International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 7 Issue 1|| January 2018 || PP. 40-49

Development of Expert System for an Unconventional Machining Process

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Abstract: *The present paper deals with development of fuzzy logic based models for electrochemical machining (ECM) process. Performance characteristics in ECM process, such as material removal rate, radial over cut and surface roughness are depends on various machining parameters namely applied voltage, tool feed rate, electrolyte concentration and reinforcement-content. Mamdani-based fuzzy logic (FL) systems are used to model the performance characteristics in ECM process. Three types of fuzzy logic models, i.e. manually constructed FL system, genetic algorithm (GA) based tuning of knowledge base of the manually constructed FL controller and automatic design of FL system using GA, are developed. Performance of the FL system depends largely on its knowledge base and it is optimized by GA. Further, the performance of all the developed models is tested with twenty experimental test cases. The prediction accuracy of the automatic FL system is found to be better than the other models.*

Keywords: - *Electrochemical machining process, fuzzy logic, genetic algorithm*

Date of Submission: 07-12-2017 Date of acceptance: 17-01-2018

I. Introduction

Electrochemical machining (ECM) is one of the commonly used unconventional machining processes to machine complex shapes and difficult-to-machine materials like super alloys, Ti-alloys, composites, etc. Electrochemical machining is also used for barrel rifling in the inner surface of complex shapes [1]. Determination of optimal machining parameters is very difficult in ECM process due to its complexity. In ECM, with combinatorial control of the various process parameters best quality of the work piece can be achieved [2]. Response surface methodology was used by Munda and Bhattacharyya [3] to develop mathematical models for metal removal rate and radial over cut in electrochemical micromachining. Response surface modeling was used to study the influence of different machining parameters namely feed rate, voltage, electrolyte conductivity and electrolyte flow rate on the responses namely electrolyzing current, width of cut and metal removal rate of electrochemical cutting process [4].

Modeling of manufacturing systems plays a major role in estimating the effects of various input process parameters on the responses. Researchers had employed several modeling techniques, such as statistical regression, artificial neural networks and fuzzy logic modeling to model the manufacturing systems [5]. Senthilkumar et al. [6] developed higher order mathematical models for electrochemical machining process using response surface methodology. Wen [7] used Free Pattern Search for explicitly modeling the performance of electrochemical machining process. Abuzied et al. [8] developed artificial neural network models for electrochemical machining process. Panda and Yadava [9] proposed an intelligent approach for the modeling of die sinking electrochemical spark machining process using finite element method and artificial neural networks in integrated manner. Fuzzy modeling-based approaches have been successfully applied to develop models for real time processes, namely microelectronic manufacturing processes [10], water jet depainting process [11], electric discharge machining process [12] and CNC milling process [13] and others. Labib et al. [14] integrated a fuzzy logic controller with ECM drilling rig to control feed rate of the tool and the flow rate of the electrolyte with the objective of improving the machining performance and accuracy.

In the present work, three FL-based approaches, namely manually constructed FL system, GA trained FL system and automatic evolution of the FL system are developed and tested with twenty experimental test cases. The experimental data available in the literature [15] has been used to develop the FL models.

II. Experimental Details

The test specimens of AMMCs with 2.5, 5 and 7.5 wt% of B_4C are fabricated through stir casting process. The specimens considered to have 25 mm diameter and 10 mm in height. Schematic diagram of ECM process is shown in Fig. 1. In order to establish the input-output relationships of ECM process, four machining parameters, namely applied voltage, tool feed rate, electrolyte concentration and reinforcement content are considered as input parameters and material removal rate (MRR), radial overcut (ROC) and surface roughness (SR) are considered as the responses. Figure 2 shows the schematic diagram of input-output model of ECM process. Table 1 shows the ranges of the four input machining parameters and their levels [15]. The design matrix and the measured response values are given in Table 2. More description of the experimental details is given in Ref. [15]. Moreover, the data required for training the fuzzy logic models is generated using the following non-linear regression equations:

$$\text{MRR} = 0.449 - (0.065\,X_1) - (0.131\,X_2) + (0.023\,X_3) + (0.022\,X_4) + (0.003\,X_1^2) + (0.718\,X_2^2) - (2.604\text{E-}04\,X_3^2) - (0.005\,X_4^2) - (0.005\,X_1X_2) - (2.19\text{E-}05\,X_1X_3) + (0.0005\,X_1X_4) - (0.002\,X_2X_3) - (0.009\,X_2X_4) - (4.45\text{E-}04\,X_3X_4) \quad (1)$$

$$\text{ROC} = 1.462 - (0.020\,X_1) - (0.823\,X_2) - (0.011\,X_3) - (0.098\,X_4) + (0.0009\,X_1^2) + (0.229\,X_2^2) + (0.0003\,X_3^2) + (0.004\,X_4^2) + (0.007\,X_1X_2) + (1.04\text{E-}05\,X_1X_3) + (0.001\,X_1X_4) + (0.007\,X_2X_3) + (0.004\,X_2X_4) - (3.33\text{E-}04\,X_3X_4) \quad (2)$$

$$\text{SR} = 11.335 - (0.794\,X_1) - (0.135\,X_2) - (0.035\,X_3) - (0.130\,X_4) + (0.026\,X_1^2) - (0.228\,X_2^2) + (0.0002\,X_3^2) + (0.022\,X_4^2) - (0.009\,X_1X_2) + (7.55\text{E-}05\,X_1X_3) - (0.002\,X_1X_4) + (0.002\,X_2X_3) - (0.002\,X_2X_4) - (6.69\text{E-}04\,X_3X_4) \quad (3)$$

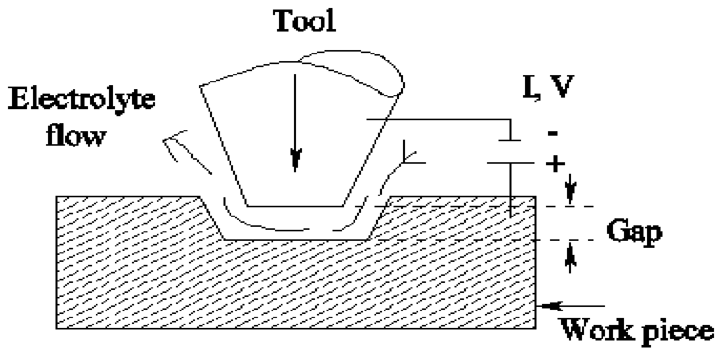


Fig. 1. Schematic diagram showing the operation of ECM

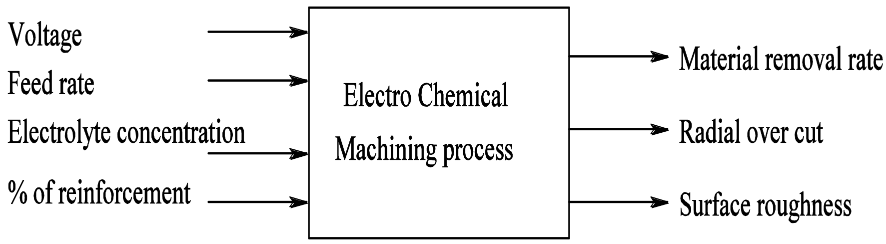


Fig. 2. Input and output parameters of electrochemical machining process

Table 1 Machining parameters and their levels

Machining parameter	Symbol	Level			Unit
		Low (-1)	Middle (0)	High (+1)	
Applied Voltage	X_1	12	16	20	Volt
Feed Rate	X_2	0.2	0.6	1.0	mm/min
Electrolyte concentration	X_3	10	20	30	g/L
Reinforcement Content	X_4	2.5	5.0	7.5	Wt %

Table 2 Experimental design matrix and results

Exp. no.	Input parameters				Responses		
	X_1	X_2	X_3	X_4	MRR (g/min)	SR (μm)	ROC (mm)
1	-1	-1	-1	-1	0.268	4.948	0.96
2	1	-1	-1	-1	0.398	5.345	1.08
3	-1	1	-1	-1	0.689	4.555	0.67
4	1	1	-1	-1	0.892	4.920	0.85
5	-1	-1	1	-1	0.447	4.456	1.05
6	1	-1	1	-1	0.684	4.787	1.17
7	-1	1	1	-1	0.932	4.068	0.86
8	1	1	1	-1	0.988	4.366	1.00
9	-1	-1	-1	1	0.130	5.204	0.75
10	1	-1	-1	1	0.282	5.472	0.91
11	-1	1	-1	1	0.498	4.823	0.47
12	1	1	-1	1	0.688	5.002	0.64
13	-1	-1	1	1	0.227	4.591	0.79
14	1	-1	1	1	0.492	4.890	0.94
15	-1	1	1	1	0.703	4.232	0.65
16	1	1	1	1	0.805	4.474	0.86
17	-1	0	0	0	0.448	4.498	0.65
18	1	0	0	0	0.564	4.712	0.86
19	0	-1	0	0	0.381	4.329	0.87
20	0	1	0	0	0.771	3.989	0.68
21	0	0	-1	0	0.379	4.540	0.76
22	0	0	1	0	0.491	3.889	0.81
23	0	0	0	-1	0.553	4.207	0.85
24	0	0	0	1	0.302	4.431	0.69
25	0	0	0	0	0.504	4.233	0.79
26	0	0	0	0	0.466	4.216	0.73
27	0	0	0	0	0.489	4.198	0.68

III. Fuzzy Logic Based Modeling of ECM Process

In the present work, Mamdani approach of FL-system has been used to model the ECM process. Three FL-based approaches (hereafter termed as FLA-1, FLA-2 and FLA-3) are developed to solve the input-output modeling of ECM process.

3.1 FLA-1: Development of Mamdani-Based Manually Constructed FL System

Here, Mamdani-based FL system is used to establish the input-output model of the ECM process. The machining parameters and the responses of ECM process are treated as inputs and outputs of Mamdani-based FL system, respectively. Membership function distributions of the FL system are developed using human expertise. In the present study, triangular membership functions are used to represent the considered variables of the FL system. Further, three linguistic terms, such as L-Low, M-Medium and H-High are used to represent a membership function. In the present work, ECM process contains four input machining parameters and each parameter is represented with the help of three linguistic terms, the total number of rules exist in the rule base of the FL system is found to be equal to 81 (34). One such rule of this FL system is:

IF X_1 is M and X_2 is L and X_3 is M and X_4 is H,

THEN MRR is L and ROC is M and SR is M.

3.2 FLA-2: GA-based tuning of knowledge base of the FL system developed in FLA-1

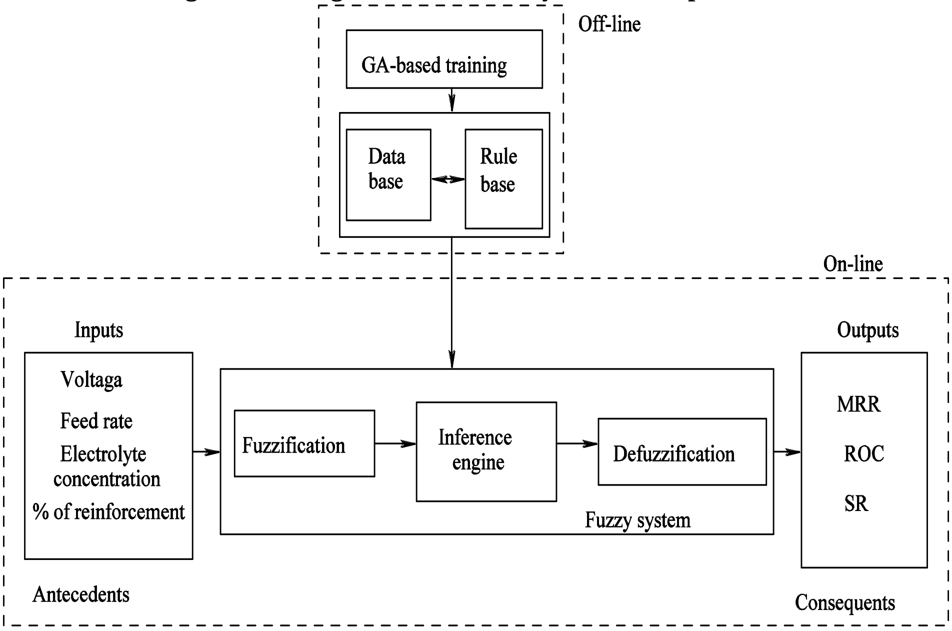


Fig. 3. Working principle of GA-FL system

In FLA-2, an attempt is made to optimize the knowledge base (that is, data base and rule base) of the FL system using, a population based search and optimization tool, genetic algorithm. As the optimization of data base, such as b1 through b7 (that is, half base widths of triangular membership function distributions) involves the real numbers and optimization of rule base deals with binary digits, a binary coded GA (refer Fig. 3) has been used to optimize the FL system. During GA-based optimization, the values of the variables b1 through b7 are varied in the ranges of 1.0 to 4.0, 0.001 to 0.4, 2.0 to 10.0, 0.1 to 2.5, 0.1 to 0.431, 0.01 to 0.704 and 0.01 to 0.3 respectively. As the FL system contains four inputs and three outputs, it requires seven variables to represent the data base of the FL system. Further, each variable is represented with the help of ten bits. Therefore, it requires 70 bits to represent the data base of the FL system. Moreover, the 81 rules explained in FLA-1 require 81 bits to represent the presence or absence of the rule (that is, 1 represents presence and 0 represents absence of the rule) of the rule base of the FL system. Finally, the GA string will be 151 bits long as shown in Fig. 4.

$$\underbrace{\underbrace{1011010110}_{b_1}\underbrace{1011010110}_{b_2}\underbrace{1011010110}_{b_3}\underbrace{1011010110}_{b_4}}_{Inputs}\underbrace{\underbrace{1011010110}_{b_5}\underbrace{1011010110}_{b_6}\underbrace{1011010110}_{b_7}}_{Outputs}\underbrace{11010\ldots10111}_{81\,bits}{}_{Rulestatus}$$

Fig. 4. GA string for FLA-2

As batch mode of training is employed in the present study, the fitness of GA string is considered as the average RMS error in prediction of all the responses and is given as:

$$\text{f} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\frac{1}{m}\sum_{j=1}^{m}(T_{oj}-O_{oj})^2} \tag{4}$$

Where N is the number of training scenarios, m is the number of responses, O_{oj} is the predicted output and T_{oj} is the target output.

3.3 FLA-3: Automatic Evolution of FL-System Using GA

Here, an attempt is made to evolve the fuzzy logic system used to model the ECM process; automatically using GA. Rule base of the fuzzy logic system contains two parts, namely antecedent part and consequent part. The antecedent part represents the rule sequence and the consequent part designates the linguistic terms assigned to various responses of the rule base. In FLA-1, the consequent part is designed by human expertise, and in FLA-2 the antecedent part of the fuzzy logic system is optimized using GA. In FLA-3, to design FL system automatically, the responsibility of searching the good knowledge base is given to GA. In addition to the 151 bits used in FLA-2, information related to the consequent part of the rule base for all the responses also need to be included in the GA string. It is important to note that there are three responses, namely MRR, ROC and SR and each response is having three linguistic terms (i.e. L, M and H). Two bits 00 for Low, 01 and 10 for Medium and 11 for High are used to represent each linguistic term of one response. Therefore, it requires 486 bits to represent the consequent part of the FL system. Finally, it requires 637 bits to represent the FL system using GA as shown in Fig. 5. The fitness of the GA-string is calculated using equation (4). During optimization, the ranges of half base widths are set equal to those mentioned in FLA-2.

$$\underbrace{\underbrace{101}_{b_1}\,\underbrace{101}_{b_2}\,\underbrace{101}_{b_3}\,\underbrace{101}_{b_4}}_{Inputs}\;\underbrace{\underbrace{101}_{b_5}\,\underbrace{101}_{b_6}\,\underbrace{101}_{b_7}}_{Outputs}\;\underbrace{\underbrace{10\ldots1011}_{81\,bits}}_{Rule\_status}$$

$$\underbrace{\underbrace{11}_{c_1}\underbrace{10}_{c_2}\ldots\ldots\underbrace{00}_{c_{81}}}_{MRR}\;\underbrace{\underbrace{10}_{c_1}\underbrace{00}_{c_2}\ldots\ldots\underbrace{01}_{c_{81}}}_{ROC}\;\underbrace{\underbrace{10}_{c_1}\underbrace{00}_{c_2}\ldots\ldots\underbrace{01}_{c_{81}}}_{SR}$$

Fig. 5. GA string for FLA-3

IV. Results and Discussions

The developed FL-based models are tested for their accuracy in prediction of the responses using twenty experimental test cases given in Table 3.

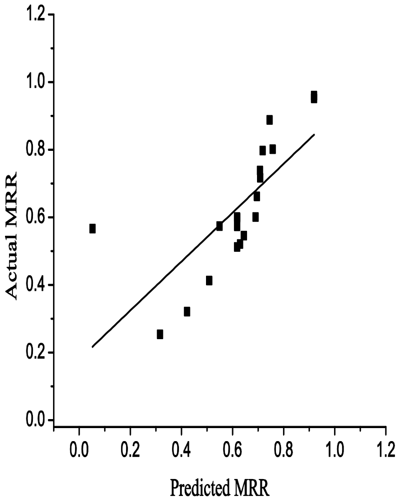
Table 3 Input-output data for the test cases

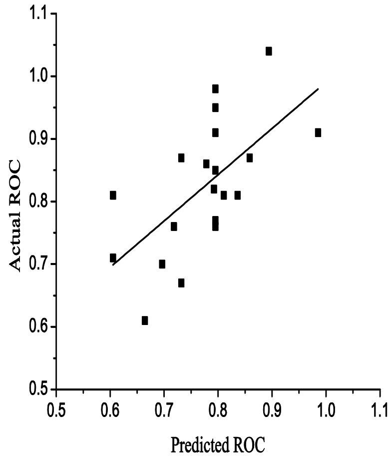
Test No.	X_1	X_2	X_3	X_4	MRR (g/min)	SR (μm)	ROC (mm)
1	15	0.5	15	5.0	0.413	4.235	0.76
2	12	0.8	25	7.5	0.567	4.325	0.81
3	16	0.8	20	2.5	0.798	4.789	0.98
4	20	0.9	25	5.0	0.801	3.856	0.87
5	18	1.0	30	7.5	0.96	3.989	0.67
6	13	0.2	15	2.5	0.286	5.231	1.08
7	14	0.7	20	5.0	0.521	4.99	0.71
8	17	0.6	30	7.5	0.512	4.123	0.95
9	19	0.4	10	7.5	0.311	4.986	0.88
10	14	1.0	25	2.5	0.952	3.845	0.91
11	15	0.8	10	2.5	0.546	5.234	0.7
12	18	0.5	30	5.0	0.601	3.856	1.04
13	13	0.3	25	7.5	0.321	4.987	0.87
14	12	0.2	15	5.0	0.254	5.345	0.76
15	20	1.0	30	5.0	0.966	3.998	0.85
16	18	0.9	15	7.5	0.662	4.459	0.61
17	17	0.7	10	2.5	0.601	5.231	0.85
18	16	0.6	30	5.0	0.599	4.853	0.77
19	19	0.3	25	7.5	0.389	5.908	0.92
20	15	0.4	30	2.5	0.574	3.981	0.91

4.1 FLA-1

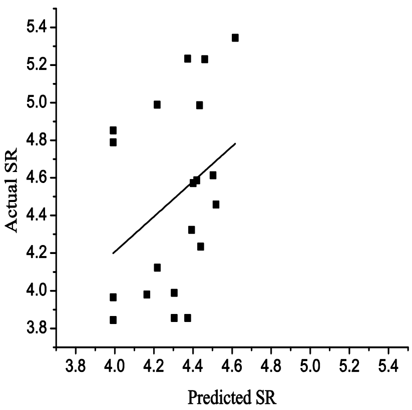
In this approach, rule base was designed by the human expertise. Half base width values of the triangular membership functions of the FL system, that is b1, b2, b3, b4, b5, b6 and b7 are decided by the designer of the FL system and seen to be equal to 4.0, 0.4, 10.0, 2.5, 0.431, 0.704 and 0.3, respectively. It is important to note that all the rules are present in rule base of FL system and interesting to note that for a particular set of input conditions, there is a chance that sixteen rules (24) are to be fired from the existing 81 rules. Further, the developed FL system has been tested for its accuracy in prediction with the help of 20 experimental test cases. Figures 6a, 6b and 6c show the scatter plot drawn between the experimental and model predicted responses for MRR, ROC and SR, respectively.

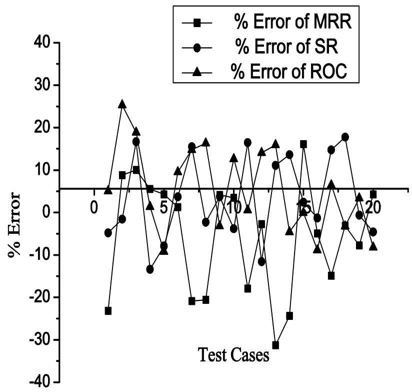
From Figs. 6(a) and 6(b) it is observed that the model predicted responses MRR and ROC are close to the actual experimental values. It may be due to the more appropriate design of the consequent part of the rule base of FL system. On the other hand from Fig. 6(c), the model predicted SR and experimental SR values are seen to be not close to each other. In this case, the design of the FL system failed to prepare appropriate consequent part of rule base. Moreover, Fig. 6(d) shows the percentage deviation for MRR, ROC and SR in electrochemical machining of AMMCs. The percentage deviation values are falling on both sides of zero and these values for MRR, ROC and SR are found to lie in the range of -31.28 to +16.08%, -13.38 to +17.7 6% and -9.21 to +25.31%, respectively.





6(a) 6(b)





6(c) 6(d)

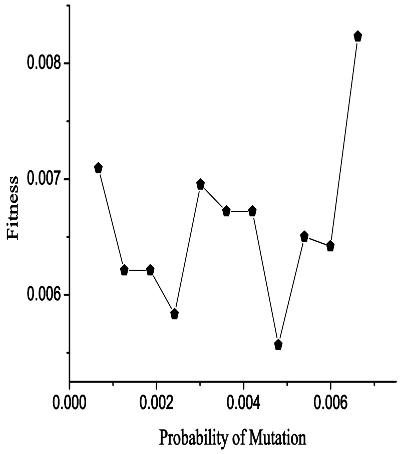
Fig. 6. Test cases experimental results for FLA-1: (a) actual MRR vs model predicted MRR(b)actual ROC vs model predicted ROC (c)actual SR vs model predicted SR (d)percentage deviation in prediction of all the responses.

4.2 FLA-2

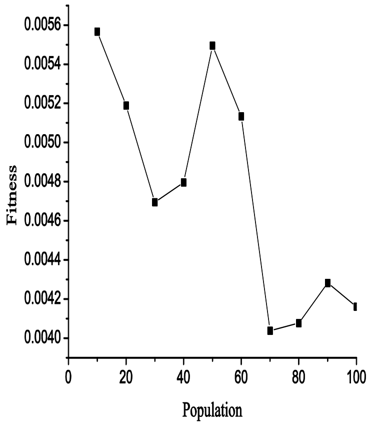
In this approach, knowledge base of the FL system is optimized using GA. Figure 7 shows the parametric study used to determine the optimal parameters of GA. The optimal parameters of GA that yield the best result are as follows:

probability of uniform crossover (pc) : 0.5
probability of bit-wise mutation (pm) : 0.00479
population size : 70
number of generations : 80

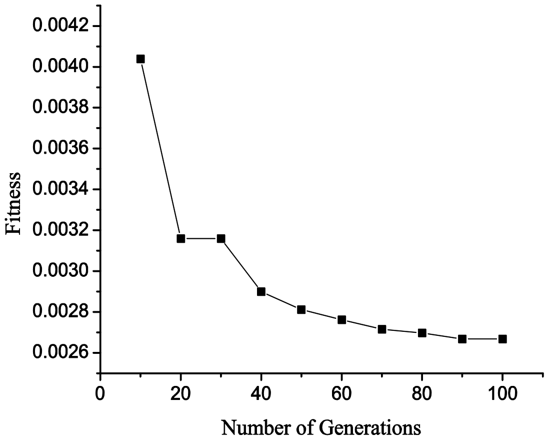
Moreover, the half-base width values of the triangular membership functions values, that is, b1 through b7 obtained from GA-based optimization are equal to 3.628, 0.370, 9.665, 2.492, 0.383, 0.702 and 0.285 respectively. Further, GA identified that 56 rules are more effective from 81 rules. After optimization the performance of the FL system is tested with the help of 20 experimental test cases. The scatter plots showing the relationship between the model predicted and experimental responses such as MRR, ROC and SR are shown in Figs. 8(a), 8(b) and 8(c) respectively.



7(a)

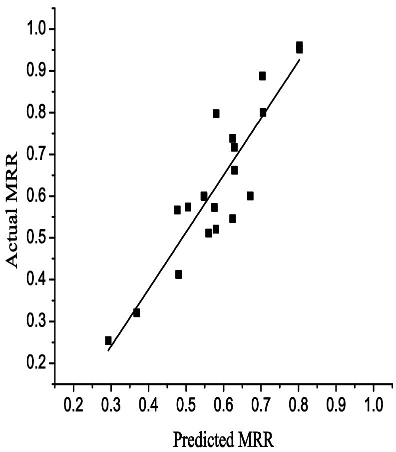


7(b)

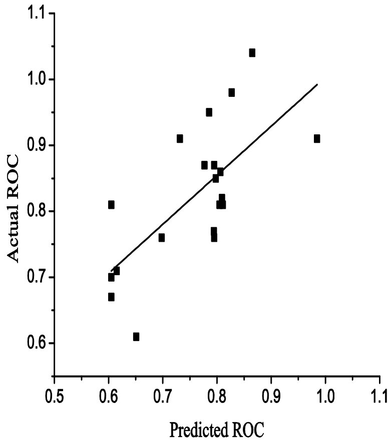


7(c)

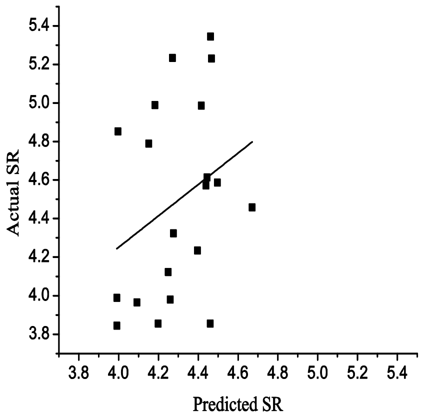
Fig. 7. GA parametric study for FLA-2: (a)Fitness vs probability of mutation, (b)Fitness vs population size, (c)Fitness vs number of generations.

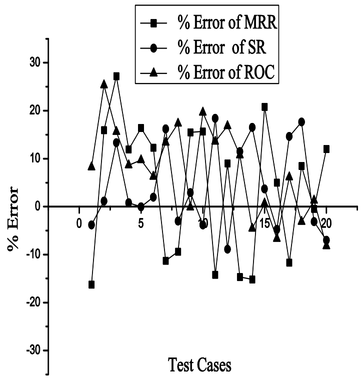


8(a)



8(b)





8(c) **8(d)**

Fig. 8. Test cases experimental results for FLA-2: (a)actual MRR vs model predicted MRR (b)actual ROC vs model predicted ROC (c)actual SR vs model predicted SR (d) percentage deviation in prediction of all the responses.

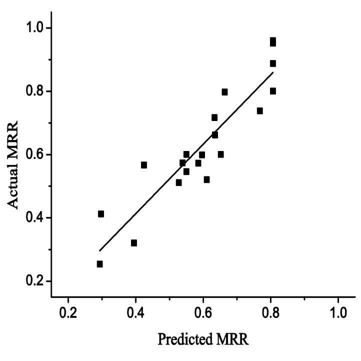
From the Fig. 8 it is observed that in this approach also, the FL system is capable of predicting the responses MRR and ROC with a reasonably good accuracy and is not true with SR. Further, the percentage deviation in prediction of MRR, ROC and SR is shown in Fig. 8(d). The percentage deviation values are seen to lie in the range of -16.27 to +27.22%, -8.20 to +25.31% and -8.87 to + 18.41% for MRR, ROC and SR respectively.

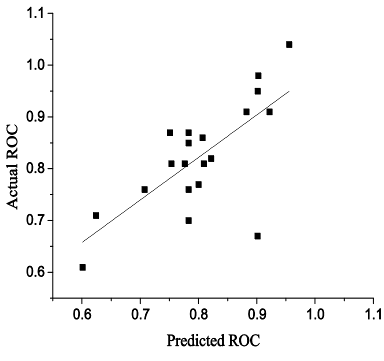
4.3 FLA-3

In this approach, the consequent part of FL system is optimized with the help of binary coded GA. The optimal parameters of GA for this approach are:

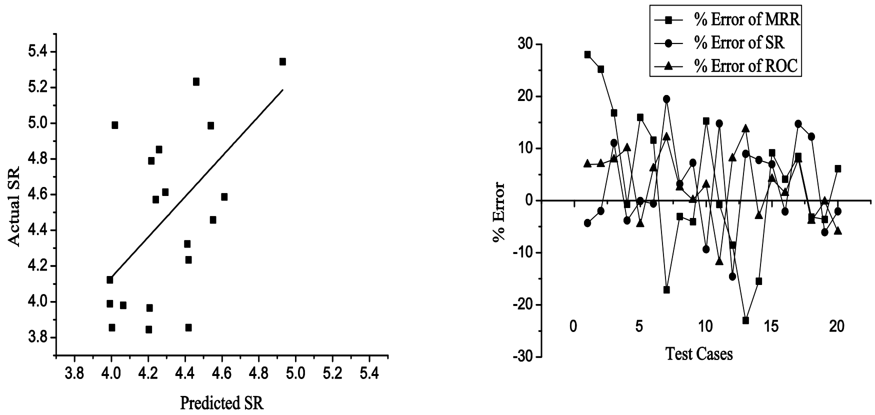
probability of uniform crossover (pc) : 0.5
probability of bit-wise mutation (pm) : 0.00016
population size : 80
number of generations : 80

The optimal values of half base width values, that is b1, b2, b3, b4, b5, b6 and b7 obtained from GA-based optimization are found to be equal to 3.226, 0.345, 9.525, 2.477, 0.385, 0.703 and 0.273, respectively. Moreover, the optimal rule base obtained after automatic evolution of FL system is found to contain 60 rules from 81-rules. Once, the optimal FL system is evolved, its performance is tested with the help of twenty experimental test cases. Figures 9(a), 9(b) and 9(c) show the scatter plot for the responses MRR, ROC and SR respectively. The model has shown better accuracy in prediction for all the responses because of data points are close to the best fit line. Moreover, the percentage deviation in prediction of all the responses is shown in Fig. 9(d) and these values are in the range of -22.98 to +28.04%, -11.81 to +13.69% and -14.58 to +13.69% for MRR, ROC and SR respectively.





9(a) **9(b)**



9(c) **9(d)**

Fig. 9. Test cases experimental results for FLA-3: (a)actual MRR vs model predicted MRR (b)actual ROC vs model predicted ROC (c)actual SR vs model predicted SR (d)percentage deviation in prediction of all the responses.

4.4 Comparison of the Developed Models

The developed FL-based approaches for modeling the ECM of AMMCs have been compared with the help of average absolute deviation in prediction of all the responses. It is interesting to note that the average absolute deviation in prediction of FLA-1, FLA-2 and FLA-3 are found to be equal to 9.644, 10.020 and 8.206 respectively as shown in Fig. 10.

It can be observed that FLA-1 has performed better than FLA-2. This may be due to the reason that in FLA-2, GA has tried several combinations of firing the rules and eliminated some of them which are having significant contribution towards the prediction of that response. Moreover, FLA-3 has outperformed FLA-1 and FLA-2 while predicting the responses. This may be due to the reason that in FLA-1 and FLA-2, human expertise is used to develop the consequent part of the rule base. In most of the cases, it may not be the optimal value which helps in degrading the accuracy in prediction of the responses. On the other hand, in FLA-3, GA is used to evolve the consequent part of the rule base of the FL system. In this approach, the GA may be tried different combinations of consequent part (that is, L, M and H) for each response over several generations and evolved the optimal consequent part.

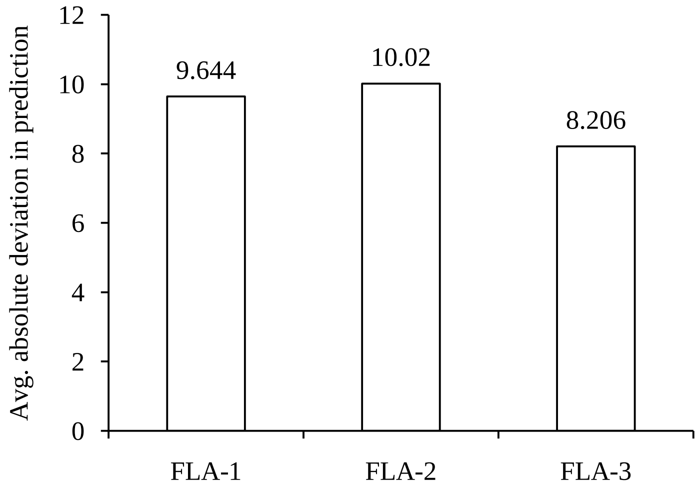


Fig. 10. Average deviation in prediction of responses for different approaches

V. Conclusions

In the present study, three FL-based models have been developed for the ECM process. The huge data required for batch mode training of FL has been generated artificially with the help of regression equations. The developed FL-based models are tested with 20 randomly generated experimental test cases.

The results of prediction show that automatic evolution of FL system (FLA-3) has performed better than manually constructed FL system (FLA-1) and GA trained FL system (FLA-2). It may be due to the reason that in FLA-3, GA is used to develop the consequent part of the rule base of the FL system, whereas it is developed with human expertise in other approaches. The developed fuzzy logic expert system eliminates the need of further experimental work, to select the most dominant ECM machining parameters on the material removal rate, radial over cut and surface roughness.

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S. Rama Rao "Development of Expert System for an Unconventional Machining Process." International Journal of Engineering Science Invention, vol. 07, no. 01, 2018, pp. 40–49.