	771.59	771.5907	198	198.0541	5.5	5.4683
11	783.4	783.4014	202	201.3245	2.9	2.954858
12	759.52	759.519	206	206.0001	6.8	6.8378
13	750.84	750.8398	184	184.0123	6.3	6.3154
14	746.27	746.662	177	174.6667	3.5	3.233322
15	753.09	753.0907	187	187.0001	4.5	4.4853
16	765.55	765.551	190	189.24	5	4.993
17	748.4	746.662	187	184.6667	5.6	5.233322
18	743.2	746.662	192	190.6667	5.4	5.233322
19	745.1	746.662	180	184.6667	5.8	5.633322
20	747.7	746.662	182	184.6667	5.6	5.233322
21	749.3	746.662	190	188.6667	5.5	5.233322
Testing set						
22	743.49	744.63	183	185.74	6.2	6.0506
23	788.82	786.7	200	200.15	5.5	5.3228
24	785.25	786.96	195	195.93	3.2	3.533
25	754.15	756.17	210	209.5	6.6	5.9639
26	748.6	747.46	194	192.93	5.5	4.9057
Validation set						
27	727.53	725.0667	184	184.549	6.4	5.8792
28	746.1	744.9805	187	186.1163	4.3	4.668198
29	791.03	792.0057	195	192.7796	3.9	4.431429
30	789.38	790.6652	205	202.4672	6.1	5.6919
31	745.39	746.6652	194	195.4672	5.4	5.126919

4.3.1. *Model validation*

The predictive ability of generated model was estimated using validation data (unseen data) which were excluded from training. The actual and predicted TS, H and BOL for validation data are also presented in Table 10. The root mean squared error (RMSE) for validation data is 1.2196; the coefficient of determination (DC) is 0.9899 and the correlation coefficient (R) is 0.9978. This results shows that the predictive accuracy of the model is high. Fig. 10 shows a comparison between actual values and model predicted output values using adopted artificial neural network model for validating data.

The importance of different input parameters of friction welding process for Incoloy 800H is shown in the Fig. 11.

From Fig. 11 it can be observed that the importance of heating pressure, upsetting pressure, upsetting time and heating time are 38.34, 25.48, 21.3 and 14.88% respectively. The order of importance of input parameters for friction welding of Incoloy 800H is observed as HP > UP > UT > HT.

4.4. *Optimization results*

The optimization of friction welding parameters for welding of Incoloy 800H is carried out using GANN tuned force approach. The optimum results obtained by GANN tuned force approach is shown in Table 9.

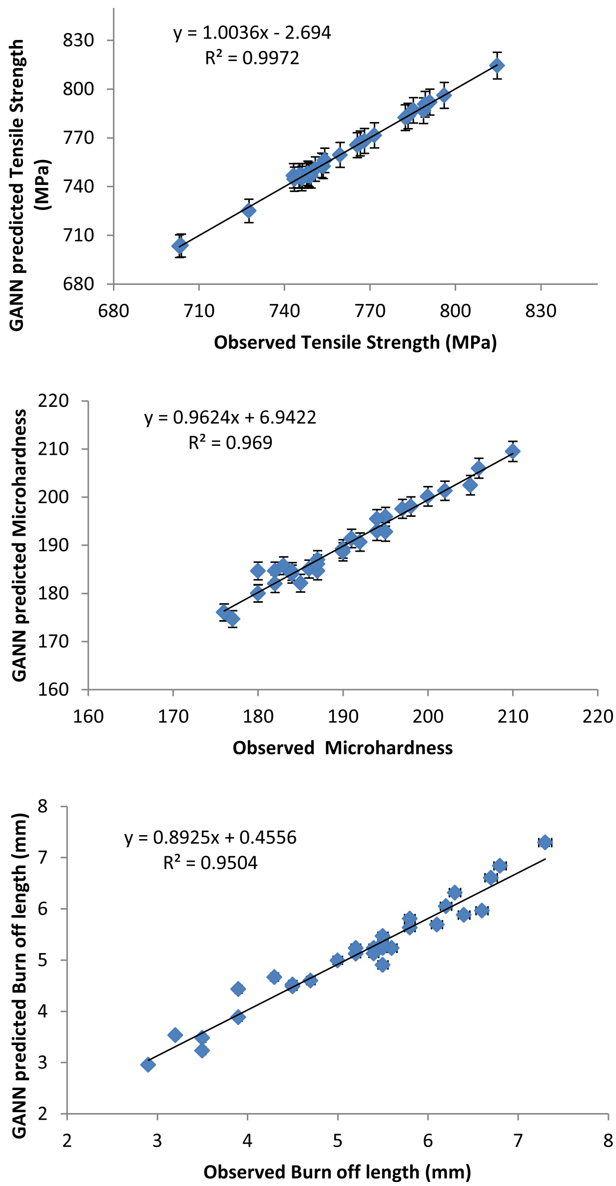


Fig. 9. The scatter plots and percentage error bar of GANN predicted tensile strength, microhardness and burn off length versus experimentally observed for all data set.

4.4.1. Confirmation test

The best input parameters obtained through GANN tuned force approach was used to process the friction joint of Incoloy 800H experimentally. The tensile strength, microhardness and burn off length were evaluated. The macrographs of friction welded specimens are presented in Fig. 12.

Typical tensile tested specimens which were machined from the processed joints at two optimized inputs parameters by GANN tuned force approach are presented in Fig. 13. It can be understood that the joints failed mostly at the nearby joint zone and partly through the parent material.

The GANN tuned force approach predicted and experimental input and output parameters of the friction processed similar joints of Incoloy 800H are presented in Table 10.

From the Table 10, it can be observed that the very close agreement between predicted and experimental data confirms the potential applicability of GANN tuned force approach optimization technique. Joints exhibit higher quality. The good agreement between GANN tuned force approach and experimentally obtained tensile strength, microhardness and burn off length confirms the applicability GANN tuned force approach for optimization of process parameters in the friction welding process.

4.4.1.1. Concluding remarks. In this study, an artificial neural network for friction welding of Incoloy 800H has been optimized through a proper selection of the training algorithm. Different ANNs, trained with standard or incremental back propagation (IBP), batch back propagation (BBP), quick propagation (QP), Levenberg Marquardt back propagation (LM) and Genetic Algorithm (GANN), have been evaluated with respect to their predictive ability. A robust comparison of the performances of the above five algorithms was made employing standard statistical indices. Artificial neural network models were used to establish the input output relationships and optimization of input parameters of this process. The friction welding of the Incoloy 800H, its input output modelling were carried out successfully in both forward & reverse directions, and optimization of process parameters were carried out successfully. The following conclusions were drawn from this study:

- The forward models developed using quick propagation neural network (QPNN), incremental back propagation neural network

Table 9
Optimization results of GANN tuned force approach.

Heating pressure (HP)	Heating time (HT)	Upsetting pressure (UP)	Upsetting time (UT)	Tensile strength (TS)	Microhardness (H)	Burn off length (BOL)
MPa	s	MPa	s	MPa	VHN	mm
60.00135	7.99792	179.42849	5.688497	813.2247	196.1963	3.83942

Table 10
Comparison between GANN tuned force approach predicted and experimental results.

	Heating pressure (HP)	Heating time (HT)	Upsetting pressure (UP)	Upsetting time (UT)	Tensile strength (TS)	Microhardness (H)	Burn off length (BOL)
Unit	MPa	s	MPa	s	MPa	VHN	mm
Test case 1							
Predicted	60.00135	7.99792	179.42849	5.688497	813.2247	196.1963	3.83942
Experimental	60	8	180	6	826	192	4.4
Percentage error					1.570	2.1388	14.60
Test case 2							
Experimental	60	8	180	6	830	190	3.5
Percentage error					2.062	3.158	8.840

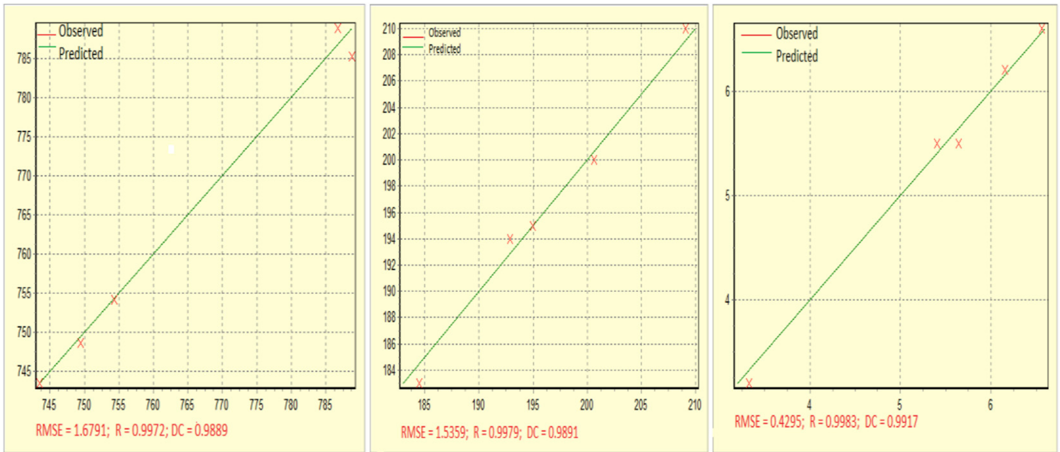


Fig. 10. Scatter plot for validation data of GANN model.

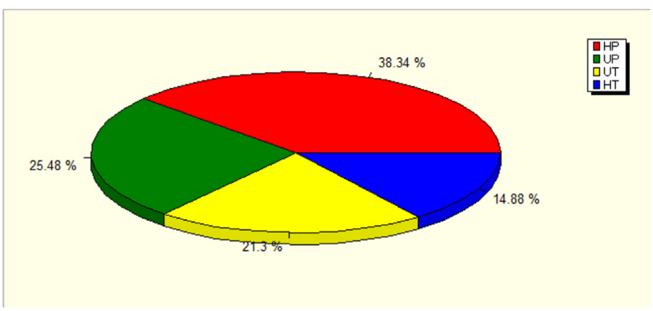
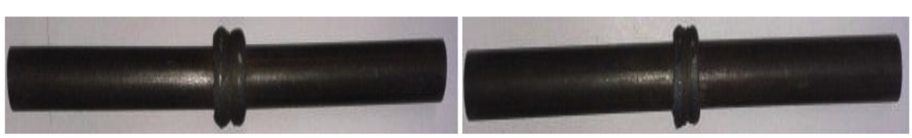


Fig. 11. Importance of input parameters using GANN model.

(IBPNN) and genetic algorithm tuned neural network (GANN) are found to be successful in predicting the responses in terms of tensile strength (TS), microhardness (H) and burn off length (BOL) of the friction welded INCOLOY 800H joint for a given set of process parameters.

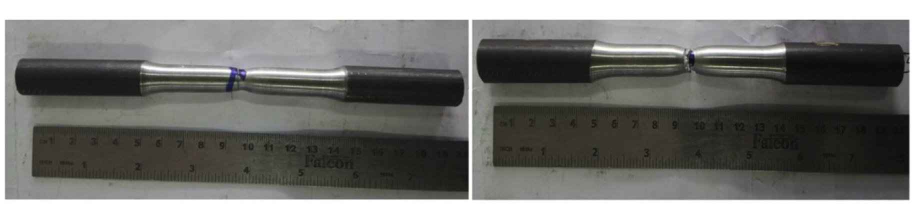
- The reverse models developed using QPNN and GANN are seen to be efficient for the prediction of required process parameters, namely heating pressure (HP), heating time (HT), upsetting pressure (UP) and upsetting time (UT) in order to obtain a desired set of outputs or responses.
- GANN is recommended for conducting both the forward and reverse mappings of this process.
- Knowledge based systems developed using the neural networks could solve the problems of both forward and reverse mappings efficiently.
- The order of importance of input parameters for friction welding of Incoloy 800 His HP > UP > UT > HT.
- The welding should be carried out at low heating pressure, upsetting time and high upsetting pressure, heating time to obtain sound quality joint.
- It can be concluded that GANN tuned force approach may provide good ability to predict the friction welding process parameters to Incoloy 800H.

4.4.1.2. Scope for future work. Experiment was carried out for the friction welding of Incoloy 800H material and same will be tried for other metals, in future. The input output modelling of the process may be carried out using other soft computing techniques. Further ANN can be used in other processes for both forward and reverse mapping of inputs and outputs effectively which might be required for automation of the process.



(a) (b)

Fig. 12. Friction welded sample. (a) Test case 1, (b) Test case 2.



(a) (b)

Fig. 13. Tensile tested sample. (a) Test case 1, (b) Test case 2.

Appendix 1

Experimental values.

Sl. no	Heating pressure (HP) MPa	Heating time (HT) s	Upsetting pressure (UP) MPa	Upsetting time (HT) s	Tensile strength (TS) MPa	Burn off length (BOL) mm	Hardness value (H) VHN	Fracture location from the weld interface (mm)
1	75	5	150	6	727.53	6.4	184	5.3
2	105	5	150	6	703.78	5.2	182	4.8
3	75	7	150	6	753.60	4.5	186	4.7
4	105	7	150	6	743.49	6.2	183	5.2
5	75	5	180	6	768.08	4.7	191	4.9
6	105	5	180	6	796.08	5.8	185	4.6
7	75	7	180	6	788.82	5.5	200	4.5
8	105	7	180	6	748.20	6.7	197	5.0
9	75	5	150	8	766.58	3.5	180	6.4
10	105	5	150	8	746.10	4.3	187	4.7
11	75	7	150	8	814.70	3.9	176	5.2
12	105	7	150	8	703.14	7.3	180	5.5
13	75	5	180	8	785.25	3.2	195	4.2
14	105	5	180	8	782.44	5.2	176	5.4
15	75	7	180	8	771.59	5.5	198	5.9
16	105	7	180	8	754.15	6.6	210	4.3
17	60	6	165	7	783.40	2.9	202	4.5
18	120	6	165	7	759.52	6.8	206	4.2
19	90	4	165	7	791.03	3.9	195	5.8
20	90	8	165	7	750.84	6.3	184	4.7
21	90	6	135	7	746.27	3.5	177	4.3
22	90	6	195	7	789.38	6.1	205	5.5
23	90	6	165	5	753.09	4.5	187	5.3
24	90	6	165	9	765.55	5	190	5.6
25	90	6	165	7	745.39	5.4	194	4.3
26	90	6	165	7	748.4	5.6	187	4.5
27	90	6	165	7	743.2	5.4	192	4.7
28	90	6	165	7	748.6	5.5	194	5.4
29	90	6	165	7	745.1	5.3	180	5.2
30	90	6	165	7	747.7	5.6	182	4.6
31	90	6	165	7	749.3	5.5	190	4.8

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