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Multi-objective optimization of TW-ECSM process parameters for machining of advanced non-conducting material

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Travelling wire electrochemical spark machining (TW-ECSM) is newly evolved and developed hybrid machining process for the machining of advanced non-conducting materials which possess significant values of the properties like high strength, high wear and fatigue resistance, high refractoriness and high strength to weight ratio, etc. The control parameters like voltage, wire feed rate, electrolyte concentration and inter-electrode gap were selected as Input Parameters and Material Removal Rate (MRR), and Surface Roughness (SR) were the corresponding output responses. In present work, for multi-objective optimization and purpose of better control of machining parameters, three approaches, grey-relational analysis-principal component analysis (GRA-PCA), fuzzy logic and desirability function approach are used to determine the optimal combination of TW-ECSM process variables. Results of fuzzy logic and GRA-PCA approach are found comparable while desirability function approach is found to be capable of predicting the optimal responses at such levels of process variables also at which experiments are not performed. Consequences of the applied approach in the present work are also validated by conducting the confirmatory experiments and results are found in well agreement with the predicted results.

Keywords: TW-ECSM, Quartz, Material Removal Rate (MRR), Surface Roughness (SR), Optimization, Fuzzy, Grey Relational, Principal component

1 Introduction

The non-conducting engineering materials which are advanced in terms of technological aspects like quartz, zirconia and silicon nitride are difficult to machine by existing conventional machining processes. To deal with this type of problems, the non-conventional or modern machining processes found to be suitable to machine advanced materials. Microengineering field needs and demands for the advanced non-conducting materials continuously which have significant value in the production of different valuable products[1]. Creation of intricate profiles in brittle, hard as well as electrically insulating materials still found to be a tough task for the machining practitioners[1,2]. To solve this problem, the focus should be on hybrid machining processes which are combination of two or more machining processes. Though, principle of hybrid process is similar to the constituent processes but characteristics of hybrid processes are much better and advantageous rather than individual machining process.

The electrochemical spark machining (ECSM) comes under the category of hybrid machining processes which has adequate capability to overcome the constraint of machining of electrically non-conductive work materials. ECSM is collaborative approach of electro-chemical machining (ECM) and electro-discharge machining (EDM) which can also be termed as electrochemical discharge machining (ECDM) process[3]. The principle of heat generation in ECSM process is due to melting and vaporization which is resultant of the electro discharge phenomenon in the process. Kurafuji[4] known as the first researcher who described this phenomenon as "Electrochemical Discharge Drilling" for manufacturing of micro-size holes in glass. Wuthrich *et al.*[5] reported that insulating gas film formation around the electrode is responsible for the electro discharge phenomena in the process. Basak and Ghosh[6] noticed the discharge phenomenon during machining carefully and prescribed a process (switching-off process) which is based on the formation of bubble bridges during the machining process.

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In electrochemical spark machining, cutting of slots in work piece can also be performed by wire electrode which is termed as travelling wire ECSM process. Tsuchiya *et al.*[7] was the first to develop travelling wire-ECDM setup for machining purpose. The study revealed several facts about the machining of various electrically insulating materials such as glass and the different ceramics by this technique. Jain *et al.*[8] further explored mechanism related to the cutting of composites using wire-ECDM. With the passage of time, many researchers[9-13] studied and improved the abilities of the TW-ECSM process.

Beyond these abilities, the performance of TW-ECSM depends on optimum combination of the different process parameters. The researchers[14-21] reported many techniques by which the responses of the machining as well other processes can be optimized. Taguchi's methodology was used to optimize the output responses by setting the different process parameters at their optimum values[14]. Wuthrich and Fascio[15] developed mathematical model for correlating the effect of the different process parameters and their effects on some responses in drilling operation using Response Surface Methodology (RSM). Similarly, other researchers also adopted RSM for formulation and optimization in different processes like EDM process[16] and stir casting process[17]. There are different optimization techniques like fuzzy techniques[18], grey relational analysis[19], artificial neural network[20], Taguchi approach[21] , etc. which have been used by the researchers in different machining and other processes to optimize the quality of the output characteristics. Genetic algorithm (GA) is an approach to find out an optimal solution of an objective function in different processes. As compared to conventional optimization techniques, GA is found to be robust, global and is not constrained to domain-specific solutions. Yan *et al.*[22] developed fuzzy logic controller based on genetic algorithm in wire driving mechanism under wire EDM machining process. Oza *et al.*[23] used Taguchi design for identify the optimal setting of the different process parameters in the TW-ECSM process. Bhuyan and Yadava[24] coupled grey relational analysis (GRA) and principal component analysis (PCA) for the multi-response optimization in TW-ECSM process. The setting of the optimal process parameters reported the enhancement of MRR and reduction of SR and kerf width against the initial combination of parameters.

From the detailed study of the literature, the observation clearly shows the need for multi-objective optimization of TW-ECSM parameters which provides logical results with easy computation. In the present paper, GRA-PCA and fuzzy techniques are used for different process control parameters like voltage, wire feed rate, electrolyte concentration, and inter-electrode gap. Individually, fuzzy logic is also desirable for multi-objective output. Fuzzy's rule-based inference system gives qualitative information as compared to statistical methods which generally produces quantitative information only. Moreover, fuzzy logic approach is easy and more reliable to apply on any systematically designed experimental work. On the other hand, intelligent computation-based techniques and various algorithms take more analysis time. Comparatively, for the small set of data, they possess complex information processing system and even found to be insufficient to give reliable results. Similarly, desirability approach is also famous and widely applicable approach for multi-response optimization due to its simplicity. In desirability approach, the variability of the response variable assumes to be stable and then the whole focus be on the optimization of mean of multiple responses. Thus, the main aim of the present study is to determine reliable and optimal machining parameters which maximize the objective function material removal rate (MRR) and minimize the objective function surface roughness in TW-ECSM process while machining quartz material.

2 Materials and Methods

2.1 Experimental setup

In the setup fabrication, machining chamber is constructed of perspex material obligating to its high transparency, chemical resistivity and corrosion resistance. Here, graphite rod (ϕ 20mm) has been used as auxiliary electrode and brass wire (ϕ 0.10 mm) as a tool electrode. Stepper motor has been used to govern the gear system which controls the linear movement of work-piece. The main physical components used for wire feeding are donor spool, perspex pulleys and receiver spool. Tool wire is essentially required to be moving at constant and desired speed during machining process. Movement of both spools and pulleys is powered by the stepper motor and its movement was directed by MACH-3 CNC software to perform the experiment on desired feed rate.

As an electrolyte, Sodium hydroxide (NaOH) has been used due to its property of high specific

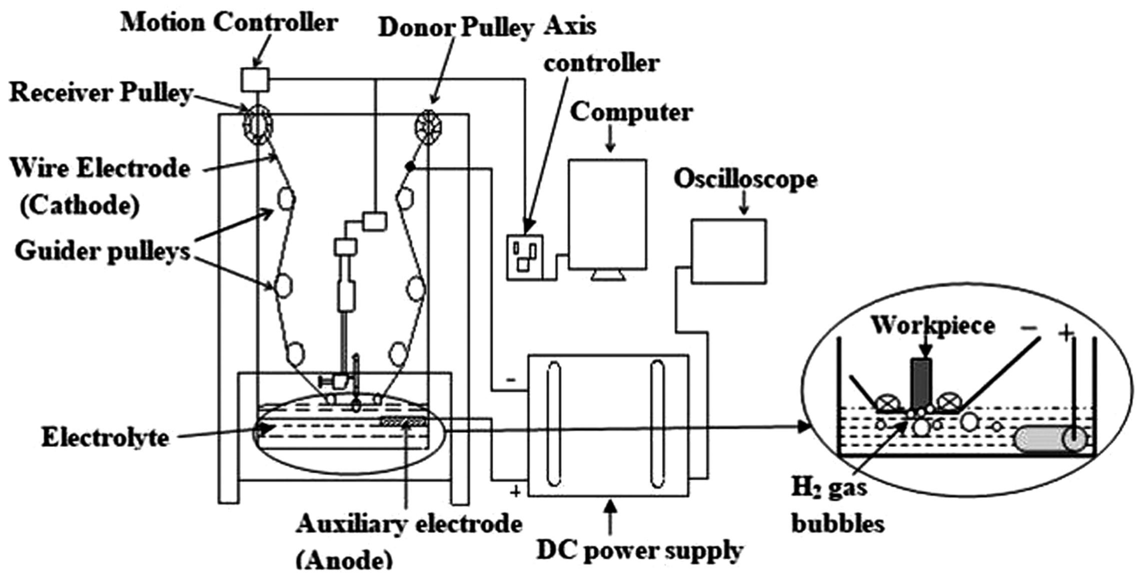


Fig. 1 — Schematic view of the TW-ECSM process.

conductance. Existing set-up (Fig. 1) is designed to be operated by DC continuous power supply. For smooth input AC power supply, a servo AC voltage regulator (5kW power capacity) has been used.

Fixture made of Teflon material has been used to hold the work-piece and connect with driving system by clenching it about vertical axis. Fixture is mounted in such a way that long axis of machining surface has become perpendicular to wire movement. Teflon being highly non-reactive, does not cause any adverse effect on the process. Quartz work-piece with specimen dimensions 25mm x 8mm x 1.6 mm has been used as work material in experiments. Quartz is found to be the first choice in high-temperature processes in various industries due to its remarkable hardness, refractory nature and high melting point. It also plays a vital role in the fabrication of piezoelectric elements such as timing, frequency control and frequency selection. The different physical and thermal characteristics associated with quartz material have been mentioned in Table 1.

Table 1 — Material properties of quartz[25]

Parameters	Description
Density	2.2×10^3 kg/m^3
Tensile Strength	5×10^7 Pa (N/m^2)
Hardness	5.5–6.5 Mohs' Scale(N/mm^2)
Young's Modulus	7.2×10^{10} Pa
Coefficient of Thermal Expansion (20°C–320°C)	5.11×10^{-7} cm/cm °C
Thermal Conductivity (at 20°C)	1.4 W/m °C
Melting temp. of quartz	2000 ^{0}C

2.2 Grey relation analysis-principal component analysis (GRA-PCA)

Hybrid approach of GRA-PCA makes use of advantages of both the approaches i.e. grey relation analysis and principal component analysis. While GRA is a grey theory-based approach, which facilitates decision-making process for a multi characteristics problem, PCA provides the weightage or importance of each characteristic based on variance and covariance between the process characteristics. Grey theory easily deals with the incomplete set of information. On the other hand, PCA method explores the variance and covariance among the predefined variables. Figure 2 explains the steps of 'GRA-PCA hybrid approach' application in detail[26,27].

In present study, a problem of multi-objective optimization is solved while considering results for two responses of TW-ECSM process i.e. material removal rate (MRR) and surface roughness (SR) as grey information. Before applying any approach, the data for experimental results of MRR and SR were normalized to bring down their values on a single scale. Therefore, values of each variable were derived between 0 and 1. This makes the comparison between many output responses which are of different nature very convenient. For normalization purpose, MRR is considered as 'higher the better' variable while SR is considered as 'lower the better'. The SR value of the machined slot was measured by using surface roughness tester (make: Tokyo Seimitsu model: Surfcom Flex-50A) and MRR was calculated by using

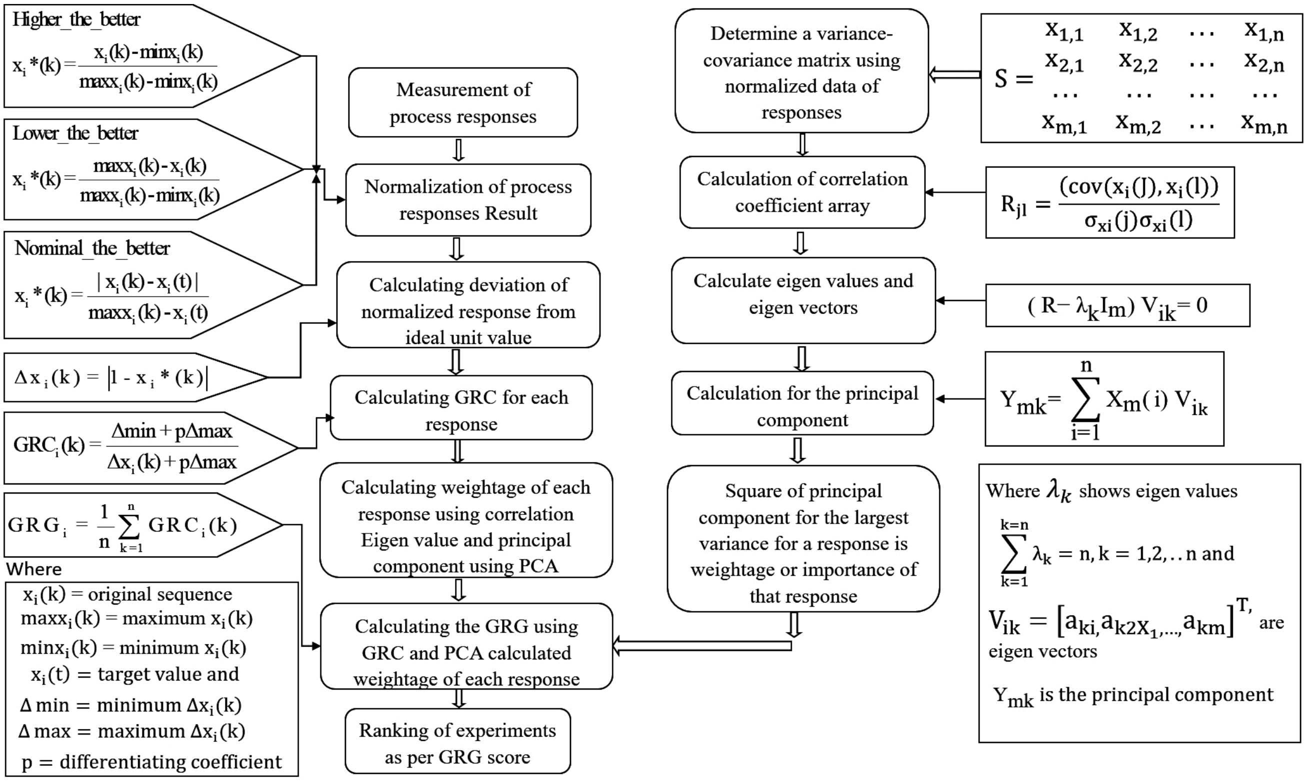


Fig. 2 — Methodology of GRA-PCA hybrid approach.

a weighing balance (make: Mettler Toledo, model: AB 104-S) with 0.1 mg of least count.

2.3 Fuzzy inference system (FIS)

Uncertainties caused by uncontrolled noise factors of a system result into errors in experimental output. The approach of fuzzy inference successfully deals with these uncertainties. A fuzzy inference system is comprised of a fuzzifier, membership functions (MF), a fuzzy rule base, an inference engine, and a defuzzifier[18]. Fuzzy values for each variable are determined using membership functions. Fuzzy inference engine processes the fuzzy data for input variables on fuzzy rule base and gives a quantitative score for each experiment.

In present study, the two responses of TW-ECSM process (MRR and SR) are provided as input variables to FIS. Model prepared for fuzzy inference system to determine a multi characteristics fuzzy index (MCFI) is shown in Fig. 3. Moreover, for each input as well as output variable, five triangular MF (refer Fig. 4) are used. Proposed fuzzy model for present study is summarized in Table 2 along with its technical details.

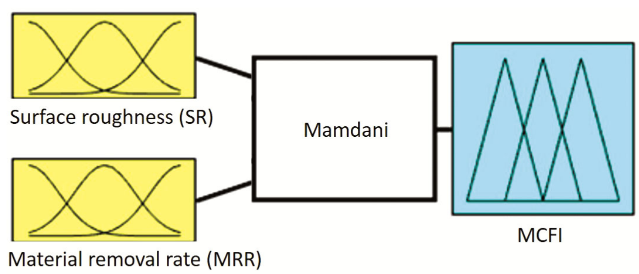


Fig. 3 — Model of fuzzy inference system for multi characteristics fuzzy index.

Table 2 — Details of the proposed fuzzy model

Type of fuzzy inference system (FIS)	Mamdani
Inputs/output	2/1
Input membership function types	Triangular
Output membership function types	Triangular
Number of input membership functions	5/5 (Very small, small, medium, large, very large)
Number of output membership function	5 (Very poor, poor, average, good, very good)
Rules weight	1
Number of fuzzy rules	25
And method	Min
Implication method	Min
Aggregation method	Max
Defuzzification method	Centroid

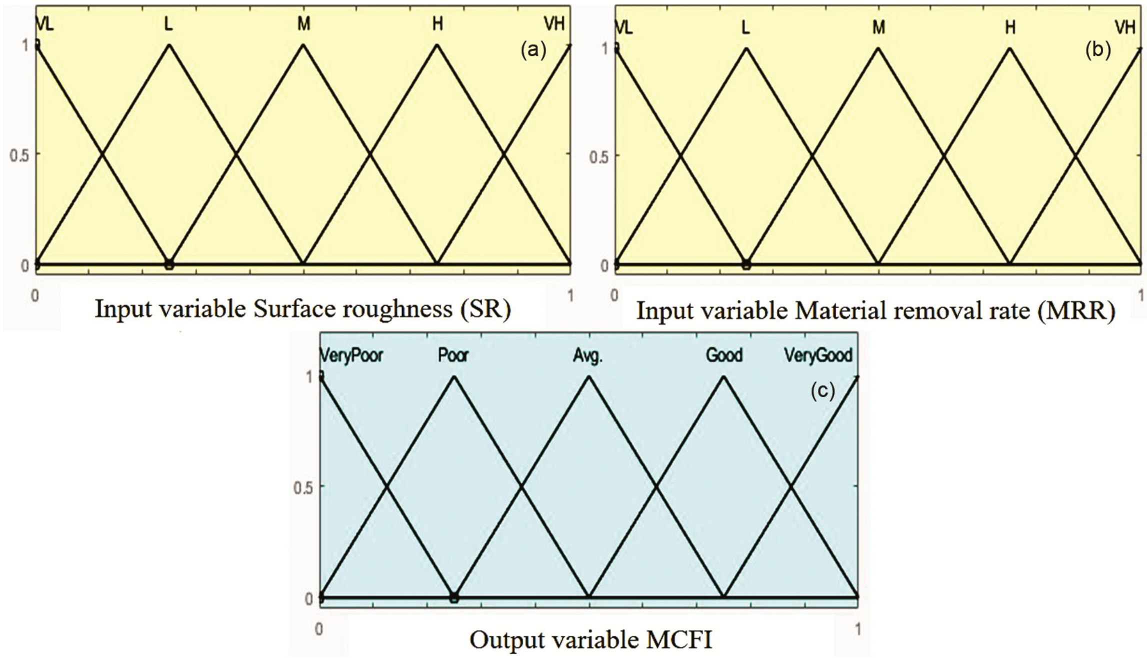


Fig. 4 — Membership Functions for (a) surface roughness (b) material removal rate, and (c) output function MCFI.

Table 3 — Fuzzy Rules for MCFI

		Material removal rate (MRR)				
		Very small	Small	Medium	Large	Very large
Surface roughness (SR)	Very small	Very poor	Very poor	Poor	Poor	Average
	Small	Very poor	Poor	Poor	Average	Good
	Medium	Poor	Poor	Average	Average	Good
	Large	Poor	Average	Average	Good	Very good
	Very large	Average	Good	Good	Very good	Very good

Using the normalized score for MRR and SR, fuzzy rules are prepared. Base for formulated fuzzy rules is ‘IF and THEN’ condition. In present study, total 25 fuzzy rules have been formulated. All 25 fuzzy rules for FIS are tabulated in Table 3.

The defuzzified output MCFI along with normalized values of input variables MRR and SR are shown in Table 4. A higher value of normalized input variables gives a higher MCFI score. Higher MCFI for a particular experiment indicates the better performance of that experiment in terms of desired process responses. Figure 5 shows the step by step process for application of fuzzy inference system.

2.4 Desirability-function

Desirability-function approach is very fruitful in solving the problem of multi-response optimization. As per desirability-function technique, an individual value of desirability function (d_i) is allotted to MRR as well as SR, expressed as $y_i(x)$ which comes out to be in between 0 - 1[28]. Complete procedure for the application of desirability function approach to a multi-response optimization problem is given in Fig 6.

Objective of present study is to find the optimal parameter setting of TW-ECSM process that maximizes the overall desirability function value while considering ‘larger the better’ criteria for MRR and ‘lower the better’ criteria for SR.

3 Results and Discussion

3.1 Results of GRA-PCA approach

As normalized data is easy for comparing, therefore, normalized data is processed using PCA approach. Table 5 shows the results for Eigen analysis on the correlation matrix of linear correlation between MRR and SR values. Coefficients of first and second principal components determined using eigen values for MRR and SR are listed in Table 6. The first principal component found with a variance score of 1.7804 which alone contributes 89% of data variation and hence, selected for calculating the weightage of MRR and SR. Importance or weightage for a response

Table 4 — Results of GRA-PCA and Fuzzy approach with GRG ranking and MCFI ranking for machining characteristics

Run order	Normalized MRR	Deviation	GRC	Normalized SR	Deviation	GRC	GRG	GRG Ranking	Fuzzy MCFI	Fuzzy Ranking
1	0.286	0.714	0.412	0.637	0.363	0.580	0.496	19	0.385	21
2	0.071	0.929	0.350	0.945	0.055	0.901	0.625	7	0.514	6
3	0	1	0.333	1	0	1	0.667	5	0.5	7
4	0.357	0.643	0.438	0.637	0.363	0.580	0.509	16	0.385	20
5	1	0	1	0.294	0.706	0.415	0.707	4	0.75	4
6	0.357	0.643	0.438	0.612	0.388	0.563	0.5	17	0.365	22
7	0.286	0.714	0.412	0.545	0.455	0.523	0.468	26	0.305	26
8	0.071	0.929	0.350	0.821	0.179	0.736	0.543	12	0.427	11
9	0	1	0.333	0.955	0.045	0.918	0.626	6	0.445	10
10	0.143	0.857	0.368	0.699	0.302	0.624	0.496	18	0.389	17
11	0.286	0.714	0.412	0.481	0.519	0.491	0.451	31	0.296	31
12	0.286	0.714	0.412	0.501	0.499	0.501	0.456	29	0.296	29
13	0.071	0.929	0.350	0.688	0.312	0.616	0.483	23	0.33	25
14	0.857	0.143	0.778	0.166	0.834	0.375	0.576	9	0.516	5
15	0.714	0.286	0.636	0.460	0.540	0.481	0.559	11	0.454	9
16	0.286	0.714	0.412	0.607	0.393	0.560	0.486	21	0.361	23
17	0.286	0.714	0.412	0.533	0.467	0.517	0.464	27	0.296	27
18	0.286	0.714	0.412	0.488	0.512	0.494	0.453	30	0.296	30
19	0.143	0.857	0.368	0.664	0.336	0.598	0.483	22	0.389	18
20	0.929	0.071	0.875	0	1	0.333	0.604	8	0.42	12
21	0.429	0.571	0.467	0.654	0.346	0.591	0.529	13	0.415	15
22	0.143	0.857	0.368	0.852	0.148	0.772	0.570	10	0.497	8
23	0.429	0.571	0.467	0.530	0.470	0.515	0.491	20	0.42	13
24	0.429	0.571	0.467	0.478	0.522	0.489	0.478	25	0.42	14
25	0.286	0.714	0.412	0.593	0.408	0.551	0.481	24	0.349	24
26	0.357	0.643	0.438	0.639	0.361	0.581	0.509	15	0.386	19
27	1	0	1	0.384	0.616	0.448	0.723	3	0.75	3
28	0.286	0.714	0.412	0.506	0.494	0.503	0.457	28	0.296	28
29	1	0	1	0.488	0.512	0.494	0.747	2	0.75	2
30	0.429	0.571	0.467	0.607	0.393	0.560	0.513	14	0.412	16
31	1	0	1	0.518	0.482	0.509	0.755	1	0.751	1

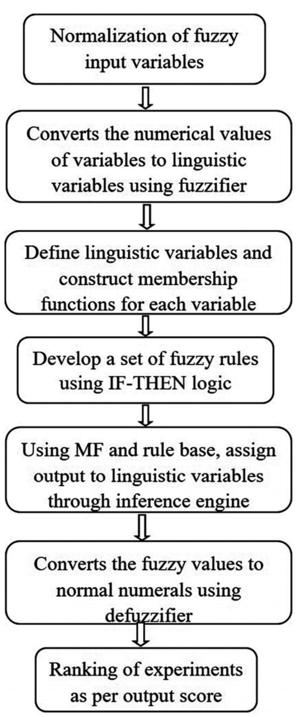


Fig. 5 — Step by step process for application of fuzzy inference system.

of TW-ECSM process is determined by squaring the first principal component coefficient for that response.

Results for intermediate steps of GRA approach i.e. normalized data for MRR and SR values for each experiment, their corresponding deviation coefficients and grey relations coefficients (GRC) are listed in Table 4. By taking into account the PCA generated weightage and grey relations coefficient of each response, a single score for each experiment i.e. grey relational grade (GRG) is calculated as listed in Table 4.

All experiments are ranked according to the GRG scores. A higher value of GRG score signifies the optimum settings of the process parameters which are delivering optimum results for process responses. As per the GRG score, experiment at run order number 31 is ranked one as it has the highest GRG score of 0.755 with results for MRR and SR as 0.15 mg/min and 11.91 µm, respectively.

3.2 Results of fuzzy inference system

Normalized data for MRR and SR is supplied to the fuzzy inference system as input variables.

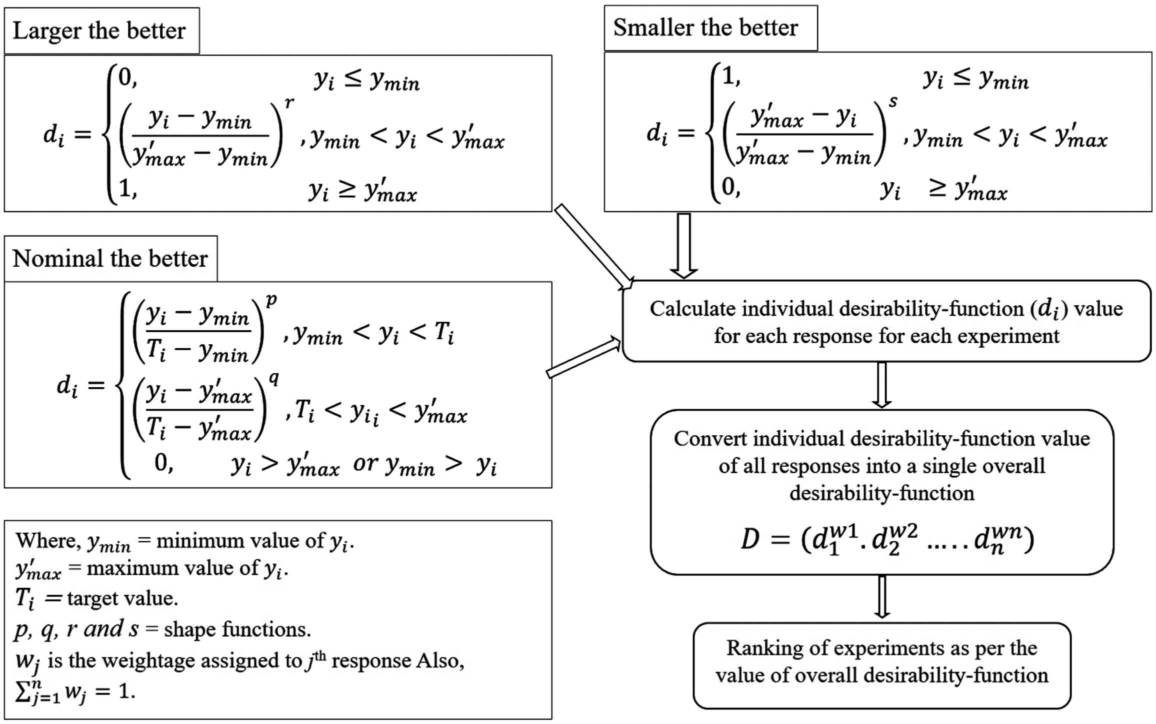


Fig. 6 — Procedure of desirability function approach.

Table 5 — Eigen analysis of the correlation matrix for PCA

Eigen value	1.7804	0.2196
Proportion	0.89	0.11
Cumulative	0.89	1.0

Table 6 — Principal components of variables

Variable	1st principal component	2nd principal component	Weightage (%)
MRR	0.707	0.707	50
SR	0.707	-0.707	50

Triangular MFs involves less computational complexity, therefore, used in this study. Using the rule base and MFs, data for input variables is processed through modeled fuzzy inference engine and a single output score, MCFI is generated. Figure 7 shows the rule viewer for experiment at run order number 31. Surface plot as shown in Fig. 8 is significant for understanding the relationship between input variables of FIS (MRR and SR) and its output score MCFI.

Ranking of all experiments is done as per the MCFI score. Similar to GRG ranking, experiment with highest MCFI score is ranked as first. Experiment at run order number 31 with MCFI score of 0.751 having MRR and SR values as 0.15 mg/min and 11.91 µm, respectively, is placed at first place. It signifies that setting of process parameters for experiment at run order number 31 is the optimal combination.

3.3 Results of desirability function approach

The desirability function is very effective and well accepted multi-objective optimization approach method in various sectors. The desirability function approach can be categorized into two different techniques which are mentioned below.

3.3.1 Single-characteristic optimization

A goal of maximization is selected for MRR while minimization target is set for SR. Process parameters of TW-ECSM process are assigned under the category of high to low. For a set goal, the shape of the desirability function is decided and controlled by its weight. Therefore, each goal was assigned with equal weight to avoid any biasing in results. Also, for keeping in view the equal importance of each goal, an importance value of '3' was selected for each. The results which comes from single-characteristic optimization using desirability approach are mentioned in Table 7. Results suggested the values of input parameters which target the highest desirability for each goal.

3.3.2 Multi-response optimization

As we know that output responses of TW-ECSM process i.e. MRR and SR are contradictory in nature, therefore, multi-response optimization approach of desirability function is applied to solve such problem. A single multi-response optimization goal considering

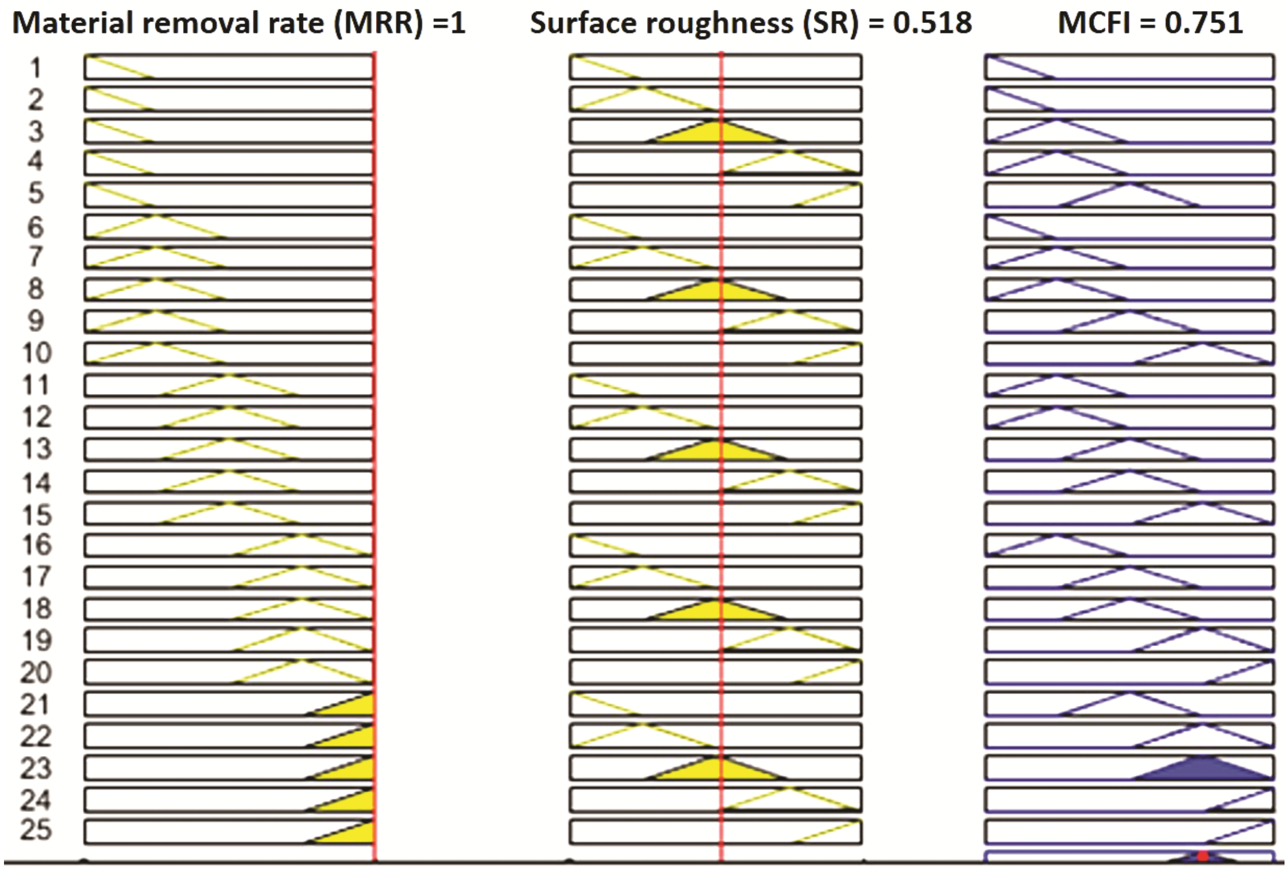


Fig. 7 — Rule viewer showing the relationship between input variables, and MCFI score of FIS.

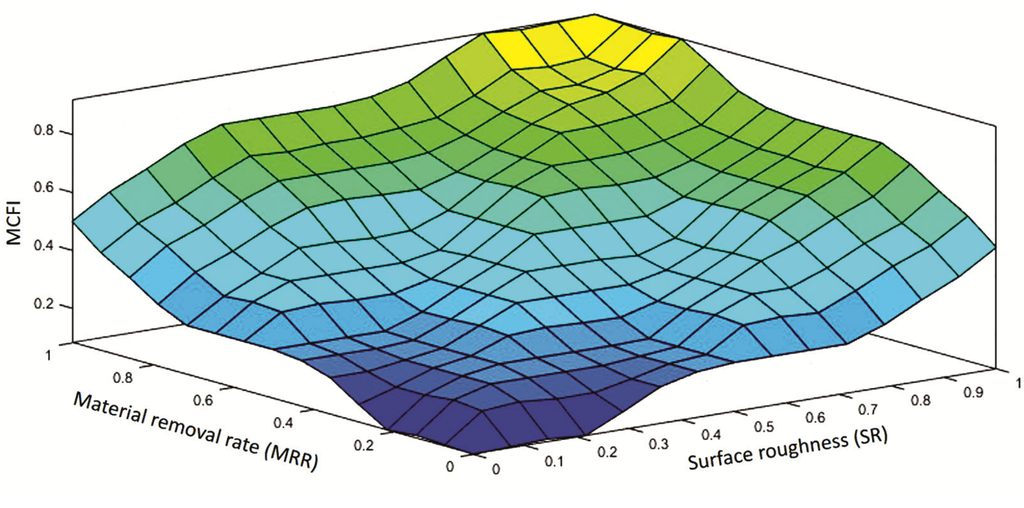


Fig. 8 — Surface plot showing relationship between fuzzy inputs and MCFI.

MRR maximization and SR minimization with equal weight and equal importance was provided. Similar to single-response optimization problem, input parameters were selected between high to low range. Suggested values of input parameters which give a highest value of desirability function are listed in Table 7.

3.4 Confirmation test

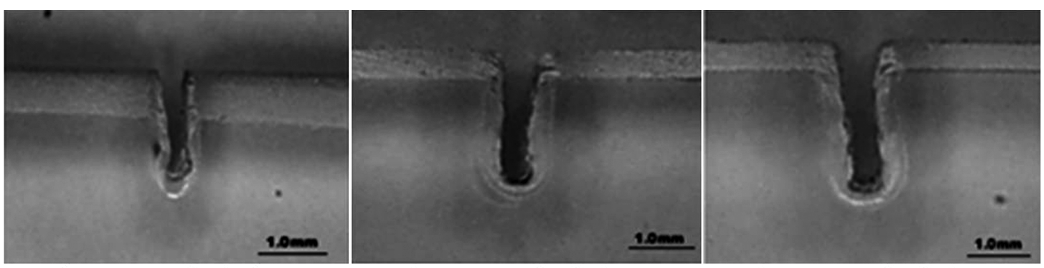
To check the prediction accuracy of desirability approach and to verify the results of GRA-PCA approach as well as fuzzy inference system approach, confirmatory experiments are carried out. Therefore, experiments were carried out at suggested optimal

Table 7 — Optimized process parameters of TW-ECSM using desirability for MRR and SR

Purpose	Voltage (V)	Wire feed rate (mm/min)	Inter-electrode distance (mm)	Elect. conc. (%)	MRR (mg/min)	SR (μm)	Desirability
MRR maximum	35.32	313.15	66.93	16.97	0.18	13.23	1.00
SR minimum	24.30	428.75	83.63	13.11	0.005	8.34	1.00
Multi-response optimization	32.57	400	60	19	0.14	12.92	0.59

Table 8 — Confirmatory experimental results and comparison of optimized and initial results

Test condition	Voltage (V)	Wire feed rate (mm/min)	Inter-electrode distance (mm)	Elect. conc. (%)	MRR (mg/min)	SR (μm)
Initial settings	30	500	90	16	0.05	11.72
Optimized as FIS/GRA-PCA	33	400	120	19	0.15	11.91
Gain/loss as compared to initial settings (%)	-	-	-	-	+200	+1.62
Optimized as Desirability multi-response	33	400	60	19	0.15	12.52
Gain/loss as compared to initial settings (%)	-	-	-	-	+200	+6.83
Error compared to predicted responses					7.14	3.1



At voltage-30V, Wire feed rate-500mm/min, Inter electrode gap-90mm, Electrolyte concentration-16%

At voltage-33V, Wire feed rate-400mm/min, Inter electrode gap-120mm, Electrolyte concentration-19%

At voltage-33V, Wire feed rate-400mm/min, Inter electrode gap-60mm, Electrolyte concentration-19%

Fig. 9 — Microscopic images of the machined slot in the quartz workpieces at different process parameters based on the confirmatory experimental results.

levels of process parameters corresponding to each approach. Details about process parameters setting and predicted as well as obtained results for confirmatory experiments are listed in Table 8. Each process parameter is set in machine nearest to its optimal suggested value, as there are constraints for machining setup.

A percentage gain or loss in each response is also calculated for each approach by comparing the results of confirmatory experiments with the results of experiments carried out at initial settings of process parameters (Eq. 1). Initial settings of process parameters are those non-optimized values of process parameters at which an operator generally runs the machine. From Table 8, it can be inferred that there is a substantial gain of 200 percent in MRR result while almost insignificant loss of 1.62% and 6.83% in surface finish for GRA-PCA/FIS approach and desirability function approach, respectively. Similarly, results of confirmatory experiments for desirability function approach are also compared with its predicted results and error is determined using Eq. 2. Error of 7.14% and 3.1% are observed for the result of MRR and SR, respectively, which is within acceptable limit for a stochastic operation like TW-ECSM.

Gain or loss = (Confirmatory result – Initial setting results) / Initial setting results ... (1)

Error = (Experimental value – Predicted value) / Predicted value ... (2)

Microscopic images of the machined slot for confirmatory experiments are shown in Fig. 9 clearly reveals that the machining slot depth increased which directly reflects enhancement in MRR. This shows that at optimum setting of the parameters based on GRA-PCA and desirability criterion MRR increased significantly as compared to the initial setting of the process parameters (non-optimized parameters setting). The error percentage is found to be under limits which also conclude that recommended setting of the process parameters is an optimum setting of the process parameters during machining under TW-ECSM process.

4 Conclusion

With an aim of multi-objective optimization of process parameters of TW-ECSM in terms of MRR and SR, experiments are designed as per CCD and three optimization approaches (GRA-PCA, fuzzy logic and desirability function) are proposed and their outcomes are verified and compared. On basis of results obtained, following conclusions are drawn.

- Central composite design (CCD) approach capable to manage the experimental design to cover full range of process variables with minimum possible number of experiments.
- Hybrid approach of GRA-PCA is advantageous in terms of its dealing ability to deal with the process responses which have a linear correlation in between such as MRR and SR. On the other hand, approach of fuzzy logic is found to successfully deal with the process uncertainties.
- Results of fuzzy logic and GRA-PCA approach are found comparable while desirability function approach is found to be capable of predicting the optimal responses at such levels of process variables also at which experiments are not performed.
- Results of confirmatory experiments carried out to verify the outcomes of GRA-PCA and fuzzy approaches have shown a substantial gain of 200% in the value of MRR.
- Similarly, results of confirmatory experiments performed to verify the prediction ability of desirability function approach are found to be in good agreement with predicted results with a maximum error of 7.14% which is acceptable for a stochastic process like TW-ECSM.
- Findings of this study are beneficial for TW-ECSM practitioner and will play the role of a guide work to set the optimized level of process parameters.

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