

Hybrid ANFIS-Rao algorithm for surface roughness modelling and optimization in electrical discharge machining

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ABSTRACT

Advanced modeling and optimization techniques are imperative today to deal with complex machining processes like electric discharge machining (EDM). In the present research, Titanium alloy has been machined by considering different electrical input parameters to evaluate one of the important surface integrity (SI) parameter that is surface roughness *Ra*. Firstly, the response surface methodology (RSM) has been adopted for experimental design and for generating training data set. The artificial neural network (ANN) model has been developed and optimized for *Ra* with the same training data set. Finally, an adaptive neuro-fuzzy inference system (ANFIS) model has been developed for *Ra*. Optimization of the developed ANFIS model has been done by applying the latest optimization techniques Rao algorithm and the Jaya algorithm. Different statistical parameters such as the mean square error (MSE), the mean absolute error (MAE), the root mean square error (RMSE), the mean bias error (MBE) and the mean absolute percentage error (MAPE) elucidate that the ANFIS model is better than the ANN model. Both the optimization algorithms results in considerable improvement in the SI of the machined surface. Comparing the Rao algorithm and Jaya algorithm for optimization, it has been found that the Rao algorithm performs better than the Jaya algorithm.

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1. Introduction

Electrical discharge machining (EDM) is used to machine materials that are difficult to machine [1-2]. In EDM, sparking takes place between the workpiece and tool electrode in the machining zone and due to sparking the removal of material takes place by melting and evaporation [3-4]. Shrivastava *et al.* reviewed the EDM-based hybrid machining process to enhance the different machining performance [5]. Titanium alloy possesses excellent mechanical properties, but it has poor machinability towards conventional machining [6]. Qudeiri *et al.* did an extensive review on EDM of the Titanium alloy and provided valuable research directions [7]. Kumar *et al.* presented an extensive review of the EDM machining of Titanium alloy and discussed important qualitative and quantitative aspects [8]. To control the EDM process, a wide range of control parameters are available. Control parameters and their range significantly affect the quality re-

sponse and hence the appropriate selection of control parameters is necessary to improve the process efficiency [9]. The most important consistency indicator of the machining method is surface roughness. The reliability, wear, and corrosion resistance and the substance are enhanced by good surface integrity [10-11]. After review of the literature, four important control parameters, peak-current (X_1), pulse-on-time (X_2), duty-factor (X_3), and voltage (X_4) selected for the research [12-13].

Response surface methodology (RSM) offers a minimum number of experiments required and inherits enormous information [14-15]. It is also used as an optimization tool for the process. RSM uses a sequence for the design of experiments (DOE) to gather information and establish a relation between input and output with a second-degree polynomial regression model [16-17].

A model depicts the relation between control parameters with one or more quality responses [18]. RSM is the most popular tool for the development of the regression model and as an optimization tool, but the regression model is not suitable for noisy data. This leads to an inefficient model with higher prediction errors [19]. Artificial intelligence is widely adopted in manufacturing industries nowadays. The ANN is a popular modeling technique [20]. Researchers concluded that the ANN model has higher performance as compared to the regression model [21-22]. The ANFIS model combines both the fuzzy set and the ANN model. The ANFIS is gaining popularity as a modeling tool [23]. Buragohain *et al.* used a full factorial design to train the ANFIS model [24]. The ANFIS model is trained by gradient descent or least square estimation. Now a day, heuristic optimization algorithms like the Genetic Algorithm (GA), and many other tools are widely used to train the model to minimize error. It is found that a heuristic-based algorithm produces better results [25-26]. The ANN model and the ANFIS model have a better prediction efficiency as compared to the regression model [27]. The ANFIS and the ANN model have approximately similar accuracy [28]. Generally, large experimental data is used as training data. To minimize the training data requirement, RSM is adopted as an experimental design, and for generating the training data set.

Model of any process generally used for prediction purposes. Researchers are interested to find an optimum solution of the process output, to effectively utilize the resource [29]. A predictable model is used in optimization where one or more response is optimized with an optimization technique. Classical optimization is not able to solve complex problems [30]. To overcome the limitation of classical optimization, metaheuristic or advanced optimization is used. Particle swarm optimization (PSO), GA, ACO, is the most popular metaheuristic optimization algorithm [31]. Klancnik *et al.* proposed a new gravitational search algorithm for optimization [32]. Jaya algorithm is a new advanced optimization tool. In this, algorithm-specific parameters are not required. The solution moves towards the best solution iteratively [33-34]. Rao *et al.* proposed MO Jaya algorithm for multi-response optimization [35]. Singh *et al.* applied MO Jaya algorithm for simultaneous optimization of three responses [36]. Al-Refaie *et al.* used pentagonal fuzzy regression modeling to optimize multiple process measures [37]. Payal *et al.* did the parametric optimization investigation for EDM of Inconel 825 with seven controllable parameters [38]. Daneshmand *et al.* investigate the effect of input parameters on surface roughness during EDM of CK45 steel [39]. Rao optimization is a newly proposed, simple, and powerful optimization tool for technique engineering optimization. Rao optimization is a metaphor-less algorithm [40]. RSM is a widely used optimization tool, but for noisy data, it is not appropriate. Rao reviewed an advanced optimization technique used in modern machining processes [41]. Recently, most researchers used RSM as a modeling and optimization tool. The ANN model is also optimized by advanced optimization by researchers with a better result. In the literature review, advanced optimization is limited to train the ANFIS model only [42]. Singh *et al.* used an integrated GA-ANFIS model where GA is adopted for the training of the ANFIS network [43]. There is no work reported on the ANFIS model optimization using advanced optimization for surface roughness or EDM machining. This is a major research gap.

After an exhaustive literature survey, the authors concluded that there is no work reported in the EDM machining process where the ANFIS model is optimized for quality measures by an advanced optimization technique. So, in this work, the ANFIS trained model is optimized for one of the major quality response i.e. surface roughness (Ra). The ANFIS offers an accurate, predicta-

ble model for complex machining processes like EDM. This ANFIS model is optimized by the Rao algorithm and Jaya Algorithm for better optimum results. The Rao algorithm is suitable to optimize the ANFIS model under 50 iterations. The ANN model for the EDM process is also developed and optimized using Rao optimization. ANFIS model offers better prediction results as compared to the ANN model.

2. Experimental setup

For the study, a plate of titanium alloy 685 was chosen. As an electrode, a copper tool with a diameter of 10 mm is picked. Minitab 18 software is used to implement the RSM design of experiments. Four important control parameters, peak current (X_1), pulse on time (X_2), duty factor (X_3), and voltage (X_4) are selected as a control parameter, surface roughness (Ra) is selected as process outcome. The thirty machining operation is performed as per DOE. Table 1 depicts parameters for process control and their level. Table 2 displays the experimental observation. Surface roughness is measured with profilometer “TESA-rugosurf 10-G” having $0.001\text{ }\mu\text{m}$ accuracy.

Table 1 Process control parameters and their level

Parameters	X_1 (A)	X_2 (μs)	X_3 (%)	X_4 (V)
Level 1	4.0	50.0	25.0	40.0
Level 2	6.0	100.0	37.5	70.0
Level 3	8.0	150.0	50.0	100.0

Table 2 Experimental observations

No.	X_1 (A)	X_2 (μs)	X_3 (%)	X_4 (V)	Ra (μm)
1	8	150	50	40	5.134
2	8	50	25	40	3.152
3	4	50	25	40	2.952
4	8	50	50	40	5.294
5	6	100	37.5	70	3.784
6	6	100	37.5	70	3.815
7	6	100	37.5	70	3.746
8	4	50	50	40	3.267
9	4	150	50	40	4.202
10	4	150	25	100	3.954
11	4	150	25	40	4.468
12	4	50	50	100	4.138
13	4	50	25	100	3.274
14	8	50	50	100	6.637
15	6	100	37.5	70	3.812
16	8	150	50	100	5.260
17	8	150	25	100	4.480
18	8	150	25	40	3.993
19	4	150	50	100	3.880
20	8	50	25	100	4.267
21	6	50	37.5	70	3.581
22	6	100	37.5	40	3.716
23	6	100	37.5	100	4.092
24	6	100	50	70	4.334
25	6	100	25	70	3.543
26	6	100	37.5	70	3.727
27	6	150	37.5	70	3.632
28	8	100	37.5	70	4.129
29	6	100	37.5	70	3.872
30	4	100	37.5	70	3.506

3. Modeling

Model is the relation between control parameters and process outcomes. Nowadays the intelligent model is popular for modeling complex processes. An artificial neural network (ANN) is an interconnected network of neurons. The adaptive neuro-fuzzy inference system (ANFIS) model combines a fuzzy set into ANN, thus it inherits the advantages of fuzzy systems and the ANN.

3.1 The ANFIS model

The ANFIS model is developed to predict the surface roughness (Ra). Fig. 1 depicts the ANFIS architecture.

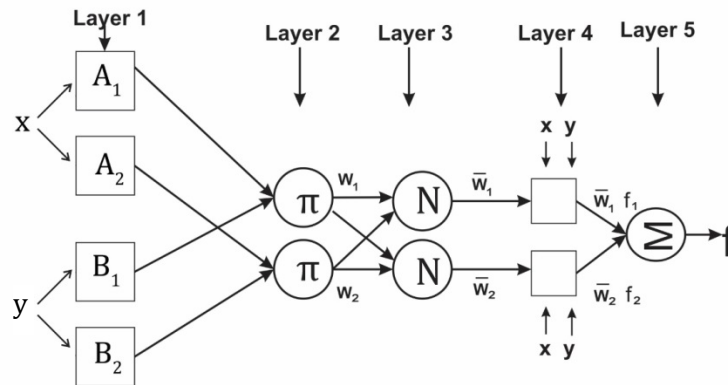


Fig. 1 The adaptive network-based fuzzy interface system architecture

There are two inputs in the model: x, y , and one output. Both fuzzy logic and ANN are merged into the ANFIS scheme. Sugeno fuzzy model first-order, there are two If-then laws used as

Rule 1: If x is A_1 and y is B_1 , then $f_1 = l_1x + m_1y + n_1$

Rule 2: If x is A_2 and y is B_2 , then $f_2 = l_2x + m_2y + n_2$

The $(l_z, m_z, \text{ and } n_z)$ is a set of parameters related to the process.

Layer 1 is known as the fuzzified layer and it calculates the membership function (MF) value of the premise parameter. Every node is square in this layer. 'Trimf' and 'trapmf' are popular MFs for the experimental data.

$$O_{1,i} = \mu A_i(x) \text{ for } i = 1, 2 \text{ or}$$

$$O_{1,i} = \mu B_i(y) \text{ for } i = 3, 4$$

$$\mu A_i(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \quad (1)$$

The $(a_i, b_i, \text{ and } c_i)$ is a set of parameters.

Layer 2 is considered as a layer of law. The second layer reflects the shooting force of the rules. Every node is a circle in this layer and labeled as Π . T-norms operator (like min, product, fuzzy AND) rule applies in this layer. The response of the second layer is given in Eq. 2.

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y) \quad \text{for } i = 1, 2 \quad (2)$$

Layer 3 is known as normalizing firing strength. Every node is a circle in this layer and labeled as N . The i -th node calculates the ratio of the i -th rule's firing strength to the sum of all rules firing strengths. It is also known as normalized firing strength as follows.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad \text{where } i = 1, 2 \quad (3)$$

Layer 4: Every node i is an adaptive node with a function as follows

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (l_i x + m_i y + n_i) \quad (4)$$

Where $i = 1, 2$ and w_i is a normalized firing strength from layer 3 and (l_i, m_i, n_i) is the set of parameters for this particular node. This layer computes the contribution of each i -th rules towards the total output

Layer 5 is known as overall output. This is labeled as Σ . By adding up all incoming signals, determines the total performance.

Overall output is given below

$$O_{5,1} = \sum \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad \text{where } i = 1, 2. \quad (5)$$

Matlab 2015a is used to form the ANFIS model. There are several MFs and MF type is available for training for the ANFIS model. Table 3 shows the ANFIS training parameters. These parameters are decided after trial and error to minimize the error. Fig. 2 shows The ANFIS model for this study. Fig. 3 depicts the error curve for the ANFIS model training. All input is connected to 'inputmf'. There is a rule layer between 'inputmf' and 'outputmf'. All output signals from 'outputmf' is summed at the junction to produce output. For X_1 and X_3 , Fig. 4 displays the surface plot. The surface plot for X_1 and X_4 is depicted in Fig. 5. The surface plot for X_3 and X_4 is shown in Fig. 6.

Table 3 ANFIS training parameters selected

ANFIS parameter	Selected parameter
Membership function (MFs)	trimf (Triangular membership function)
Numbers of Mfs	2 2 2 2
Numbers of epochs	1000
Output MF function	Linear
Training function	Hybrid

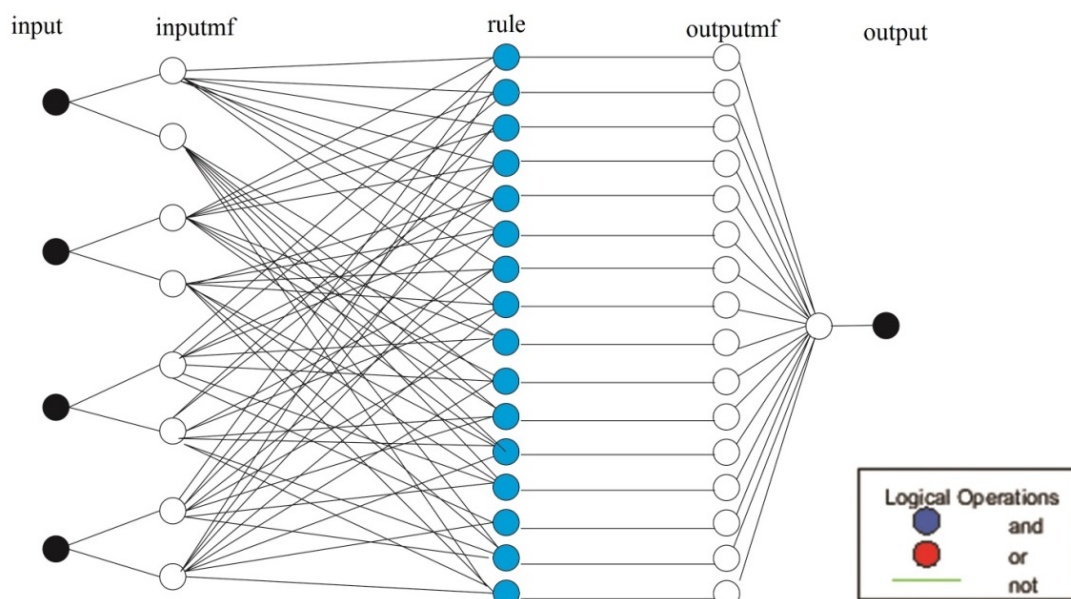


Fig. 2 The ANFIS architecture with four inputs and one output

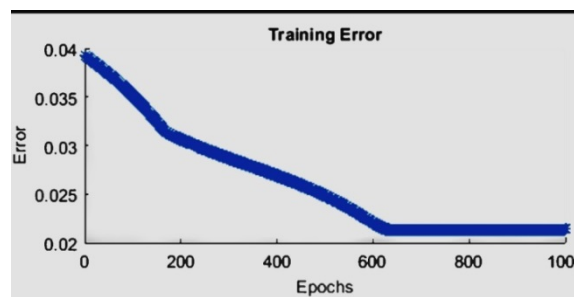


Fig. 3 Error curve for the training of the ANFIS model

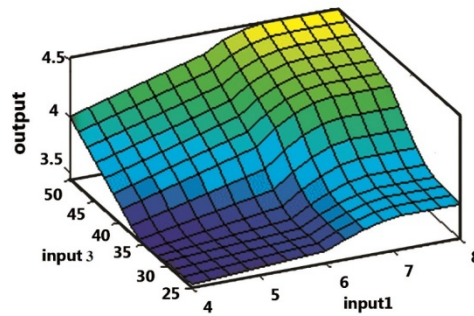


Fig. 4 The surface plot for surface roughness where output is Ra , input1 is X_1 , input3 is X_3 (hold values $X_2 = 100 \mu s$ and $X_4 = 70 V$)

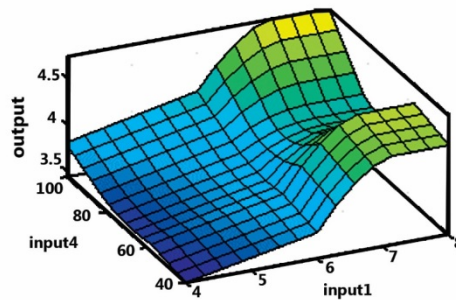


Fig. 5 Surface plot for surface roughness where output is Ra , input1 is X_1 , input4 is X_4 (hold values $X_2 = 100 \mu s$ and $X_3 = 37.5 \%$)

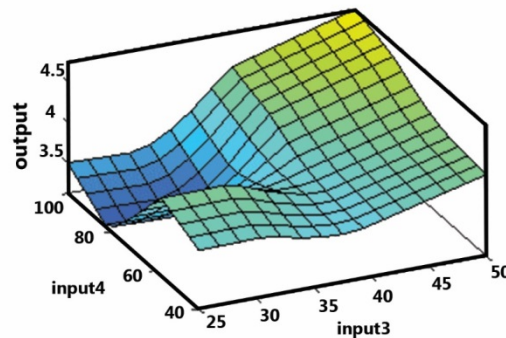


Fig. 6 Surface plot for surface roughness where output is Ra , input3 is X_3 , input4 is X_4 (hold values of X_2 is $100 \mu s$ and $X_1 = 6A$)

3.2 The ANN Model

Several interconnected neurons form an ANN network. There are an input layer, an output layer and a hidden layer exist in an ANN network. The input layer and output layer are connected by few hidden layers. The cumulative number of neurons in the input layer equals to the number of input. There are four input parameters, hence input layer has four neurons. The output layer's number of neurons is equal to the model's output. There is one output, hence output layer has a single neuron. After experimenting with various combinations, it is found that a single hidden layer with the five neurons generates a better predictive model. The activation function 'logsig' is used between the input layer and hidden layer. The 'purelin' transfer function is used for the output layer.

The activation function 'purelin' is used with the output layer. To train the network, the back-propagation algorithm is adopted. It is based on gradient descent. It updates the weight of the layer to minimize the mean square error (MSE). The network is trained using the experimental data from Table 2. Fig. 7 shows the ANN architecture.

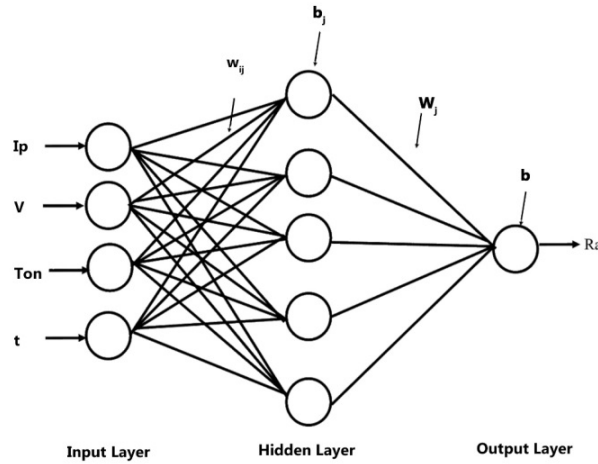


Fig. 7 The ANN architecture

Input layer: There are four inputs in the model, hence four neurons present in this layer.

Hidden Layer: Every neuron of the hidden layer receives input from all neurons of the input layer. It is multiplied by weight w_{ij} with addition to bias b_j . The net input received by each neuron as the following Eq. 6.

$$net_j = \sum_{i=0}^j w_{ij}x_i + b_j \quad (6)$$

Where j is a number of neurons in the hidden layer, x_i is input quantity, w_{ij} is weight of i -th input to j -th neuron, b_j is bias of j -th neuron.

The output from the input layer's neurons is fed into the activation function 'logsig' which converts the input signal into the output of the given neuron. The net summation of the j -th neuron is fed into activation function 'logsig' and the output of j -th neuron is given in the following Eq. 7.

$$out_j = f_{(net_j)} = \frac{1}{1 + e^{(-net_j)}} \quad (7)$$

Output layer: There is 1 neuron in this layer. The output from each of the hidden layer's neurons is now multiplied by the individual weight. The signal from all neurons goes to the summation junction with an addition of the bias, then fed into activation function 'purelin' to generate the final output (Ra). The output is represented in the following Eq. 8, where b is the bias for the output.

$$output = \sum_{j=0}^j w_j out_j + b \quad (8)$$

3.3 The evaluation criteria

There is a statistical tool used to calculate the error and efficiency of the model. MSE measures the average of the square of the errors, MAE is the average of the absolute errors, RMSE is the square root of MSE, MBE is the average value of errors, MAPE is the mean absolute percentage error, whereas NSE is the efficiency of the model.

$$MSE = \frac{\sum_{i=1}^n (E_i - P_i)^2}{n} \quad (9)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (E_i - P_i)^2}{n}} \quad (10)$$

$$MAE = \frac{\sum_{i=1}^n |E_i - P_i|}{n} \quad (11)$$

$$MBE = \frac{\sum_{i=1}^n (E_i - P_i)}{n} \quad (12)$$

$$MAPE = \frac{\sum_{i=1}^n \left| \frac{(E_i - P_i)}{E_i} \right|}{n} \quad (13)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (E_i - P_i)^2}{\sum_{i=1}^n (E_i - \bar{E})^2} \quad (14)$$

Where E_i is observed value, P_i is predicted value from the model, n is total number of experiments, $\bar{E}$ is mean of the observed value.

4. Optimization

4.1 Rao optimization for the ANFIS model

The ANFIS model is made with Matlab software. A Matlab program is written to optimize the ANFIS model. The flow chart is given in Fig. 8. The objective is to minimize the surface roughness (Ra).

Step 1: All variables are randomly generated within the upper bound and lower bound as an initial solution Constraints are $4 \leq X_1 \leq 8$, $50 \leq X_2 \leq 150$, $25 \leq X_3 \leq 50$, $40 \leq X_4 \leq 100$. Initial solutions are simulated in the ANFIS model and corresponding Ra is recorded in Table 4.

Table 4 Initial solution for Rao optimization.

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)	Status
1	7.6672	95.14	42.6479	80.5815	4.3819	
2	5.6282	106.4608	32.7404	42.4912	3.7440	
3	7.6384	100.0375	49.1606	94.5473	4.8520	worst
4	7.4458	144.7569	46.2096	73.229	4.6217	
5	4.9393	51.6323	27.4826	90.5408	3.0694	best

Step 2: New value of the variable is calculated as follows the formula, Eq. 15.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}(X_{j,best,i} - X_{j,worst,i}) \quad (15)$$

There are a number of iterations required to solve this optimization problem. If i is current iteration, j represents for j -th variable, k represents for candidate number. Where $X'_{j,k,i}$ is new value of variable, $X_{j,k,i}$ is old value of variable, $r_{1,j,i}$ is random number of variable j , $X_{j,best,i}$ is best value j -th variable k -th candidate at i -th iteration, $X_{j,worst,i}$ is worst value j -th variable k -th candidate at i -th iteration. Candidate 5 is chosen as the best candidate since it has the lowest Ra value and all variables are marked as best variable as X_{1_best} is 4.9393, X_{2_best} is 51.6323, X_{3_best} is 27.4826, X_{4_best} is 90.5408. Candidate 3 has highest value of objective function Ra , hence it selected as worst candidate and corresponding variables are marked as worst candidate as X_{1_worst} is 7.6384, X_{2_worst} is 100.0375, X_{3_worst} is 49.1606, X_{4_worst} is 94.5473. There are four random number $r_1 = 0.3135$, $r_2 = 0.5200$, $r_3 = 0.1954$, $r_4 = 0.0131$ for X_1 , X_2 , X_3 , and X_4 respectively. The new calculated value of variables are shown in Table 5.

The new value of the variable for candidate 1 is:

X_1 for candidate 1: $7.6672 + 0.3135(4.9393 - 7.6384) = 6.8211$,

X_2 for candidate 1: $95.14 + 0.5200(51.6323 - 100.0375) = 69.9679$,

X_3 for candidate 1: $42.6479 + 0.1954(27.4826 - 49.1606) = 38.413$,

X_4 for candidate 1: $80.5815 + 0.0131(90.5408 - 94.5473) = 80.5289$.

Similarly, candidates 2, 3, 4, and 5 are calculated. All candidates to the ANFIS model simulated for Ra value and the corresponding Ra value is recorded in Table 5.

Table 5 New value of variables for Rao optimization

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)
1	6.8211	69.9679	38.413	80.5289	4.8138
2	4.7821	81.2887	28.5056	42.4386	4.0047
3	6.7922	74.8654	44.9257	94.4947	5.6586
4	6.5996	119.5847	41.9748	73.1764	3.8493
5	4.0931	50	25	90.4882	3.0212

Step 3: There is a comparison between Tables 4 and 5 for a better value of Ra . Since candidate 1 of Table 4 has a lower Ra value as compare to Table 5, hence candidate 1 is selected from Table 4 and placed as nominee 1 in Table 6. Similarly, members 2, 3 are selected from Table 4 and inserted into Table 6 as candidates 2 and 3. Similarly, candidate 4 and candidate 5 have better objective values in Table 5 hence candidate 4 and candidate 5 are selected from table 5 and inserted into Table 6 as candidate 4 and candidate 5 respectively. Table 6 shows a modified variable value for the Rao algorithm.

Step 4: Repeat 100 iteration and report the optimum solution. Table 7 shows the iteration-wise best results.

Table 6 The modified variable value for the Rao algorithm

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)	Status
1	7.6672	95.14	42.6479	80.5815	4.3819	From Table 4
2	5.6282	106.4608	32.7404	42.4912	3.7440	From Table 4
3	7.6384	100.0375	49.1606	94.5473	4.8520	From Table 4
4	6.5996	119.5847	41.9748	73.1764	3.8493	From Table 5
5	4.0931	50	25	90.4882	3.0212	From Table 5

Table 7 The best result selected from each iteration for Rao optimization

Iteration No.	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)
1	4.9393	51.6323	27.4826	90.5408	3.0694
2	4.0931	50	25	90.4882	3.0212
3	4	50	25	88.6559	2.9679
4	4	50	25	87.0529	2.9246
5	4	50	25	87.0529	2.9246
6	4	50	25	76.1071	2.9158
7	4	50	25	85.2707	2.8766
8	4	50	25	80.0359	2.8181
9	4	50	25	80.9771	2.7949
10	4	50	25	80.9771	2.7949
11	4	50.5715	25	81.5514	2.7859
12	4	50	25	81.5721	2.7804
24	4.0097	50.0018	25.0032	81.6323	2.7793
27	4.0008	50.0008	25	81.6348	2.7789
30	4	50	25	81.6445	2.7787

4.2 Jaya algorithm for the ANFIS model optimization

With the Jaya algorithm, a Matlab program is written to optimize the ANFIS model. In Fig. 8, the flow diagram of the process is given.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i} * (X_{j,best,i} - |X_{j,k,i}|) - r_{2,j,i} * (X_{j,worst,i} - |X_{j,k,i}|) \quad (16)$$

Where If i is current iteration, j represents for j -th variable, k represents for candidate number. Where $X'_{j,k,i}$ is new value of variable, $X_{j,k,i}$ is old value of variable, $r_{1,j,i}$, and $r_{2,j,i}$ are random numbers for j -th variable, $X_{j,best,i}$ is best value j -th variable k -th candidate at i -th iteration, $X_{j,worst,i}$ is worst value j -th variable k -th candidate at i -th iteration.

Step 1: Inside the upper and the lower boundaries, all variables are created randomly as an initial solution. Constraints are $4 \leq X_1 \leq 8$, $50 \leq X_2 \leq 150$, $25 \leq X_3 \leq 50$, $40 \leq X_4 \leq 100$. A set of variables (candidate) are communicated to the ANFIS model and a corresponding response (Ra) of the ANFIS model is recorded in Table 8. Since if surface roughness is lower, the criteria will be

better, hence candidate 1 is marked as the best candidate (marked best variable as $X_{1_best} = 7.1251$, $X_{2_best} = 109.6631$, $X_{3_best} = 29.36$, $X_{4_best} = 44.8277$) while candidate 2 is marked as the worst candidate because it has the highest value of Ra (hence marked worst variables are as $X_{1_worst} = 7.315$, $X_{2_worst} = 96.5559$, $X_{3_worst} = 44.8495$, and $X_{4_worst} = 52.0834$).

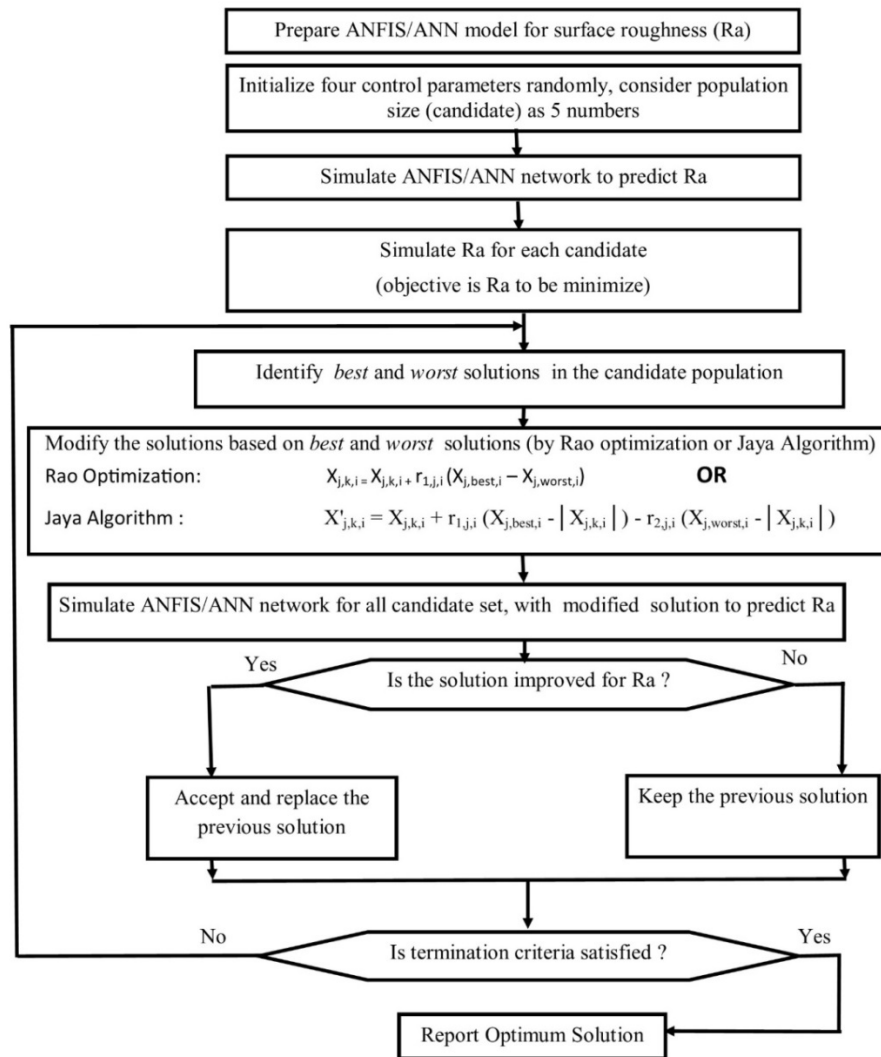


Fig. 8 Flow diagram of the ANFIS/ANN model optimization

Table 8 The initial solution for Jaya algorithm

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)	Status
1	7.1251	109.6631	29.3623	44.8277	3.5789	best
2	7.315	96.5559	44.8495	52.0834	5.0244	worst
3	4.6139	96.2368	41.8183	55.3064	3.6694	
4	4.2459	140.9336	47.9749	77.332	3.5931	
5	6.3595	65.9438	39.0437	62.5608	4.4153	

Step 2: Eq. 16 is used to calculate the value of new variables. Consider the random number $r_1 = 0.3590$, $r_2 = 0.0287$ for X_1 , $r_3 = 0.7674$, and $r_4 = 0.2374$ for X_2 , $r_5 = 0.6659$, $r_6 = 0.7485$ for X_3 , $r_7 = 0.7284$, $r_8 = 0.8143$ for X_4 .

X_1 for candidate 1:

$$7.1251 + 0.3590(7.1251 - |7.1251|) - 0.0287(7.315 - |7.1251|) = 7.1197$$

X_2 for candidate 1:

$$109.6631 + 0.7674(109.6631 - |109.6631|) - 0.2374(96.5559 - |109.6631|) = 112.7745$$

X_3 for candidate 1:

$$29.3623 + 0.6659(29.3623 - |9.3623|) - 0.7485(44.8495 - |29.3623|) = 17.7701$$

(= 25 lower bound)

X_4 for candidate 1:

$$44.8277 + 0.7284(44.8277 - |44.8277|) - 0.8143(52.0834 - |44.8277|) = 38.9193$$

(= 40 lower bound)

These new variables are communicated to the ANFIS model and corresponding Ra records in Table 9, similar calculation is done for candidates 2, 3, 4 and 5 and recorded in the table.

Step 3: The Ra of Tables 8 and 9 are compared for better value and select the candidate with better Ra and insert into Table 10.

Step 4: The first iteration is over, now repeat a similar procedure for a few iterations. A total of 67 iterations are required to achieve the solution.

Table 9 New value of variables for Jaya algorithm

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)
1	7.1197	112.7745	25*	40*	3.4345
2	7.2469	106.614	34.5364	46.7981	3.9293
3	5.4379	106.464	31.2549	50.2978	3.8770
4	5.1915	127.472	37.9199	74.2143	3.3248
5	6.607	92.226	28.2512	58.175	4.2568

* Means adjusted to lower/upper bound

Table 10 The updated value of the variable for the Jaya algorithm

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)	Status
1	7.1197	112.7745	25	40	3.4345	From Table 9
2	7.2469	106.614	34.5364	46.7981	3.9293	From Table 9
3	4.6139	96.2368	41.8183	55.3064	3.6694	From Table 8
4	5.1915	127.472	37.9199	74.2143	3.3248	From Table 9
5	6.607	92.226	28.2512	58.175	4.2568	From Table 9

Table 11 Best result selected from each iteration for Rao optimization

Iteration No.	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra (μ m)
1	7.12	109.6631	29.3623	44.8277	3.5789
2	5.1915	127.472	37.9199	74.2143	3.3248
3	5.1915	127.472	37.9199	74.2143	3.3248
4	4.4527	136.1197	36.8609	81.7775	3.2419
5	4.4868	121.3322	35.2794	77.0596	3.1456
40	4	120.5003	36.1024	74.6033	3.0936
55	4	92.1362	29.0386	84.1491	3.0655
59	4	94.2808	28.7777	81.9607	3.0152
62	4	62.3788	27.9143	81.973	2.8921
63	4	54.0164	27.605	82.1781	2.8256
64	4	52.8637	27.5728	81.6957	2.8026
65	4	50.4888	27.5587	81.5481	2.7831
66	4.0061	50	27.0561	81.5907	2.7784
67	4.007	50	26.6052	81.6279	2.7779
68	4.0041	50	26.6336	81.6432	2.7774

4.3 Optimization of the ANN model

A predictable ANN model of Ra is developed. The Jaya algorithm is used to optimize this model.

Step 1: Population size 5 is considered. Table 12 shows the initial solution. Random numbers within the selected range serve as initial variables. The ANN model is simulated for this input set and corresponding responses of Ra are recorded. The flow chart is shown in Fig. 8. Since surface roughness is better for smaller values, hence candidate 3 is marked as the best candidate while candidate 2 is marked as the worst candidate.

Table 12 Initial solution and corresponding predicted Ra value

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Predicted Ra (μ m)	Status
1	7.2589	140.5792	28.1747	94.8026	4.5768	worst best
2	6.5294	145.7507	48.9292	65.3057	5.1702	
3	4.3902	146.4889	37.1344	94.9441	3.7971	
4	5.114	65.7613	45.007	87.5324	4.061	
5	6.1875	147.0593	28.5472	97.5695	4.603	

Eq. 15 is used to calculate the new value of parameters. These new values of parameters are used to simulate Ra from the ANN model and corresponding Ra values are recorded in Table 13. Matlab 2015 software is used for the calculation.

Step 2: Two random numbers $r_1 = 0.82$ and $r_2 = 0.86$ are considered for calculation. Variables corresponding to the best candidate 3 are marked as the best variables, hence Marked $X_{1_best} = 4.3902$, $X_{2_best} = 146.4889$, $X_{3_best} = 37.1344$, and $X_{4_best} = 94.9441$. Corresponding to candidate 2, all variable have been marked as worst variables as $X_{1_worst} = 6.5294$, $X_{2_worst} = 145.7507$, $X_{3_worst} = 48.9292$ and $X_{4_worst} = 65.3057$. The calculation for the new value of the variables is as per the Eq. 15 as follows.

X_1 for candidate 1:

$$7.2589 + 0.82(4.3902 - |7.2589|) - 0.86(6.5294 - |7.2589|) = 5.533936$$

X_2 for candidate 1:

$$140.5792 + 0.82(146.4889 - |140.5792|) - 0.86(145.7507 - |140.5792|) = 140.977664$$

X_3 for candidate 1:

$$28.1747 + 0.82(37.1344 - |28.1747|) - 0.86(48.9292 - |28.1747|) = 17.672784$$

(=25 as lower limit)

X_4 for candidate 1:

$$94.8026 + 0.82(94.9441 - |94.8026|) - 0.86(65.3057 - |94.8026|) = 120.285964$$

(=100 upper limit)

A similar calculation was done for X_1 , X_2 , and X_3 , X_4 for candidates 2, 3 4, and 5.

Step 3: Tables 12 and 13 are compared, select the candidate with better Ra , and insert into Table 13.

Step 4: This process continues for some iterations. A total of 17 iterations of the Jaya algorithm is used to achieve an optimum solution. Table 15 shows the iteration-wise best result.

Table 13 New value of the variable with predicted Ra

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Predicted Ra (μ m)
1	5.5339	140.9776	25*	100*	4.9376
2	4.7752	146.3560	39.2574	89.6091	3.7629
3	4*	147.1237	26.9908	100*	3.9144
4	4*	63.1670	35.1783	100*	3.6689
5	4.4196	147.7169	25*	100*	4.1232

*Adjusted to lower or upper limit.

Table 14 Updated value of the variable with corresponding Ra value

Candidate	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Predicted Ra (μ m)	Status
1	7.2589	140.5792	28.1747	94.8026	4.5768	From Table 12
2	4.7752	146.3560	39.2574	89.6091	3.7629	From Table 13
3	4.3902	146.4889	37.1344	94.9441	3.7971	From Table 12
4	4	63.1670	35.1783	100	3.6689	From Table 13
5	4.4196	147.7169	25*	100*	4.1232	From Table 13

Table 15 Iteration-wise best result.

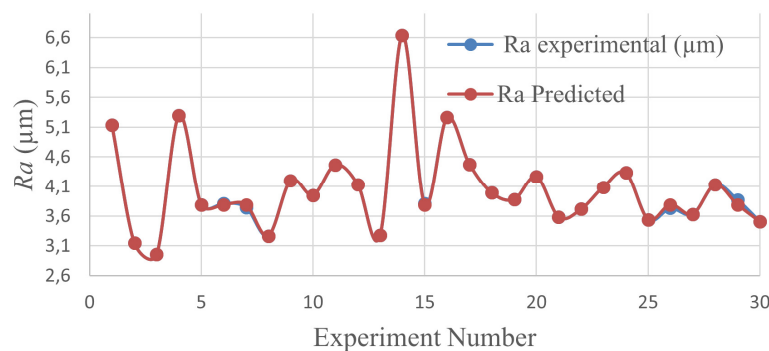
Iteration No.	X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)	Ra
1	4.3902	146.4889	37.1344	94.9441	3.7971
2	4	63.1670	35.1783	100	3.6689
3	4	74.8268	40.9319	94.8336	3.4462
4	4	76.4593	39.5315	95.6589	3.3627
5	4.4139	78.2127	39.6985	58.0534	3.2436
6	4	50	36.3944	66.47	3.1736
7	4.0315	52.6894	30.3658	56.4976	2.9378
8	4	53.1526	30.5158	56.4976	2.9972
9	4	50	31.795	40	2.8705
17	4	50	28.5	52.1	2.8427
100	4	50	28.5	52.1	2.8427

5. Result and discussion

The ANFIS model has a very low MSE 4.5×10^{-4} and the regression coefficient is ' R ' = 0.9995. Fig. 9 compares the experimental values of quality characteristics Ra with the ANFIS model predicted values. This indicates a good prediction model. A confirmatory experiment is performed with an optimum set of input variables. The result of confirmatory experiments is given in Table 16. Since the limitation of the EDM machine setting, the value of X_4 is selected as 81 instead of 81.6445. Therefore, the experimental value is rather similar to the expected value, validating the ANFIS model.

The ANN model is developed for quality measure (Ra) and the mean square error of Ra is calculated as 0.0122 and the regression coefficient is ' R ' = 0.98862 which is closer to 1. Fig. 10 shows the comparison between experimental versus the ANN model predicted data for Ra . The ANN model is optimized using the Jaya algorithm. The result of confirmatory experiments is given in Table 16.

Comparison between the ANN and ANFIS model: Regression coefficient R and Nash Sutcliffe Efficiency coefficient are higher for the ANFIS model. The error MSE, RMSE, MAE, and MBE are lower for the ANFIS model. Therefore the ANFIS model has better prediction accuracy. Table 17 shows the comparison between the ANN model and the ANFIS model.

**Fig. 9** Comparison result of experimental vs. the ANFIS model predicted data for Ra **Table 16** Confirmatory experiments result

Response	Model	Process variables				Predicted	Experimental	Error (%)
		X_1 (A)	X_2 (μ s)	X_3 (%)	X_4 (V)			
Surface roughness (Ra)	ANFIS	4	50	25	81*	2.790 μ m	2.861 μ m	2.48
Surface roughness (Ra)	ANN	4	50	28*	52*	2.843 μ m	2.945 μ m	3.59

*Adjusted to the nearest available setting of the EDM machine

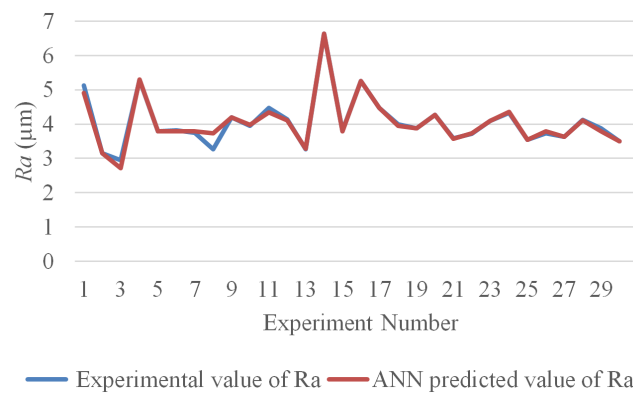


Fig. 10 Comparison results of experimental vs. the ANN model predicted data for R_a

Table 17 Comparison between the ANN and ANFIS model

Property	Measurement	ANFIS	ANN
Model error	MSE	4.5×10^{-4}	0.012205
	RMSE	0.021394	0.110474
	MAE	0.00807701	0.050963
	MBE	4.5169×10^{-5}	0.009038
	MAPE	0.212868 %	1.388436 %
Model efficiency	Nash Sutcliffe efficiency coefficient (NSE)	0.999149	0.97732
	Regression coefficient	0.9995	0.9886

6. Conclusion

Successful machining of Titanium alloy has been done in the present research by using EDM process and performance comparison of Rao Optimization Algorithm and Jaya Algorithm has been done for one of the important surface integrity parameters. Followings are the important findings of the present research work:

- The Rao optimization algorithm demonstrates better performances than the Jaya algorithm as 68 iterations were required by the Jaya algorithm for optimization of the ANFIS model, whereas Rao optimization required only 30 iterations for the same.
- Both the algorithms successfully optimized the ANFIS model and predicted the identical set of input control factors. The input control factors predicted are; peak current $X_1 = 4$ A, pulse-on time $X_2 = 50$ μ s, duty factor $X_3 = 25$ %, and voltage $X_4 = 81.6445$ V.
- The ANFIS model is found more accurate prediction model for the machining response as compared to the ANN model for this study. Hence, it can be inferred that the ANFIS model is better than the ANN model under the present machining environment.
- ANN model and the ANFIS model are successfully optimized using the Jaya algorithm and the Rao algorithm.

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