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FUZZY MODELING AND PARAMETRIC ANALYSIS OF NON-TRADITIONAL MACHINING PROCESSES

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Abstract
The application of artificial intelligence (AI) in modeling of various machining processes has been the topic of immense interest among the researchers since several years. In this direction, the principle of fuzzy logic, a paradigm of AI technique, is effectively being utilized to predict various performance measures (responses) and control the parametric settings of those machining processes. This paper presents the application of fuzzy logic to model two non-traditional machining (NTM) processes, i.e. electrical discharge machining (EDM) and electrochemical machining (ECM) processes, while identifying the relationships present between the process parameters and the measured responses. Moreover, the interaction plots which are developed based on the past experimental observations depict the effects of changing values of different process parameters on the measured responses. The predicted response values derived from the developed models are observed to be in close agreement with those as investigated during the past experimental runs. The interaction plots also play significant roles in identifying the optimal parametric combinations so as to achieve the desired responses for the considered NTM processes.

Keywords
Non-traditional machining process, fuzzy model, process parameter, response, interaction plot.

Introduction

A rapid advancement in the field of manufacturing and technology development has simulated the application and growth of various non-traditional machining (NTM) processes for generating complex and intricate shape geometries on different difficult-to-machine advanced engineering materials. These processes are now being widely deployed to economically machine materials which are usually hard to machine using the conventional machining processes [1]. These NTM processes principally utilize mechanical, thermal, electrical, chemical energy or a combination of them where removal of material usually takes place in the form of tiny chips or atoms enabling attainment of high dimensional accuracy and surface smoothness. Unlike the conventional machining processes, in NTM processes, the tool material needs not to be harder than the work material or even there may be no contact between the tool and the workpiece. For example, in case of electrochemical machining (ECM) process, material removal occurs in the form of atoms due to electrochemical dissolution; and for electro discharge machining (EDM) process, material is eroded from the workpiece by a series of sparks due to rapidly recurring current discharges between two electrodes, separated by a dielectric liquid and subjected to an electrical voltage [2, 3]. These NTM processes require a careful selection of their controllable (input) parameters so as to achieve the desired quality characteristics (responses) and explore their fullest machining capabilities. Wrong selection of any of the NTM process parameters may often lead to serious consequences, like short circuit, tool wear, damage of the workpiece, and even accident to the operator. The presence of a wide array of various NTM process parameters, conflicting responses and complicated material removal mechanisms often make it a challenging task to identify the most appropriate combinations of different NTM process parameters for which the operators' technological knowledge and experience are frequently sorted.

The traditional process to attain desired response values from various NTM processes involves trial and error method, is often time-consuming involving errors. Therefore, a reliable methodology when exact mathematical information are not available for ensuring quality responses is supposed to be the adoption of soft computing techniques. However, they also have few drawbacks, like approximation, uncertainty, meta-heuristics, inaccuracy and partial truth. Recently, artificial intelligence (AI) is gaining interest among the researchers, and has been successfully applied in various domains of manufacturing science and technology. It is based on the principles of developing intelligent machines, mainly intelligent computer programs. It consists of a number of powerful tools, like artificial neural network (ANN), simulated annealing, expert system, fuzzy logic, ant colony optimization, genetic algorithm (GA), particle swarm optimization etc., which are now being practically augmented in the field of machining technology to solve complex problems requiring human intelligence.

Abellan-Nebot and Subirón [4] presented a review on the detailed applications of different AI techniques for optimizing, predicting and controlling machining processes in various monitoring systems. Rajesekaran et al. [5] showed that fuzzy logic technique could be effectively employed to study the effects of various machining parameters so as to attain the desired quality of surface roughness (SR) while turning carbon fibre reinforced plastics (CFRP) composites and also to predict its values under different machining conditions. Azmi [6] developed a tool condition monitoring system based on the measured machining forces and adaptive network-based fuzzy inference system to predict tool wear during end milling operation of glass fibre reinforced plastic (GFRP) composites. Soori et al. [7] applied finite element analysis method for modeling of a virtual manufacturing system so as to analyze the accuracy of tool deflection error to increase the quality of milled surfaces in part manufacturing. Santhanakrishnan et al. [8] developed a model utilizing response surface methodology and GA technique to investigate the effects of different geometrical and machining process parameters, such as cutting speed, depth of cut, rake angle, feed rate and nose radius on temperature rise during an end milling operation. Kumar et al. [9] presented a mathematical model based on dimensional analysis for predicting tool wear rate (TWR) while considering the derived results from the Taguchi method and thermo-physical properties of different tool materials. Kumaran et al. [10] proposed an ANFIS model while combining the modeling function of fuzzy inference along with the learning ability of ANN for predicting SR during machining of CFRP composites using abrasive waterjet machining (AWJM) process. Marzban and Hemmati [11] developed a model using ANN technique to predict material removal rate (MRR) and SR for an abrasive flow rotary machining process, and finally, compared it with the experimental values while showing a close agreement between both the observations. Chakraborty et al. [12] adopted a grey-fuzzy-based optimization approach in solving the parametric optimization problems for three NTM processes and also proved its superiority over the existing multi-objective optimization methods.

Fuzzy logic is widely used for the state-of-the-art modeling, inferencing and decision making in identifying systems, and also in machine monitoring and diagnostics [13]. This approach of modeling is highly expedient when a particular machining process is highly complex and uncertain in nature. Peres et al. [14] presented a hierarchical structure of fuzzy control and fuzzy model for optimization of an end milling process. Dweiri et al. [15] applied ANFIS to model a down milling process of Alumic-79 to predict the effects of spindle speed, feed rate, depth of cut and number of flutes on the quality of surface finish. Kovac et al. [16] adopted fuzzy logic along with regression analysis to develop an empirical model so as to predict the value of SR, while showing a substantial improvement in surface quality for a dry face milling process. In recent years, fuzzy logic has also been emerged out as an efficient tool for modeling of diverse machining processes. Ramesh et al. [17] performed fuzzy modeling for prediction of tool flank wear, SR and specific cutting pressure in turning operation of titanium alloy. Ren et al. [18] considered fuzzy-based modelling in prediction of cutting forces during micro milling of cold-work tool steel X155CrVMo12-1. Barzani et al. [19] applied fuzzy-based modeling for prediction of surface roughness in CNC turning of Al-Si-Cu-Fe die casting alloy. Chakraborty and Das [20] employed fuzzy modeling for prediction and optimization of various yarn characterisitcs in ring spinning of cotton fibres. From the extensive review of the past literature, it can be noticed that a large number of researchers have already adopted various mathematical techniques to solve complex problems related to modeling of diverse machining processes while correlating different input parameters with the achievable responses. In this paper, an endeavor is taken to develop fuzzy models relating the process parameters and responses for two NTM processes, i.e. EDM and ECM processes. The achieved response values from the developed fuzzy models are found to be in high similitude with the experimental observations as attained by the past researchers. Interaction plots are also developed so as to analyze the effects of various NTM process parameters on the responses, while determining the optimal parametric mixes to achieve the target response values.

Fuzzy-based modeling

It has been observed that the NTM processes usually involve complex material removal mechanisms having a large number of controllable parameters and related responses. Many a times, these responses are also conflicting in nature, like maximization of MRR along with minimization of SR, maximization of machining efficiency with minimum power requirement etc. Modeling of these NTM processes becomes more and more challenging with the increased number of input parameters and responses. Fuzzy systems are based on the principles of fuzzy set theory and associated techniques as proposed by Zadeh [21]. Fuzzy logic is mainly attractive because of its ability to solve complex problems in absence of accurate mathematical models. A schematic diagram of the fuzzy logic unit consisting of a fuzzifier, a database, an inference engine, a rule base and a defuzzifier is shown in Fig. 1. It is possible to model the reasoning process of

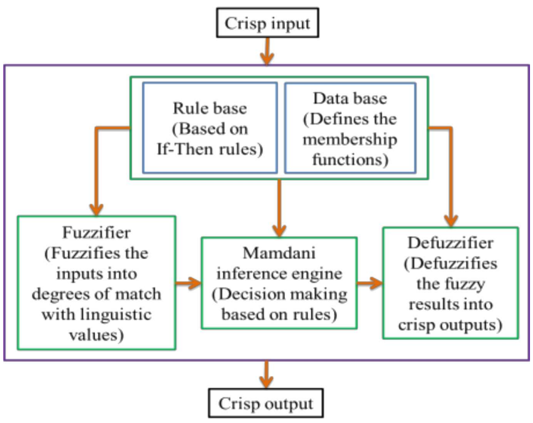

Fig. 1. Fuzzy decision making unit.

a human being using fuzzy logic mainly in linguistic terms by the way of appropriate definition of inputs to the systems along with the desired outputs. The fuzzy system takes the decisions based in the form of linguistic variables.

The fuzzy values are governed by the membership functions that define the degree of membership of an object in a fuzzy set [22]. However, till now, there has been no standard procedure for identifying the suitable shapes of the membership functions in order to define the corresponding fuzzy sets. Principally, it is based on trial and error methods. The fuzzifier employs the membership functions that convert the crisp inputs to the fuzzy system into fuzzy sets. A rule base is developed based on a set of ‘If-Then’ control parameters, which reflects the inference relationship between the inputs and outputs. Based on these fuzzy rules, the Mamdani implication method is employed for fuzzy inference reasoning [23, 24]. The inference engine performs fuzzy inference reasoning based on fuzzy rules for generating fuzzy values. Finally, the defuzzifier converts those generated fuzzy values into crisp numeric values. Although, a number of methods are available for the purpose of defuzzification, the centroid of area defuzzification method has been widely adopted due to its capability to provide more accurate results. A typical example of the fuzzy rule base developed based on a set of ‘If-Then’ control parameters is presented as below:

Rule 1: If x_1 is a_1 and x_2 is b_1 and x_3 is $c_1, \ldots$, then output y_1 is r_1 and y_2 is s_1 and y_3 is t_1.

... (1)

Rule n: if x_1 is a_n and x_2 is b_n and x_3 is $c_n, \ldots$, then output y_1 is r_n and y_2 is s_n and y_3 is t_n,

where a_i, b_i, and c_i are the fuzzy subsets for the inputs, defined by the corresponding membership functions, i.e. μ_{ai}, μ_{bi} and μ_{ci} respectively, and r_i, s_i, and t_i are the fuzzy subsets for the outputs. The inference engine performs fuzzy reasoning on fuzzy rules while taking max-min inference for generating the fuzzy outputs, $\mu_{c_1}(y_1)$, $\mu_{c_2}(y_2)$ and $\mu_{c_3}(y_3)$

$$\mu_{C_i}(y_i) = \max\{\min_i[\mu_{a_1}(x_1), \mu_{b_1}(x_2), \mu_{c_1}(x_3), \ldots]\} \tag{2}$$

where, $i = 1, 2, \ldots, n$.

Finally, defuzzification method is employed to transform the fuzzy multi-response output, $\mu_{c_i}(y_i)$ into a crisp numerical value.

$$y_i = \frac{\sum y_i \mu_{c_i}(y_i)}{\sum \mu_{c_i}(y_i)}. \tag{3}$$

Illustrative examples

In this section, the past experimental data for two NTM processes, i.e. EDM and ECM processes are considered for analysis and subsequent development of the corresponding fuzzy models, and studying the influences of various NTM process parameters on the responses.

Example 1: EDM process

Based on Taguchi's L_{27} orthogonal array, Kandpal et al. [25] investigated the effects of three EDM process parameters, i.e. peak current (I) (in A), pulse-on time (T_{on}) (in µs) and duty factor (DF) on four important responses, e.g. MRR (in mg/min), TWR (in mg/min), SR (in µm) and overcut (in mm) while machining AA6061/10%Al2O3 composite materials. In total, 27 experiments were conducted while setting each of the EDM process parameters at three different levels, as shown in Table 1. Those levels of the considered EDM process parameters were so selected that they would be within the industrially acceptable ranges. Amongst the four responses, MRR is the only larger-the-better (beneficial) quality characteristic, whereas, the other three responses are of smaller-the-better (non-beneficial) type. The details of the experimental design plan along with the measured responses for the considered EDM process are provided in Table 2.

In order to model and analyze this EDM process in fuzzy logic, peak current, pulse-on time and duty factor are considered as the inputs to the system, while MRR, TWR, SR and overcut are treated as the outputs. A schematic diagram of this three-input-four-output fuzzy model is exhibited in Fig. 2. For fuzzy modeling, triangular membership functions with three fuzzy subsets are considered to represent the three levels for each of the EDM process parameters. These fuzzy subsets for the input variables are considered as low (L), medium (M) and high (H), as shown in Fig. 3. On the other hand, for the responses too, triangular membership functions are considered, but with nine fuzzy subsets as lowest (LT), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH) and highest (HT), as depicted in Fig. 4. Table 3 provides the minimum and maximum values of the input parameters and responses to represent the universe of discourse (range) in this fuzzy modeling process.

Table 1
EDM process parameters and their levels [25].

Parameter	Level		
	1	*2*	*3*
Peak current (I)	6	10	14
Pulse on time (T_{on})	75	100	200
Duty factor (DF)	0.5	0.6	0.7

Table 2
Design layout and experimental observations for the EDM process [25].

Exp. No.	Process parameter			Response			
	I	T_{on}	DF	MRR	TWR	SR	Overcut
1	6	75	0.5	19.008	0.225	6.44	0.204
2	6	75	0.6	18.025	0.106	7.88	0.234
3	6	75	0.7	18.367	0.041	7.45	0.243
4	6	100	0.5	13.931	0.212	7.65	0.249
5	6	100	0.6	14.569	0.110	7.5	0.257
6	6	100	0.7	14.781	0.025	7.45	0.262
7	6	200	0.5	15.507	0.187	7.56	0.277
8	6	200	0.6	13.673	0.063	7.45	0.283
9	6	200	0.7	15.593	0.401	6.44	0.323
10	10	75	0.5	28.888	0.425	6.7	0.326
11	10	75	0.6	25.333	0.302	6.85	0.327
12	10	75	0.7	23.72	0.098	6.72	0.329
13	10	100	0.5	29.575	0.361	6.7	0.330
14	10	100	0.6	25.978	0.245	7.83	0.336
15	10	100	0.7	23.2	0.118	7.76	0.339
16	10	200	0.5	18.492	0.242	8.9	0.341
17	10	200	0.6	17.631	0.200	7.83	0.344
18	10	200	0.7	17.5	0.092	10.39	0.336
19	14	75	0.5	33.629	0.387	8.8	0.341
20	14	75	0.6	32.471	0.322	10.55	0.348
21	14	75	0.7	33.357	0.144	10.58	0.352
22	14	100	0.5	30.138	0.308	12.83	0.357
23	14	100	0.6	28.75	0.265	9.77	0.362
24	14	100	0.7	27.163	0.162	9.77	0.365
25	14	200	0.5	24.25	0.344	12.83	0.370
26	14	200	0.6	22.78	0.212	13.12	0.373
27	14	200	0.7	21.49	0.167	13.19	0.377

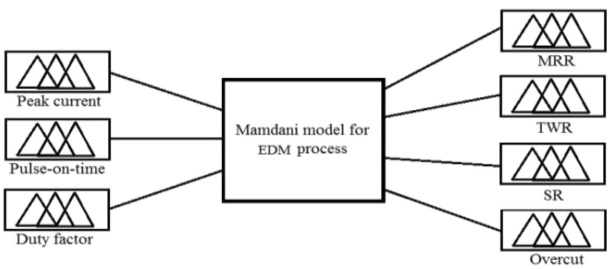

Fig. 2. Architecture of the three-input-four-output fuzzy model for the EDM process.

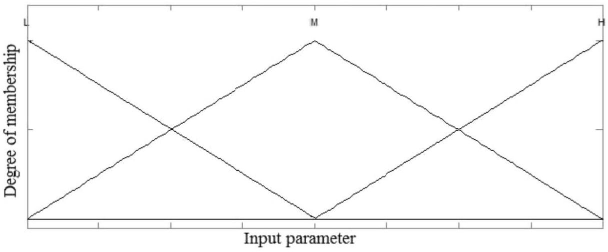

Fig. 3. Fuzzification of input process parameters.

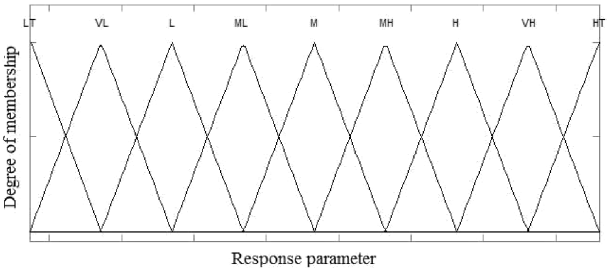

Fig. 4. Fuzzification of the responses.

Table 3
Ranges of inputs and outputs to fuzzy logic modeling for the EDM process.

Parameter/ Response	Input/ Output	Minimum value	Maximum value
Peak current	Input	6	14
Pulse-on time	Input	75	200
Duty factor	Input	0.5	0.7
MRR	Output	13.673	33.629
TWR	Output	0.025	0.425
SR	Output	6.44	13.19
Overcut	Output	0.204	0.377

Based on the observations of 27 experimental trials, a total of 27 fuzzy rules are subsequently developed in the form of linguistic statements, defining the relationships between the input process parameters and responses. The developed fuzzy expressions representing the relations between the three inputs as peak current, pulse-on time and duty factor, and four outputs as MRR, TWR, SR and overcut are exhibited in Table 4. These fuzzy rules are subsequently transferred in the fuzzy toolbox of MATLAB (R2014b) to develop the corresponding rule viewer, as shown in Fig. 5. In this rule viewer, the 27 rows represent the developed fuzzy rules exhibiting the relationships between the input process parameters and output responses. The first three columns denote the three EDM process parameters, while the last four columns represent the responses. The location of each triangle signifies the corresponding fuzzy membership function and the height of the darkened area corresponds to the fuzzy membership value for that fuzzy set [26].

Table 4
Fuzzy expressions for input and output parameters for the EDM process.

Exp. No.	If					Then			
	I	Link	T_{on}	Link	DF	MRR	TWR	SR	Overcut
1	L	and	L	and	L	L	M	LT	LT
2	L	and	L	and	M	VL	VL	VL	VL
3	L	and	L	and	H	L	LT	VL	L
4	L	and	M	and	L	LT	M	VL	L
5	L	and	M	and	M	LT	VL	VL	L
6	L	and	M	and	H	LT	LT	VL	ML
7	L	and	H	and	L	LT	ML	VL	ML
8	L	and	H	and	M	LT	LT	VL	M
9	L	and	H	and	H	LT	HT	LT	H
10	M	and	L	and	L	H	HT	LT	H
11	M	and	L	and	M	MH	H	LT	H
12	M	and	L	and	H	M	VL	LT	H
13	M	and	M	and	L	VH	VH	LT	H
14	M	and	M	and	M	MH	M	VL	H
15	M	and	M	and	H	M	L	VL	VH
16	M	and	H	and	L	L	M	ML	VH
17	M	and	H	and	M	VL	ML	VL	VH
18	M	and	H	and	H	VL	VL	MH	H
19	H	and	L	and	L	HT	HT	ML	VH
20	H	and	L	and	M	HT	H	MH	VH
21	H	and	L	and	H	HT	L	MH	VH
22	H	and	M	and	L	VH	H	HT	VH
23	H	and	M	and	M	H	MH	M	HT
24	H	and	M	and	H	H	ML	M	HT
25	H	and	H	and	L	M	VH	MH	HT
26	H	and	H	and	M	M	M	HT	HT
27	H	and	H	and	H	ML	ML	HT	HT

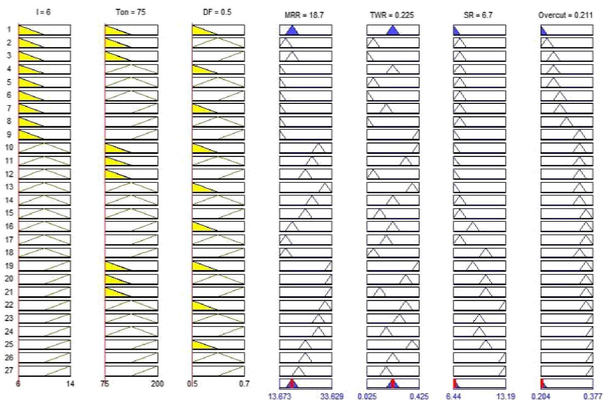

Fig. 5. Rule viewer for the EDM process.

It can be observed from Fig. 5 that when the values of different EDM process parameters are set as peak current = 6 A, pulse-on time = 75 µs and duty factor = 0.5, the corresponding responses are achieved as MRR = 18.7 mg/min, TWR = 0.225 mg/min, SR = 6.7 µm and overcut =

0.211 mm. On the other hand, it can be noticed from Table 2 that for the same parametric combination of the considered EDM process, the output responses are MRR = 19.008 mg/min, TWR = 0.225 mg/min, SR = 6.44 µm and overcut = 0.204 mm, which almost match with those obtained from the developed fuzzy model for the said process. The response values as obtained from the experimental observations and predicted from the fuzzy model are portrayed in Figs 6–9. These figures also exhibit a very close resemblance between the experimental and the predicted outputs which confirms that the developed fuzzy model can efficiently be adopted in envisaging the values of MRR, TWR, SR and overcut while machining of AA6061/10%Al_2O_3 composite materials using EDM process.

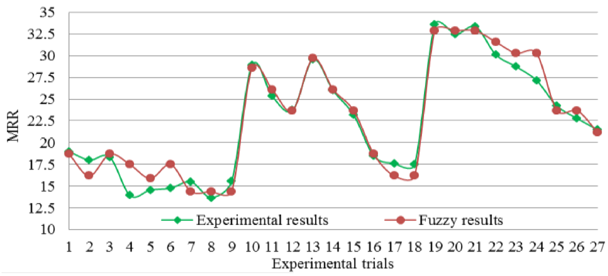

Fig. 6. Comparison of the experimental and fuzzy MRR values for the EDM process.

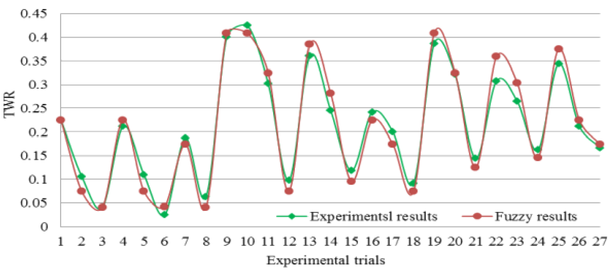

Fig. 7. Comparison of the experimental and fuzzy TWR values for the EDM process.

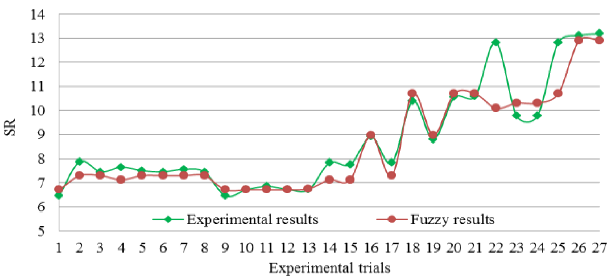

Fig. 8. Comparison of the experimental and fuzzy SR values for the EDM process.

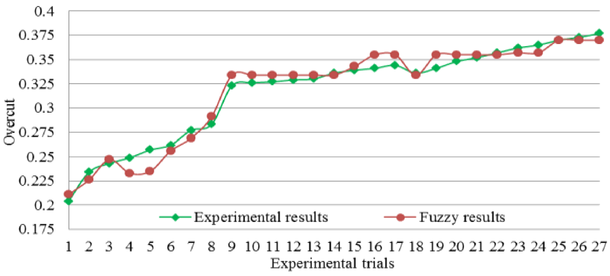

Fig. 9. Comparison of the experimental and fuzzy overcut values for the EDM process

Furthermore, to investigate the influences of the three EDM process parameters, i.e. peak current, pulse-on time and duty factor on the responses, i.e. MRR, TWR, SR and overcut, the corresponding interaction plots are analyzed through Figs 10–13. These interaction plots are developed using Minitab R17 software. Figure 10 represents the effects of peak current, pulse-on time and duty factor on MRR. It can be revealed from this figure that with the increasing values of peak current, MRR gradually increases, but it decreases with increase in the pulse-on time and duty factor values. As the peak current increases, there is an increase in the rate of discharge energy, as high concentration of discharge ener-

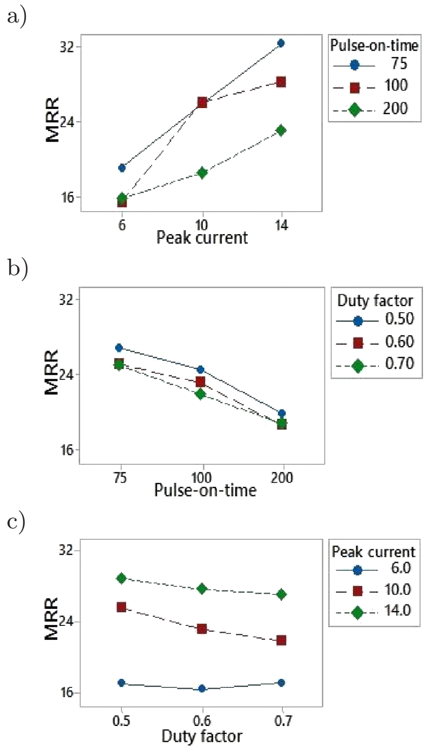

Fig. 10. Effects of different input parameters on MRR for the EDM process: a) effect of peak current on MRR (duty factor = 0.6), b) effect of pulse-on time on MRR (peak current = 10 A), c) effect of duty factor on MRR (pulse-on time = 100 µs).

gy leads to rapid melting and vaporization of the work material resulting in an increase in MRR, as shown in Fig. 10a. Figure 10b reveals a rapid decrease in the value of MRR with increase in pulse-on time. This is mainly because of the fact that longer duration of pulse-on time causes melting of more amount of workpiece material. Thus, proper flushing of molten material from the inter-electrode gap (IEG) between the tool and the workpiece resulting in forming of a passive layer which accounts for decreasing values of MRR. It also gets clearly reflected with a decreasing trend of MRR in Fig. 10c as duty factor is the ratio of pulse-on time to the total cycle time. Thus, an increase in duty factor indicates increase in pulse-on time along with a reduction in pulse-off time resulting in decreased values of MRR.

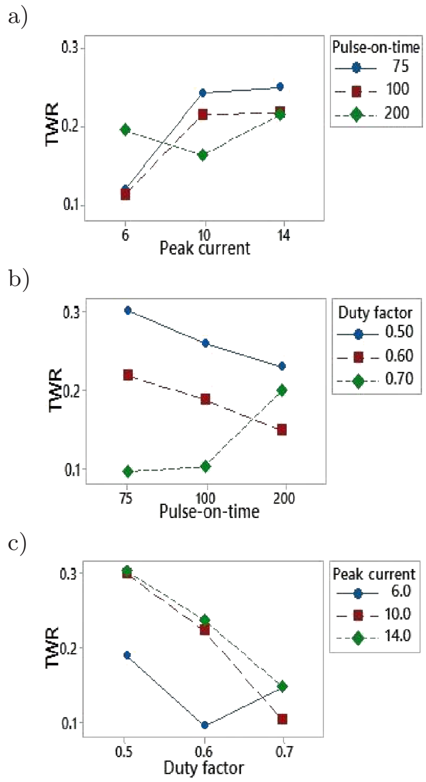

Fig. 11. Effects of different input parameters on TWR for the EDM process: a) effect of peak current on TWR (duty factor = 0.6), b) effect of pulse-on time on TWR (peak current = 10 A), c) effect of duty factor on TWR (pulse-on time = 100 µs).

It can be seen from Fig. 11a that an increase in peak current causes an increment in the value of TWR as heavy discharge of current leads to high concentration of heat resulting in melting (wear) of tool material. At longer duration of pulse-on time, the amount of carbon deposited on the tool is more. Thus, an increase in pulse duration causes an increase in the possibility of carbon deposition which further reduces the melting of tool material because of low discharge, as investigated in Fig. 11b. Figure 11c also confirms this finding where an increase in duty factor causes a reduction in TWR. Higher value of peak current results in an increase of discharge energy per pulse, which further produces deeper and wider overlapping craters and generation of micro-cracks on the machined surface, causing SR to increase, as exhibited in Fig. 12a. The value of SR is also strongly influenced by pulse-on time. Figure 12b depicts that an increase in pulse duration results in a relative increase of spark energy, causing the melting boundary (spark gap) to become deeper and wider, and hence, resulting in an increase of SR value. On the other hand, a moderate increment in SR value is observed over the changing values of duty factor, as shown in Fig. 12c.

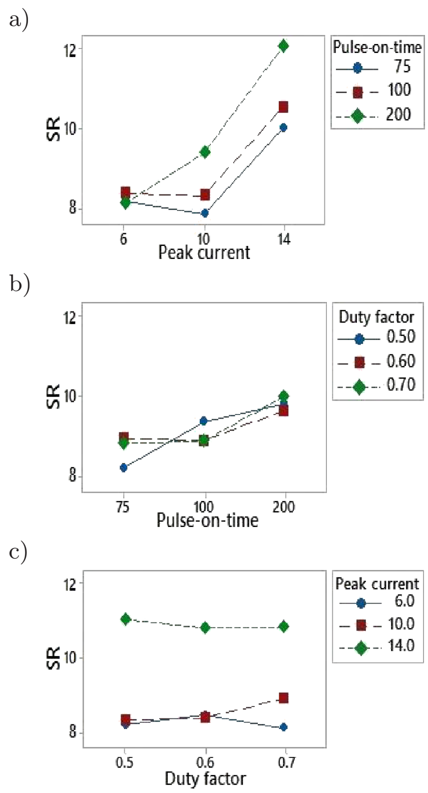

Fig. 12. Effects of different input parameters on SR for the EDM process: a) effect of peak current on SR (duty factor = 0.6), b) effect of pulse-on time on SR (peak current = 10 A), c) effect of duty factor on SR (pulse-on time = 100 µs).

From Fig. 13a, it can be revealed that with increasing values of peak current, overcut increases because of more energy transfer to the machined zone for which there is an increase in spark gap. On the other hand, pulse-on time also significantly influences overcut. Figure 13b exhibits that overcut increases with an increase in pulse-on time, due to high concentration of discharge energy for longer duration resulting in more melting of the work material. It can be further validated with an increasing trend of overcut with an increase in duty factor, as represented in Fig. 13c. This detailed study showing the effects of different EDM process parameters on the considered responses is in close agreement with the observations of Kandpal et al. [25] while machining AA6061/10%Al_2O_3 composite materials. Thus, for higher MRR, higher values of peak current and lower values of pulse-on time and duty factor; for lower TWR, lower values of peak current and higher values of pulse-on time and duty factor; and for both SR and overcut, lower values of all the three EDM process parameters are recommended.

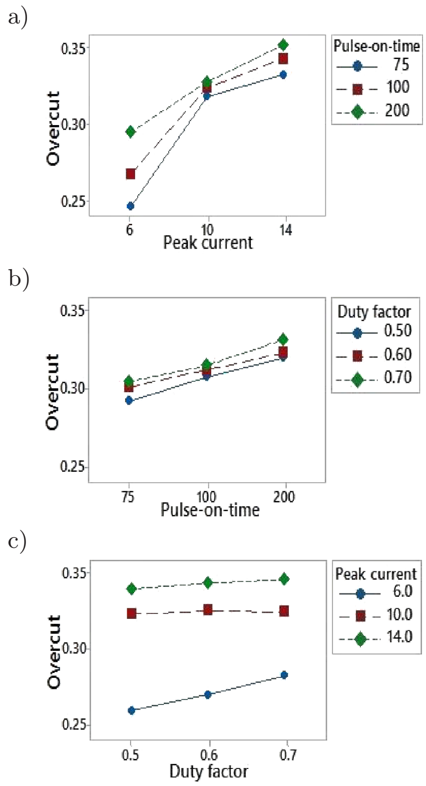

Fig. 13. Effects of different input parameters on overcut for the EDM process: a) effect of peak current on overcut (duty factor = 0.6), b) effect of pulse-on time on overcut (peak current = 10 A), c) effect of duty factor on overcut (pulse-on time = 100 µs).

Example 2: ECM process

In this example, Rao and Padmanabhan [27] studied the effects of varying values of four ECM process parameters, e.g. applied voltage (AV) (in V), electrode feed rate (FR) (in mm/min), electrolyte concentration (EC) (in g/lit) and reinforcement content (RC) (in wt%) on three responses, i.e. MRR (in g/min), SR (in µm) and radial overcut (ROC) (in mm) while machining LM6 Al/B_4C composite materials. Each of those ECM process parameters was set at three different levels, as shown in Table 5. Based on Taguchi's L_{27} orthogonal array, 27 experiments were conducted while taking a 25 mm diameter and 20 mm long LM6 Al/B_4C composite work material sample. Among these responses, MRR is the only beneficial attribute, whereas, SR and ROC are both non-beneficial quality characteristics. Table 6 shows the detailed experimental design plan and values of the measured responses.

Table 5
ECM process parameters and their levels [27].

Process parameter	Unit	Level		
		1	*2*	*3*
Applied voltage (AV)	V	12	16	20
Feed rate (FR)	mm/min	0.2	0.6	1.0
Electrolyte concentration (EC)	g/l	10	20	30
Reinforcement content (RC)	wt%	2.5	5.0	7.5

Table 6
Experimental design plan along with the response values for the ECM process [27].

Exp. No.	Process parameter				Response		
	AV	FR	EC	RC	MRR	SR	ROC
1	1	1	1	1	0.268	4.948	0.96
2	1	1	2	2	0.335	5.002	0.94
3	1	1	3	3	0.227	4.591	0.79
4	1	2	1	1	0.353	4.920	0.75
5	1	2	2	2	0.448	4.498	0.65
6	1	2	3	3	0.420	4.725	0.80
7	1	3	1	1	0.689	4.555	0.67
8	1	3	2	2	0.545	4.356	0.64
9	1	3	3	3	0.703	4.232	0.65
10	2	1	1	2	0.321	4.882	0.91
11	2	1	2	3	0.329	4.823	0.94
12	2	1	3	1	0.488	4.254	1.05
13	2	2	1	2	0.379	4.540	0.76
14	2	2	2	3	0.302	4.431	0.69
15	2	2	3	1	0.583	3.998	0.99
16	2	3	1	2	0.615	4.274	0.75
17	2	3	2	3	0.619	4.346	0.70
18	2	3	3	1	0.812	3.598	0.93
19	3	1	1	3	0.282	5.472	0.91
20	3	1	2	1	0.599	4.797	1.10
21	3	1	3	2	0.603	4.640	1.16
22	3	2	1	3	0.526	5.214	0.85
23	3	2	2	1	0.688	4.897	1.03
24	3	2	3	2	0.732	4.531	1.08
25	3	3	1	3	0.688	5.002	0.64
26	3	3	2	1	0.887	4.389	0.99
27	3	3	3	2	0.944	3.989	1

Now, in order to develop the corresponding model for the considered ECM process using the principle of fuzzy logic, these four ECM process parameters are treated as the inputs, while the three responses are considered to be the outputs. The schema of this four-input-three-output fuzzy model is exhibited in Fig. 14. Table 7 presents the corresponding minimum and maximum values of the considered input parameters and outputs. Like the previous example, triangular membership functions are also adopted here with three fuzzy subsets to represent the three levels of all the input parameters, and with nine fuzzy subsets to symbolize all the outputs in the fuzzy system. Now, based on 27 experimental trial runs, the relationships between various input and output parameters in the form of linguistic statements are also developed, as shown in Table 8. The corresponding rule viewer for this ECM process is portrayed in Fig. 15. It can clearly be observed from this figure that when the values of different ECM process parameters are set as applied voltage = 12 V, feed rate = 0.2 mm/min, electrolyte concentration = 10 g/l and reinforcement content = 2.5 wt%, the corresponding responses are predicated as MRR = 0.255 g/min, SR = 5.01 μm and ROC = 0.965 mm. For these same settings of ECM process parameters, the experimental data of Table 6 provide values of the corresponding responses as MRR = 0.268 g/min, SR = 4.948 μm and ROC = 0.96 mm. Thus, it can be concluded that for this ECM process,

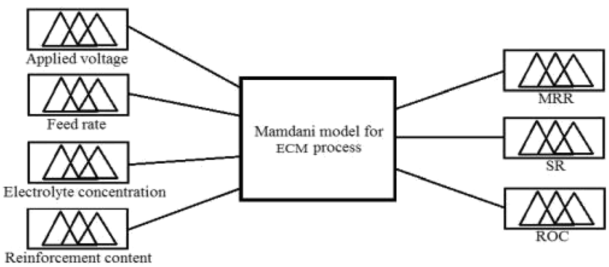

Fig. 14. Four-input-three-output fuzzy model for the ECM process.

Table 7
Ranges of input and output parameters for the ECM process.

Parameter/ Response	Input/ Output	Minimum value	Maximum value
Applied voltage	Input	12	20
Feed rate	Input	0.2	1.0
Electrolyte concentration	Input	10	30
Reinforcement content	Output	2.5	7.5
MRR	Output	0.227	0.944
SR	Output	3.598	5.472
Radial overcut	Output	0.64	1.16

Table 8
.Fuzzy expressions of input and output parameters for the ECM process

Run order	If							Then		
	AV	Link	FR	Link	EC	Link	RC	MRR	SR	ROC
1	L	and	L	and	L	and	L	LT	H	MH
2	L	and	L	and	M	and	M	VL	H	MH
3	L	and	L	and	H	and	H	LT	M	L
4	L	and	M	and	L	and	L	VL	H	VL
5	L	and	M	and	M	and	M	LT	M	LT
6	L	and	M	and	H	and	H	L	MH	L
7	L	and	H	and	L	and	L	MH	M	LT
8	L	and	H	and	M	and	M	ML	ML	LT
9	L	and	H	and	H	and	H	MH	ML	LT
10	M	and	L	and	L	and	M	VL	H	M
11	M	and	L	and	M	and	H	VL	MH	MH
12	M	and	L	and	H	and	L	ML	ML	VH
13	M	and	M	and	L	and	M	VL	M	L
14	M	and	M	and	M	and	H	LT	M	LT
15	M	and	M	and	H	and	L	M	VL	H
16	M	and	H	and	L	and	M	M	ML	VL
17	M	and	H	and	M	and	H	M	ML	VL
18	M	and	H	and	H	and	L	VH	LT	MH
19	H	and	L	and	L	and	H	LT	HT	M
20	H	and	L	and	M	and	L	M	MH	VH
21	H	and	L	and	H	and	M	M	MH	HT
22	H	and	M	and	L	and	H	ML	VH	ML
23	H	and	M	and	M	and	L	MH	H	H
24	H	and	M	and	H	and	M	H	M	VH
25	H	and	H	and	L	and	H	MH	H	LT
26	H	and	H	and	M	and	L	HT	ML	H
27	H	and	H	and	H	and	M	HT	VL	H

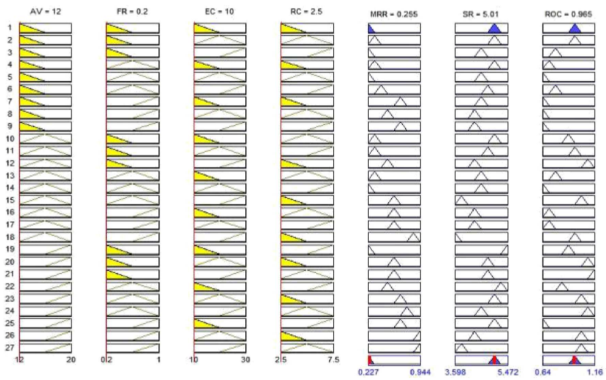

Fig. 15. Developed fuzzy rule viewer for the ECM process.

the values of the three responses as predicted employing the fuzzy model also closely match with the true experimental results. Figures 16–18 exhibit the detailed comparisons of the actual experimental observations and the predicted responses for the considered ECM process.

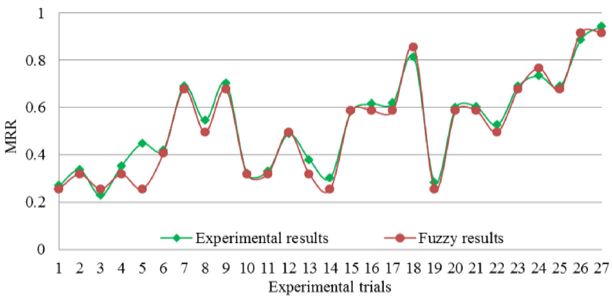

Fig. 16. Comparison of experimental and fuzzy MRR values for the ECM process.

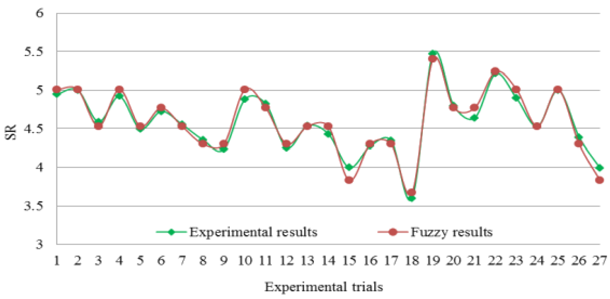

Fig. 17. Comparison of experimental and fuzzy SR values for the ECM process.

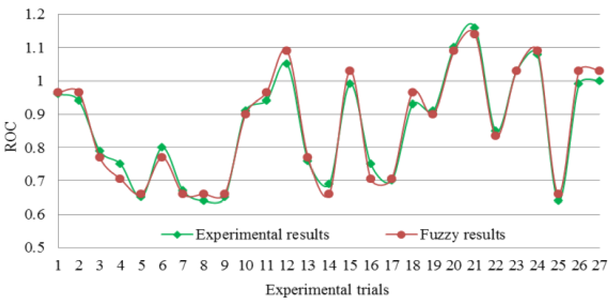

Fig. 18. Comparison of experimental results and fuzzy ROC values for the ECM process.

Like the first example, the developed interaction plots also help the concerned process engineers in studying the effects of different ECM process parameters on the three responses, i.e. MRR, SR and ROC. Figure 19 exhibits how the values of MRR change with varying values of the four ECM process parameters. It can be investigated from Fig. 19a that an increase in applied voltage causes an increase in MRR, as the current density in the IEG increases resulting in enhanced value of MRR. On the other hand, as the feed rate increases, the IEG decreases causing an accumulation of induction current to a smaller area resulting in a rapid anodic dissolution and an increase in current density which ultimately is responsible for having higher value of MRR, as observed in Fig. 19b. A higher value of electrolyte concentration increases the electrical conductivity of the electrolyte that releases a large number of ions in the IEG, resulting in an increase in MRR, as depicted in Fig. 19c. An increase in the percentage of reinforcement content decreases the electrical conductivity of the workpiece. It is because of the fact that the reinforced particles are basically poor conductors of electricity, resulting in lower MRR, as shown in Fig. 19d.

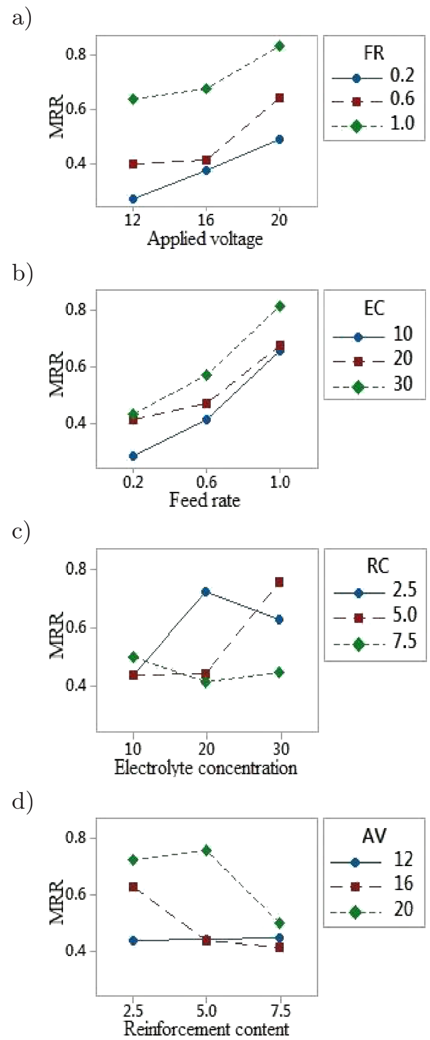

Fig. 19. Effects of various ECM process parameters on MRR: a) effect of applied voltage on MRR (electrolyte concentration = 20 g/l, reinforcement content = 5 wt%), b) effect of feed rate on MRR (applied voltage = 16 V, reinforcement content = 5 wt%), c) effect of electrolyte concentration on MRR (applied voltage = 16 V, feed rate = 0.6 mm/min), d) effect of reinforcement content on MRR (feed rate = 0.6 mm/min, electrolyte concentration = 20 g/l).

It can be observed from Fig. 20a that at lower values of applied voltage, the SR is initially high, which then decreases, and finally increases with the higher values of applied voltage. The current density at the IEG in the initial stage is low, resulting in generation of etching pits causing rough surface. With increase in applied voltage, heating of the workpiece material is observed, due to which the value of SR deteriorates. On further increase of applied voltage, SR increases drastically due to generation of excessive heat leading to distortion of the machined surface. On the other hand, increasing feed rate leads to a decrease in SR value, resulting from a steady and uniform metal dissolution in anodic dissolution process, as noticed from Fig. 20b. Figure 20c shows a moderate increase in SR value with the increment in electrolyte concentration as it causes low depletions of ions resulting in a better surface finish. Moreover, Fig. 20d presents a decreasing trend in the value of SR with an increase in reinforcement content. The percentage increment in reinforcement content reduces the conductivity of the workpiece material while distressing the electrolytic action further lowering the quality of surface finish.

The ROC value increases with an increase in applied voltage, as observed from Fig. 21a, as high electrolyzing current at the IEG results in a higher stray current intensity, thereby increasing ROC. On the other hand, increase in feed rate reduces the IEG, resulting in a low current and decreasing ROC, as shown in Fig. 21b. A higher value of electrolyte concentration results in formation of reaction

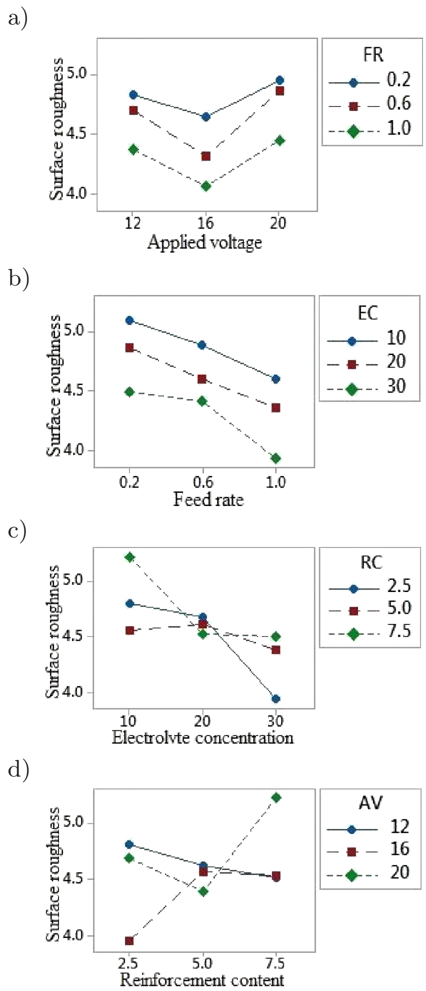

Fig. 20. Effects of various ECM process parameters on SR: a) effect of applied voltage on SR (EC = 20 g/l, RC = 5 wt%), b) effect of feed rate on SR (AV = 16 V, RC = 5 wt%), c) effect of electrolyte concentration on SR (applied voltage = 16 V, feed rate = 0.6 mm/min), d) effect of reinforcement content on SR (feed rate = 0.6 mm/min, electrolyte concentration = 20 g/l).

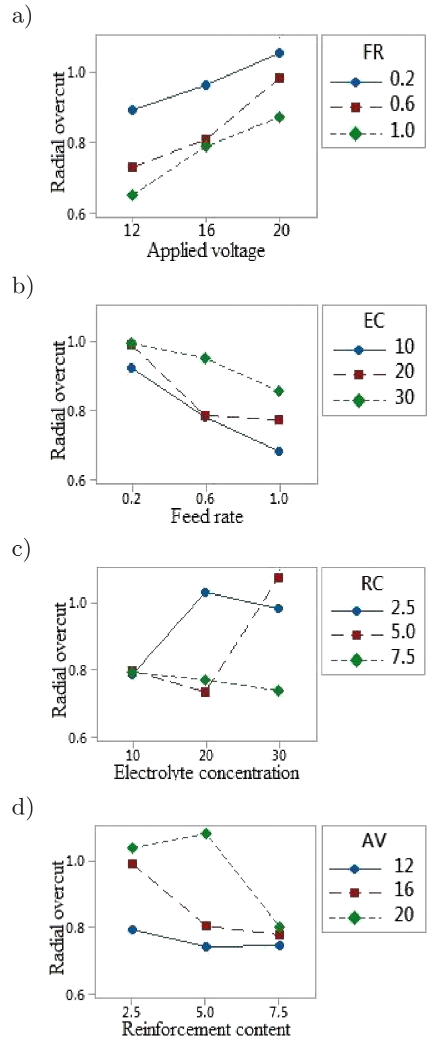

Fig. 21. Effects of various ECM process parameters on ROC: a) effect of applied voltage on ROC (electrolyte concentration = 20 g/l, reinforcement content = 5 wt%), b) effect of feed rate on ROC (applied voltage = 16 V, reinforcement content = 5 wt%), c) effect of electrolyte concentration on ROC (applied voltage = 16 V, feed rate = 0.6 mm/min), d) effect of reinforcement content on ROC (feed rate = 0.6 mm/min, electrolyte concentration = 20 g/l).

by-products, e.g. sledges, precipitates etc. and also gas bubbles which lead to the generation of stray current at the machining periphery causing an increment in the value of ROC, as observed from Fig. 21c. Figure 21d presents a decreasing trend in ROC value with an increase in reinforcement content as the percentage increase in reinforced particles reduces the electrical conductivity leading to reduction in MRR in radial direction. Now, based on the detailed analyses of the interaction plots and comparing them with the actual experimental results, it can be concluded that the analyses presented in this paper are in close agreement with the observations of Rao and Padmanabhan [27]. For the considered ECM process, higher values of MRR can be attained while setting higher applier voltage, higher feed rate, higher electrolyte concentration and lower reinforcement content. For lower SR values, moderate applier voltage, higher feed rate, higher electrolyte concentration and moderate reinforcement content can be set. Also, lower applier voltage, higher feed rate, lower electrolyte concentration and higher reinforcement content lead to lower values of ROC.

Conclusions

In this paper, based on the experimental investigations of the past researchers, two NTM processes (EDM and ECM processes) are selected for modeling using the fuzzy logic technique. The subsequent fuzzy relations are developed representing the associations between the considered NTM process parameters and responses. It can be clearly observed that the results derived from the proposed fuzzy model are in close agreement with the experimental values as observed by the past researchers. Thus, these fuzzy models can effectively guide the process engineers to easily predict the tentative values of different responses for any given combination of the NTM process parameters. Moreover, the developed interaction plots exhibit the influences of various NTM process parameters on the responses which may further help the concerned process engineers to identify the optimal parametric settings so as to attain the target response values. This fuzzy logic approach can be effectively deployed to other machining processes (conventional as well as non-conventional) to predict their optimal output performance while achieving better quality products with the maximum machining efficiency.

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