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A comprehensive review of parametric optimization of electrical discharge machining processes using multi-criteria decision-making techniques

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Optimization of electrical discharge machining (EDM) processes is a critical issue due to complex material removal mechanism, presence of multiple input parameters and responses (outputs) and interactions among them and varying interest of different stakeholders with respect to relative importance assigned to the considered responses. Multi-criteria decision making (MCDM) techniques have become potent tools in solving parametric optimization problems of the EDM processes. In this paper, more than 130 research articles from SCOPUS database published during 2013–22 are reviewed extracting information with respect to experimental design plans employed, materials machined, dielectrics used, process parameters and responses considered and MCDM tools applied along with their integration with other mathematical techniques. A detailed analysis of those reviewed articles reveals that the past researchers have mostly preferred Taguchi's L_9 orthogonal array as the experimental design plan; EDM oil as the dielectric fluid; medium and high carbon steels as the work materials; peak current and pulse-on time as the input parameters; material removal rate, tool wear rate and surface roughness as the responses; and grey relational analysis as the MCDM tool during conducting and optimizing EDM operations. This review paper would act as a data repository to the future researchers in understanding the stochastic behaviour of EDM processes and providing guidance in setting the tentative operating levels of varying input parameters along with achievable response values. The extracted dataset can be treated as an input to any of the machine learning algorithms for subsequent development of appropriate prediction models. This review also outlines potential future research avenues, emphasizing advancements in EDM technology and the integration of innovative multi-criteria decision-making tools.

KEYWORDS
EDM process, optimization, MCDM, process parameter, response

1 Introduction

The EDM, developed by two Soviet scientists B. Lazarenko and N. Lazarenko in 1943 while investigating the destructive effect of electrical discharges on removing material from conductive workpieces, is one the most popular and industrially-accepted non-traditional machining processes in the present-day manufacturing scenario. It is an electro-thermal process in which material removal takes place due to a series of continuous repetitive high-frequency controlled pulse discharges between the tool (cathode) and the workpiece being machined (anode) (Pandey and Shan, 2017). During the EDM operation, a small gap (0.005–0.05 mm) is always maintained between the tool and the workpiece which is responsible for formation of a plasma channel raising the temperature around 8,000°C–12000°C resulting in melting and vaporization of material to provide the final shape to the workpiece according to the tool geometry (Youssef and El-Hofy, 2020). Both the tool and workpiece are immersed in a dielectric medium (deionized water/kerosene/EDM oil) which basically helps in plasma formation, cools the machining zone and removes the molten material (debris) by flushing action. When sufficient voltage and current are applied to the tool and the workpiece, electrons break away from the tool and accelerate towards the workpiece, thereby hitting and breaking the conductive dielectric medium, causing creation of tiny craters and removal of material from the workpiece surface (Ho and Newman, 2003; Phan N. H. et al., 2022). The working principle of an EDM process is demonstrated in Figure 1.

Unlike the conventional machining processes, EDM is a non-contact spark erosion process which is capable of generating complex shapes with high dimensional accuracy and tolerance on most of the conductive and difficult-to-cut advanced engineering materials irrespective of their physical and mechanical properties. It can efficiently machine medium and high carbon steels, aluminium and titanium and their alloys, MMCs and hybrid MMCs, superalloys (Inconel, Monel, Nimonics, *etc.*), shape memory alloys, tungsten carbide, *etc.*, which have found wide ranging applications in many of the die and mold making, automobile, aerospace, defense, electronics, nuclear and medical industries (Muthuramalingam and Mohan, 2014; Pramanik et al., 2020). With appropriate modifications in the machining setup, it can also machine non-conductive materials, such as ceramics and glasses and generate micro-features (like micro-holes, cavities, pockets, *etc.*) in the above-mentioned materials (Prakash et al., 2019; Kumar et al., 2020; Thangaraj et al., 2020; Pandey and Anas, 2022). It has several advantages, like no formation of mechanical stress, chatter, burr and vibration, higher flexibility and dimensional accuracy, economical operation, *etc.* But it also suffers from some major disadvantages, like low MRR, poor surface quality, high tool wear, not suitable for mass production, formation of recast layer, white layer and surface cracks, heat affected zone, *etc.* Although it has been experimented that proper selection of dielectric fluid and tool material can help in achieving higher MRR along with lower SR and TWR on some of the selected work materials, use of hydrocarbons as the dielectric medium, excessive noise, emission of toxic substances, formation of aerosol and unhealthy working environment hinder its real-time applications in many of the industries (Chakraborty et al., 2015; Liu et al., 2022). Research works have now been directed towards adoption of green or dry EDM process with minimum consumption of dielectric, use of deionized water as dielectric, minimum energy consumption, minimum emission of toxic substances, *etc.*, leading to sustainable manufacturing in present-day Industry 4.0 scenario (Leão and Pashby, 2004; Singh et al., 2016; Gouda et al., 2021; Ming et al., 2021).

Based on the working principle, EDM processes can be broadly divided into die-sinking EDM, rotary EDM (instead of a stationary tool, it is rotated to have better MRR and surface quality), ultrasonic EDM (ultrasonic pulses are made to pass between the tool and the workpiece), cryogenically cooled EDM (the tool is constantly cooled applying cryogenic fluids), powder-mixed EDM (abrasive particles, e.g., silicon carbide, boron carbide, *etc.*, are proportionally mixed with dielectric fluid), vibration-assisted EDM (the tool is vibrated for easy removal of eroded material due to flushing action of the

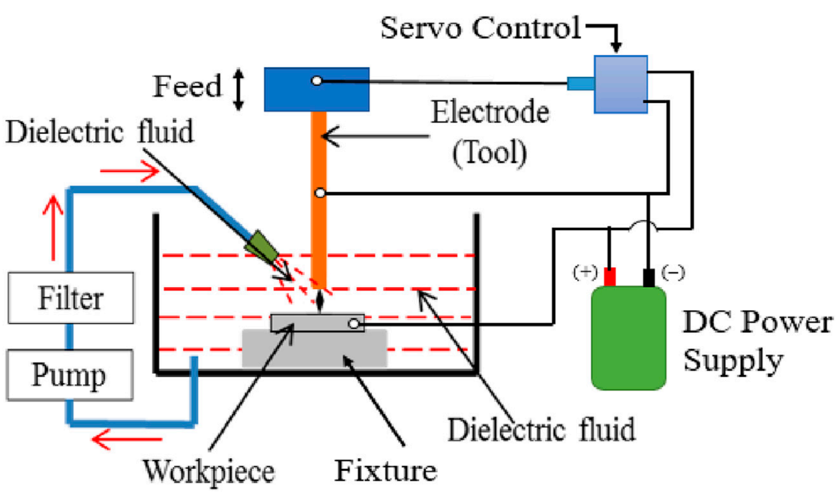

FIGURE 1
Schematic of an EDM process.

dielectric medium), wire EDM (a thin strand of continuous wire made of tungsten, molybdenum, brass or copper is employed as the tool electrode) *etc.* (Huu Phan and Muthuramalingam, 2021). Among all these variants, die-sinking (sinker/conventional) EDM is most commonly used in almost all the industries, in which the electrode (tool) having a distinctive shape sink (penetrates) into the material (hence, its name is sinker) causing material removal.

Like all other non-traditional machining processes, the performance of conventional EDM process with respect to MRR, SR, TWR, WLT, SCD and different form errors is noticed to be significantly influenced by its various input parameters which can be broadly classified as electrical and non-electrical (Muthuramalingam and Mohan, 2015). The examples of electrical parameters are Ton, Toff, Ip, voltage, pulse duration, DF, resistance, capacitance, *etc.* On the other hand, type of the dielectric and its pressure, tool material, work material thickness, TL, Sg, *etc.*, are the examples of non-electrical parameters. Several studies have already been conducted to explore the relationships of those EDM parameters on the responses and it has been realized that maximum machining efficiency can only be achieved when an EDM process is operated at the optimal settings of its various input parameters. Nonlinear relationship between the inputs and outputs, stochastic and complicated electrical discharge mechanism, involvement of multiple conflicting responses (higher MRR *versus* lower SR, higher efficiency *versus* lower energy consumption, *etc.*) and varying opinions of the stakeholders (machine operators, process engineers and end users) regarding relative importance of the process characteristics make parametric optimization of an EDM process a complicated task. Occasionally, opinions of the machine operators/technical experts are sought and machining data handbooks are consulted for optimizing the performance of an EDM process which may sometimes lead to near or sub-optimal solutions. To resolve this issue, applications of some sound and systematic multi-objective optimization tools are highly recommended. In this direction, several MCDM techniques have been appeared as potent tools in identifying the optimal settings of varying EDM parameters leading to attainment of the most desired response values. They are mathematically quite simple and easy to implement helping the concerned engineers in optimizing the processes. Kalita et al. (2022) recently reviewed the applications of various MCDM techniques for solving parametric optimization problems of many of the non-traditional machining processes and identified GRA and TOPSIS as the two most popular tools employed for the said purpose. A separate literature review of the MCDM applications for optimizing only EDM processes along with identification of the experimental design plans employed, work materials machined, dielectrics used, process parameters considered along with their operational settings, measured response values and MCDM tools deployed is really scarce. This review paper attempts to bridge this gap while analyzing the contents of more than 130 research articles published during 2013–22 in the reputed international journals available in the SCOPUS database and identifies how different MCDM techniques have been employed for solving parametric optimization problems of standalone EDM processes. It would act as a data repository to help the process engineers in singling out the tentative settings of different EDM parameters for attaining the desired responses while relieving them from conducting pilot experiment trials. It would also help in identifying the most appropriate experimental design plan to be deployed for a given EDM application with known number of process parameters and their operating levels. The extracted information with respect to parametric settings and measured responses can be utilized as the training dataset in any of the machine learning algorithms to develop the corresponding predictive models. This paper is structured as follows: Section 2 provides the framework for the literature review and a brief overview of MCDM techniques is presented in Section 3. Applications of different MCDM tools for parametric optimization of EDM processes are shown in Section 4 through succinct tabular forms. The derived results are analyzed in Section 5 and Section 6 concludes the paper along with future research directions.

2 Framework for the literature review

As mentioned earlier, the main aim of this paper is to critically review the applications of various MCDM tools leading to parametric optimization of standalone EDM processes. Keeping this objective in mind, the SCOPUS database has been exhaustively searched with the keyword "Optimization of EDM process using MCDM methods" (Optimization AND EDM process AND MCDM techniques) in the title, keywords and abstract with identification of more than 250 research articles published during the stipulated time duration of 2013–2022 (last 10 years). To keep the number of papers to be reviewed into a manageable quantity, those articles published during the last 10 years are only considered here. An initial screening has then been performed to exclude those articles published in conference proceedings and as book chapters. Although there are different variants of EDM process, like rotary EDM, vibration-assisted EDM, powder-mixed EDM, ultrasonic EDM, electrical discharge milling, *etc.*, this review paper only considers optimization of die-sinking EDM (conventional EDM) using varying MCDM tools. Finally, the contents of 137 research articles are analyzed with subsequent extraction of the relevant information with respect to experimental design plan employed, work material machined, dielectric utilized, process parameters considered along with their operating levels, response values measured, MCDM technique deployed and other mathematical tools considered for criteria weight measurement/comparison purposes. The analyzed results are presented in succinct tabular forms to help the fellow researchers/readers in diverse dimensions, like consideration of the appropriate experimental design plan depending on the number of input parameters and their levels, suitable dielectric to be utilized, tentative operating levels of EDM parameters, achievable response values, selection of suitable criteria weight measurement technique and deployment as the training dataset in any of the machine learning algorithms to develop the corresponding prediction tools.

3 MCDM techniques

The MCDM techniques are those mathematical tools employed for identification of the most apposite alternative from a pool of candidate solutions in presence of multiple conflicting attributes/

criteria (Chakraborty et al., 2023). There are several different types of MCDM techniques, like WSM (Miller and Starr, 1969), WPM (Miller and Starr, 1969), AHP (Saaty, 1980), MOORA (Brauers et al., 2008), TOPSIS (Behzadian et al., 2012), VIKOR (Opricovic and Tzeng, 2004), PROMETHEE (Brans and Vincke, 1985), COPRAS (Kaklauskas et al., 2006), ELECTRE (Roy and Vincke, 1981), PSI (Maniya and Bhatt, 2010), EDAS (Keshavarz et al., 2015), CODAS (Ghorabaee et al., 2016), MARCOS (Stević et al., 2020), DEAR (Liao and Chen, 2002), GRA (Kuo et al., 2008) *etc.*, having their own merits and demerits. The basic input to any of the MCDM methods is a decision matrix consisting of a set of feasible alternatives whose performance needs to be evaluated based on multiple conflicting criteria. Most of these techniques are mathematically easy to understand and computationally uncomplicated to implement. Due to their simplicity, they have widely been acknowledged by the researchers to solve parametric optimization problems of many of the machining processes where the experiment trials having different combinations of the input parameters are treated as the alternatives and measured responses as the evaluation criteria. Based on the derived performance scores, all the experimental trials can be ranked from the best to the worst with identification of the optimal intermix of input parameters leading to subsequent attainment of the compromised response values. Although in most of the MCDM methods, equal importance (weight) has usually been assigned to the considered responses to avoid mathematical complexity, but depending on the preference of different stakeholders, relative weights measured using different subjective and objective techniques, like AHP, EM, PCA, WPCA, CRITIC, *etc.*, have also been occasionally integrated with MCDM tools to derive more practical solutions.

4 Optimization of EDM processes using MCDM methods

4.1 AHP method

The AHP method, developed by Saaty (Saaty, 1980), is based on the principle of pair-wise comparison to compute the performance score of each of the alternatives under consideration. Using a 1-9 scale, the relative importance of each pair of criteria is first compared to determine their weights. Subsequently, the performance of the alternatives is again pair-wise evaluated against each of the criteria. The relative performance of the alternatives and criteria weights are finally aggregated together to calculate the overall scores of all the alternatives leading to their rankings. It is a subjective MCDM method, heavily relying on the individual judgments of the participating decision makers. These pair-wise comparisons can only be accepted when the resulting consistency ratios are observed to be less than 0.10. Table 1 shows the applications of AHP method for optimizing EDM processes. While performing EDM operation on Al 6061 alloy, Okponyia and Oke (Okponyia and Oke, 2020) proposed a novel approach while integrating present worth method, fuzzy theory and AHP to determine the optimal values of the considered input parameters and responses. The present worth method when applied as a diagnostic tool identified the said EDM operation as healthy and observed Ip as the most significant input parameter influencing the responses. Using AHP method, Sidhu et al. (2021) first determined the relative weights of RS, MRR and SR as 0.5815, 0.3090 and 0.1095 respectively and then pair-wise compared all the nine experiments against each of the responses (criteria) to identify trial number 4 (Ton = 45 μs, Toff = 15 μs, Ip = 8 A and graphite tool material) as the optimal choice during EDM of Al MMC with different tool materials.

4.2 MOORA method

It is one of the most computationally simple MCDM methods, in which the sum of the normalized performance scores of the non-beneficial criteria (smaller-the-better type) is subtracted from that of the normalized performance scores of the beneficial criteria (larger-the-better type) to obtain the overall scores of all the alternatives (Brauers et al., 2008). Sometimes, these performance scores are multiplied by the corresponding criteria weights to derive more pragmatic solutions. The applications of MOORA method considered for determination of the optimal parametric intermixes of EDM processes are enlisted in Table 2. While optimizing an EDM process, Paul et al. (2019) presented the application of a hybridized approach in the form of MOORA-PCA and contrasted its performance against conventional MOORA method. It was concluded that the proposed approach would provide better values of the considered responses as compared to standalone MOORA method. Kumar et al. (2022) developed a regression model correlating multi-performance characteristic index (determined based on MOORA method) and EDM parameters which was later optimized using GA. The most significant EDM parameters influencing MRR and TWR were also identified.

4.3 TOPSIS

The TOPSIS method (Behzadian et al., 2012) is based on calculation of the Euclidian distances of the considered alternatives from the ideal and the anti-ideal solutions and identification of the best alternative having the minimum distance from the ideal solution and maximum distance from the anti-ideal solution. Table 3 provides information of those EDM processes which have been optimized using this method. Singh et al. (2020) performed EDM operation on Inconel 718 material and optimized the process while considering different criteria weight measurement schemes, like SDV, MW, EM and AHP in fuzzy decision-making environment. It was noticed that almost all the criteria weight measurement methods coupled with TOPSIS would identify the same parametric combination as the optimal choice for the said EDM process. Based on the experimental data of EDM operation on mild steel using Cu-multi-walled carbon nanotube-coated 6061Al electrode, Mandal and Mondal (2021) employed MOPSO technique to search out the non-dominated solutions and developed the corresponding Pareto Frontier. The TOPSIS was later utilized to find out the most appropriate solution from the Pareto optimal set. The EDM operation of Ti-6Al-4V alloy was optimized by Sahu et al. (2022) employing a hybrid grey-TOPSIS-based QPSO technique. It was concluded that both MRR and MH

TABLE 1 AHP method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Okponyia and Oke (2020)	CCD	Deionized water, oil	Al 6061	Ton (75–200 μs), Ip (6–14 A), DF (50%–70%)	MRR (31.753 mg/min), SR (8.228 μm)	Fuzzy theory
					TWR (0.171 mg/min), OC (0.292 mm)	
Sidhu et al. (2021)	L_{18} OA	EDM oil	Al MMC	Ton (10–50 μs), Toff (15–45 μs), Ip (4–12 A), tool material (Cu, Gr, Cu-Gr)	RS (93.7 MPa), MRR (23.38 mg/min), SR (2.09 μm)	

TABLE 2 MOORA method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Paul et al. (2019)	CCD	Deionized water	Inconel 800	Ton (100–500 μs), Toff (20–150 μs), Ip (12–18 A)	MRR (0.183 gm/min), SR (4.799 μm)	PCA
Chaudhury and Samantaray (2020)	L_{27} OA	Kerosene	SiC composite	Ton (50–150 μs), Ip (1–3 A), Vg (30–70 V), DF (5%–9%)	MRR (2.66 mm^3/min), SR (2.11 μm), RLT (2.584 μm), PFE (77.86%)	WPCA
Debnath and Ghosh (2021)	CCD	Water	Al MMC	Ton (1–10 μs), Toff (1–10 μs), Ip (10–25 A)	MRR (0.16 mm^3/min), SR (6.694 μm), TWR (0.00578 mm^3/min)	AHP
Srikanth et al. (2021)	L_9 OA	Vegetable oil	Ti-6Al-4V	Ton (300–500 μs), Toff (500–700 μs), Ip (4–8 A)	MRR (0.2976 mm^3/min), TWR (0.061 mm^3/min)	
Kumar et al. (2022)	L_9 OA	Mineral water	Titanium grade 9	Ip (7–11A), Ton (100–200 μs), Toff (50–100 μs), Vg (50–70 V)	MRR (0.018289 g/min), TWR (0.000611 g/min)	GA

were significantly affected by Ip, whereas, tool material was the most influential input parameter for TWR, SR and SCD. On the other hand, WLT and closeness coefficient calculated by TOPSIS were controlled by Ton.

4.4 VIKOR method

The VIKOR method, proposed by Opricovic and Tzeng (2004), is a compromise-based ranking approach, employed for solving MCDM problems having conflicting and non-commensurable criteria. It derives a compromise solution closest to the ideal solution and farthest from the anti-ideal solution based on an agreement established by the mutual concessions between the decision makers. The EDM processes have also been optimized using VIKOR method, as highlighted in Table 4. Using Taguchi's L_{18} OA, Kumar J. et al. (2021) performed 18 EDM experiments on AZ-91 Mg alloy and endeavored to optimize the said process based on VIKOR method. In the later stage, fuzzy logic was integrated with VIKOR to predict the values of MRR and SR which were noticed to be quite close to the experimental observations.

4.5 PROMETHEE

This method was developed by Brans and Vincke (1985) and is an outranking-based approach able to provide a complete ranking of the alternatives under consideration. The performance of the alternatives is assessed based on pair-wise comparisons against each criterion utilizing preference functions which are subsequently aggregated using criteria weights to derive the corresponding net outranking flows considered for ranking of the alternatives. Table 5 enlists the applications of PROMTHEE method leading to optimization of EDM processes. While machining Nimonic C263 alloy using three different electrode materials (copper, tungsten and cooper-tungsten), Shastri and Mohanty (2021) proposed a hybrid approach combining PROMETHEE with CS algorithm to optimize an EDM process. Besides MRR, SR and TWR, two other important responses, i.e., SEC and N were also considered to provide sustainable machining environment. A confirmatory experiment was finally conducted which had shown 6.02% overall improvement for the considered responses at the achieved optimal combinations of the EDM parameters.

4.6 COPRAS method

The COPRAS (Kaklauskas et al., 2006) follows step-wise ranking and evaluation procedure of the alternatives with respect to their relative significance and utility degree while considering both the ideal and the anti-ideal solutions. It basically assumes direct and proportional dependences of the significance and utility degree of the alternatives in presence of multiple conflicting criteria. Based on a BBD plan, Shastri and Mohanty (2022) performed EDM operation on Nimonic C263 material using EDM oil as the dielectric medium. During experimentation, each of the four EDM parameters was set at three different levels, i.e., Ton (100, 200, 300 μs), Vg (50, 60, 70 V), Ip (3, 5, 7 A), DF (80, 85, 90%) and tool material (W, Cu-W, Cu) and the corresponding values of various responses were measured/calculated as SR = 13.05 μm, SCD = 0.0026 μm/μm, RLT =

TABLE 3 TOPSIS method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Senthil et al. (2014)	L_{18} OA	Kerosene	Al MMCs	Ip (15–35 A), Ton (33–99 μs), Toff (3–9 μs)	MRR (15.37 × 10^{-2} g/min), TWR (0.34 × 10^{-3} g/min), SR (4.49 μm)	
Sidhu et al. (2014)	L_{27} OA	EDM oil	Al MMCs	Ton (10–50 μs), Toff (15–45 μs), Ip (4–12 A), tool material (Cu, Gr, Cu-Gr)	MRR (57.99 mg/min), TWR (2.54 mg/min), SR (7.4 μm)	
Dewangan et al. (2015a)	CCD	EDM oil	AISI P20 tool steel	Ip (1–5 A), Ton (10–150 μs), work time (0.2–1 s), TL (0–1.5 s)	WLT (6.684 μm), SCD (0.023 μm/μm^2), SR (1.82 μm), OC (0.0417 mm)	Fuzzy theory
Prabhu and Vinayagam, 2016)	L_9 OA	Kerosene	AISI D2 tool steel	Ton (1–5 μs), Ip (2–8 A), Vg (60–100 V)	MRR (1.846 mm^3/min), fractal dimension (1.847 mm), SR (2.167 μm)	AHP, GA
Manivannan and Kumar (2016)	L_{27} OA	Deionized water	AISI 304	Ton (10–20 μs), Vg (10–30 V), Ip (10–20 A)	MRR (0.16180 mm^3/min), TWR (0.087585 mm^3/min), OC (0.125069 mm), TA (0.222191°), Cent (0.120511 mm), Cexi (0.041111 mm)	
Satpathy et al. (2017)	L_9 OA	EDM oil	Al MMC	Ton (50–100 μs), Ip (3–7 A), Vg (30–150 V), DF (70%–90%)	MRR (14 mm^3/min), SR (3.6 μm), TWR (0.04 mm^3/min)	PCA
Raj and Prabhu (2017)	L_9 OA	Kerosene	AISI D2 tool steel	Ton (1–11 μs), Toff (1–6 μs), Ip (3–5 A)	MRR (0.11869 mm^3/s), SR (4.025 μm), TWR (0.00953 mm^3/s)	AHP
Nadda et al. (2018)	L_{18} OA	EDM oil	Cobalt bonded tungsten carbide	Ton (25–250 μs), Toff (40–67 μs), Ip (4–12 A), Vg (50–60 V), tool material (Cu, Gr)	MRR (4.0125 mm^3/min), SR (2.28 μm), TWR (0.00012 gm/min)	AHP
Mohanty et al. (2018)	BBD	Paraffin oil	Inconel 718	Ton (100–300 μs), Ip (3–7 A), Vg (70–90 V), PF (0.2–0.4 Bar), DF (80%–90%), cryogenic treatment soaking duration (0–36 h)	SR (7.7 μm), TWR (73.312%), ROC (0.07 mm)	TLBO
Huo et al. (2019)	L_9 OA	EDM oil	AISI 304	Ip (9–15 A), Vs. (40–80 V), DF (40%–80%)	SR (0.802 μm), RLT (1.0208 μm), RS (335.62 MPa)	Simo's weighting method
Roy and Dutta (2019)	L_9 OA	Servo oil	AISI 304	Ton (200–800 μs), Ip (10–40 A), Vs. (50–90 V), DF (20%–80%)	MRR (1.0 mm^3/min), TWR (0.39 mm^3/min), OC (0.98 mm)	AHP, fuzzy theory
Rajamanickam and Prasanna (2019)	CCD	Distilled water	Ti-6Al-4V	Ton (6–10 μs), Toff (1–9 μs), Ip (1–5 A), C (20–60 nF)	MRR (3.6996 mm^3/sec), TWR (0.0625 mm/s), OC (330 μm)	
Singh et al. (2020)	L_9 OA	EDM oil	Inconel 718	Ton (50–200 μs), Ip (18–22 A), PF (0.3–0.5 kgf/cm^2)	MRR (0.2088095 mm^3/min), TWR (0.0150057 mm^3/min)	SDV, MW, EM, AHP, fuzzy theory
Routara et al. (2020)	L_9 OA	Kerosene	Al 7075	Toff (30–70 μs), Ip (4–8 A), Sg (0.2–0.4 mm)	MRR (0.03558 mm^3/min), SR (4.5 μm), TWR (0.00101 mm^3/min), Rq (5.6 μm)	
Raj et al. (2020)	L_{16} OA	SAE-40 grade oil	Inconel 825	Ton (50–200 μs), Ip (4–10 A), Vg (15–30 V)	MRR (3.6850 mm^3/min), SR (6.473 μm), TWR (0.004 mm^3/min)	
				DF (55%–100%)		
Payal et al. (2020)	L_{36} OA	EDM oil	Inconel 825	Ton (20–75 μs), Ip (4–12 A), Vg (40–80 V), DF (10%–12%), TL (0.1–0.3 s), tool material (Cu, Cu-W, Gr)	MRR (4.8870 mm^3/min), SR (7.426 μm)	
					TWR (1.2518 mm^3/min)	
Zeng et al. (2021a)	L_{18} OA	Kerosene	Al_2O_3 ceramics	Ton (50–200 μs), Ip (2–4 A), Vs. (40–70 V), IH (0.4–1.2 A), EJT (2–4 s)	MRR (0.126 mm^3/min), SR (16.25 μm), TWR (0.0067 g/min)	AHP
Srinivasan et al. (2021a)	L_{21} OA	Deionized water	Si_3N_4-TiN ceramic	Ton (16–32 μs), Toff (6–10 μs), Vs. (30–42 V), Ip (4–8 A)	MRR (0.0280 g/min), SR (0.185 μm), TWR (0.00113 g/min)	RSM
Mandal and Mondal (2021)	L_9 OA	EDM oil	Mild steel	Ton (12–38 μs), Toff (2–8 μs), Ip (3–7 A), Vg (30–50 V)	TWR (3.064 × 10^{-3} gm/min), MRR (112.43 mm^3/min)	MOPSO
	L_{27} OA	Kerosene	Al 8,011			

(Continued on following page)

TABLE 3 (*Continued*) TOPSIS method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Alagarsamy et al. (2021)				Ton (300–900 µs), Toff (30–90 µs), Ip (5–15 A), tool material (Cu, Br, EN8)	MRR (0.6551 g/min), TWR (0.0758 g/min)	
Bodukuri and Kesha (2021)	L_{27} OA	EDM 30 oil	Al 6061	Ton (20–100 µs), Toff (50–200 µs), Ip (9–15 A), TL (1.5–4.5 µs)	MRR (0.103 g/min), SR (4.108 µm), TWR (0.022 g/min), SCD (0.0048 µm)	
Rao et al. (2021)	L_9 OA	Sunflower oil	AISI D_2 steel	Ton (300–500 µs), Ip (6–8 A), Vs. (40–60 V)	MRR (17.1×10^{-3} g/min), SR (2.7 µm) TWR (0.37×10^{-3} g/min)	AHP
Sharma (2021)	L_9 OA	Kerosene	Ti-6Al-4V	Ton (50–100 µs), Toff (5–9 µs), Ip (10–20 A), Vg (40–80 V)	MRR (0.006224 g/min), TWR (0.00074 g/min)	
Kumar et al. (2021a)	L_{16} OA	Deionized water	Inconel X750	Ton (1–99 µs), Ip (1–20 A), Toff (1–9 µs), Vg (5–60 V)	MRR (0.4378 mm^3/min), SR (3.1 µm), TWR (0.001 mm^3/min)	PCA
Sahu et al. (2022)	L_{27} OA	EDM oil	Ti-6Al-4V	Ip (10–20 A), Ton (100–300 µs), DF (67%–83%), Vg (20–30 V), tool material (AlSi10Mg, Cu, Gr)	MRR (0.5454 mm^3/min), TWR (0.6706 mm^3/min), SR (6.4 µm), SCD (0.0145963 µm/$µm^2$), WLT (17.0278 µm), MH (509 HV)	QPSO
Hema et al. (2022)	L_{16} OA	Deionized water, kerosene	Copper	Vg (25–55V), DF (55%–85%)	MRR (0.35 mm^3/min), TWR (0.046 mm^3/min)	

TABLE 4 VIKOR method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Mohanty et al. (2017)	L_9 OA	Deionized water	High carbon steel	Ton (100–500 µs), Ip (5–15 A), Vg (30–50 V)	MRR (1.779 mm^3/min), SR (3.484 µm), TWR (0.556 mm^3/min), ROC (0.256 mm)	Regression analysis
Gangil and Pradhan (2018a)	CCD	EDM oil	Titanium alloy	Ton (50–100 µs), Ip (4–10 A), Vg (30–50 V) DF (14%–18%)	MRR (0.512 g/min), SR (5.44 µm), TWR (0.3190 g/min)	
Kumar and Edwin (2021)	BBD	Kerosene	AISI D3 die steel	Ton (30–90 µs), Toff (3–9 µs), Ip (10–30 A), Vg (25–75 V)	MRR (0.7507 g/min), SR (17.605 µm), OC (0.295 mm), PAR (0.0735 mm)	
Kumar et al. (2021b)	L_{18} OA	EDM oil	AZ-91 Mg alloy	Ton (30–50 µs), Toff (20–30 µs), Ip (4–6 A), tool material (Cu, Gr, Cu-W)	MRR (0.089 g/min), SR (0.08 µm)	Fuzzy logic
Somu et al. (2021)	L_{25} OA	EDM oil	Inconel 718	Ton (2–10 µs), Toff (2–10 µs), Ip (3–15 A), GC (3–7 mm), tool material (Br, Cu, Cu-Gr)	MRR (50.042 mm^3/min), SR (5.177 µm), TWR (0.1 mm^3/min)	

TABLE 5 PROMETHEE method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Sharma et al. (2019)	L_9 OA	EDM oil	Inconel 718	Ton (150–200 µs), Toff (5–7 µs), Ip (5–7 A), Vg (50–54 V)	MRR (0.062774 gm/min), TWR (0.000017 gm/min)	AHP
Patel and Pradhan (2021)	L_9 OA	EDM oil	AISI D_2 tool steel	Ton (0.5–1.5 µs), Toff (5–15 µs), Ip (4–12 A) Vs. (45–55 V)	MRR (3.0052 mm^3/min), SR (2.66 µs), TWR (0.1563 mm^3/min), flatness (0.0470 µm)	AHP
Shastri and Mohanty (2021)	BBD	Kerosene	Nimonic C263	Ton (100–300 µs), Ip (3–7 A), Vg (50–70 V), DF (80%–90%), tool material (Cu, W, Cu-W)	MRR (5.099 mm^3/min), SR (13.82 µm), TWR (3.773%), SEC (0 0.353010 J/mm^3), N (82.9 dB), ROC (0.039 mm)	AHP, CS
Bhattacharjee et al. (2022)	CCD	Lamp oil mixed hydrocarbon	Al MMC	Ton (4–8 µs), Ip (5–15 A), RC (2%–10%)	MRR (0.016573 gm/min), SR (2.463 µm), TWR (0.004069 gm/min)	

8.112 mm, MH = 319.12 HV and MC = 73.310 INR. Finally, the EDM process was optimized using COPRAS method with identification of the corresponding input parameters as Ton = 100 µs, Vg = 60 V, Ip = 5 A, DF = 85% and tungsten tool material. A confirmatory experiment was also conducted to validate the derived results showing only 6.13% error between the predicted and actual solutions.

4.7 PSI method

The PSI, developed by Maniya and Bhatt (2010), is a simple MCDM method requiring no information regarding weights of the considered criteria. In this approach, the candidate alternatives are sorted from the best to the worst depending on their preference selection indexes. Using PSI method, an EDM operation on titanium alloy was optimized by Phan NH. et al. (2022) while performing 16 experiments based on Taguchi's L_{16} OA. Nickel-coated aluminium was used as the electrode material and HD-1 oil was the dielectric medium. Each of the EDM parameters was set at four different levels, i.e., Ton (100, 500, 1,000, 1,500 µs), Vg (40, 45, 50, 55 V) and Ip (10, 20, 30, 40 A). Using high-precision electronic weighing balance, the MRR and TWR values were recorded as 0.096 mm^3/min and 0.027 mm^3/min respectively at the derived optimal parametric combination of the said EDM process.

4.8 EDAS method

With respect to mathematical modelling, EDAS method slightly differs from TOPSIS as it is based on calculation of the distances from the average solution rather than ideal and anti-ideal solutions (Keshavarz et al., 2015). In this method, the arithmetic mean of the performance values of the alternatives against each of the criteria is taken into account to compute the average solution. In case of rank reversal problems, it sometimes performs better than TOPSIS. The EDAS method was utilized by Ganesh et al. (2020) to optimize the EDM operation of Inconel 718 material using brass as the tool material and EDM oil as the dielectric. Using BBD plan, 13 experiments were performed at three different levels of Ton (100, 250, 400 µs), Toff (60, 105,150 µs) and Ip (8, 10,12 A) and their effects on MRR and TWR were studied. The corresponding MRR and TWR values were obtained as 1.14626 mm^3/min and 0.12875 mm^3/min respectively. The EDAS method was employed to search out the optimal combinations of the considered EDM process parameters as three different criteria weighting scenarios. It was later integrated with NSGA-II and GP techniques. The NSGA-II was adopted to develop the corresponding Pareto front and GP metamodeling technique was applied to correlate the responses with EDM parameters. It was noticed that the developed GP-based metamodels would have better prediction accuracy for both the responses as compared to the conventional polynomial regression models.

4.9 CODAS method

In CODAS method (Ghorabaee et al., 2016), the candidate alternatives are evaluated and subsequently ranked based on their two relative distance measures (Euclidean and Taxicab) from the anti-ideal solution. The best alternative should have the maximum distance from the anti-ideal solution. When the performance of any two alternatives cannot be compared according to the Euclidean distance, the Taxicab distance is then considered as the secondary measure. Pandiyan et al. (2022) employed Taguchi's L_{27} OA plan to study the effects of Ton, Vg and Ip on MRR, TWR, CIR and CYL while performing EDM operation on AA6061-T6 alloy using a copper electrode and EDM oil as the dielectric fluid. During experimentation, each of the EDM parameters was varied at three different levels, i.e., Ton (50, 75, 100 µs), Vg (30, 35,40 V) and Ip (9, 12, 15 A). The corresponding weights of MRR, TWR, CIR and CYL were estimated as 0.164, 0.128, 0.402 and 0.306 respectively using EM. Finally, the EDM process was optimized applying CODAS method with identification of the optimal settings of the input parameters as Ton = 100 µs, Vg = 40 V and Ip = 9 A, providing the measured values of MRR, TWR, CIR and CYL as 0.168 g/min, 0.017 g/min, 0.003 mm and 0.046 mm respectively.

4.10 MARCOS method

The MARCOS (Stević et al., 2020) is a recently developed MCDM tool, based on specifying the inherent relationship between the alternatives and some reference values. Usually, the ideal and the anti-ideal solutions are treated as the references. These relationships lead to the calculation of utility functions and a compromise ranking of the alternatives under consideration. The utility functions define the positions of all the alternatives with respect to ideal and anti-ideal solutions. The best alternative must be located nearest to the ideal solution and farthest from the anti-ideal solution. Treating Ip, Ton and Vg as the input parameters and MRR and SR as the responses, Biswal et al. (2022) applied MARCOS method for optimization of an EDM operation considering L_9 OA as the design plan, deionized water as the dielectric and Al 6061-WC-B_4C and Al 7175-WC-B_4C as the work materials. It was interestingly noticed that there had been two different combinations of the EDM parameters for the two considered work materials. Finally, tensile strength, ultimate tensile strength and hardness values of the machined components were measured to validate the applicability of EDM process in machining of composite materials.

4.11 DEAR method

The DEAR method (Liao and Chen, 2002) is an easy to understand and implement tool and can be effectively integrated with Taguchi methodology to act as a multi-objective optimization technique to search out the most suitable intermix of input parameters of any of the machining processes. In this method, the alternatives are ranked based on the computed values of multi-response performance index. It has the inherent advantage of calculating the corresponding criterion weight considering the ratio of the criterion value for any alternative to the sum of criteria values for all the alternatives. Table 6 depicts the applications of Taguchi-DEAR method in optimizing EDM processes. Sameer et al. (2021) performed EDM operation on maraging steel treating Ip, DT and PF as the input parameters

TABLE 6 DEAR method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses
Reddy and Reddy (2016)	L_9 OA	EDM Oil	Al 6082	Ip (8–24 A), Ton (50–150 μs), Toff (35–95 μs)	MRR (49.12 mm^3/min), TWR (0.392 mm^3/min), SR (8.96 μm)
Vaddi et al. (2018)	L_9 OA	EDM oil	Ti-6Al-4V	Ton (100–200 μs), Toff (65–185 μs), Ip (12–28 A)	MRR (2.30 mm^3/min), SR (7.02 μm), TWR (0.84 mm^3/min)
Sameer et al. (2021)	L_9 OA	EDM oil	Maraging steel C300	Ip (10–20 A), DT (10–14 mm), PF (0.2–0.6 MPa)	MRR (56.907 mm^3/min), SR (4.4 μm), TWR (0.016 mm^3/min)
Phan et al. (2021)	L_{16} OA	Water	Ti alloy	Ton (100–1,500 μs), Ip (10–40 A), Vg (40–55 V)	MRR (0.0139 g/min), SR (9.313 μm)
					TWR (0.0089 g/min)

and MRR, SR and TWR as the responses and optimized the said process using Taguchi-DEAR method. In the similar direction, an EDM operation on titanium alloy was optimized by Phan et al. (2021) with identification of the optimal combination of EDM parameters as Ton = 1,000 μs, Vg = 55 V and Ip = 40 A which would yield the corresponding values of MRR, SR and TWR as 0.0139 g/min, 9.313 μm and 0.0089 g/min respectively.

4.12 GRA method

The GRA technique (Kuo et al., 2008) is based on the concept of grey theory, where it is assumed that any system in nature is neither white nor black, but it is mostly grey. A grey system deals with those problems with some known and some unknown information. It has proved itself as one of the most powerful tools in optimizing machining processes in presence of incomplete experimental dataset, measurement error and “larger-the-better” and “smaller-the-better” responses. In this method, the absolute difference between two data sequences is evaluated, while calculating the approximate grade of correlation existing between them. The basic objective of GRA is to transform multiple responses into a single performance measure (GRG) which finally helps in ranking of the considered alternatives (experimental trials). Its uncomplicated mathematical steps and independency of criteria weights make it a popular choice in optimizing diverse machining processes. In Table 7, details of the EDM operations are presented which have been optimized using GRA technique.

Soepangkat et al. (2014), Dewangan et al. (2015b), Prabhu and Vinayagam (2015), Vijayanand and Ilangkumaran (2017) and Sharma et al. (2021) conducted EDM operations on various difficult-to-cut advanced engineering materials based on Taguchi’s OA plans and attempted to integrate GRA with fuzzy logic to frame simple “If-Then” clauses to depict the relationships between the calculated GRG values and different input parameters. It would also lead to identification of the optimal combinations of EDM parameters achieving the target response values. Treating Ton, Vg, DF and type of the tool material as the EDM parameters and MRR, SR, TWR, WLT, SCD and MH as the responses, Sahu and Mahapatra (2021) first compared the performance of the tool made of AlSi10 Mg over solid copper and graphite electrodes. A novel optimization technique, combining desirability-based GRA with FA, was later employed to optimize the said process. Finally, the response values at varying combinations of the EDM parameters were predicted using LSSVM while achieving satisfactory values of the root mean squared error.

4.13 Utility theory

Every product needs to be manufactured keeping in mind the need and expectation of the end users (customers). In general, utility can be defined as the usefulness of a specific product/process with reference to the customer expectations having its performance evaluated based on various objectives. The performance scores of a product/process are assessed with respect to each quality attribute and aggregated together to define a composite index (utility) (Kumar et al., 2000). Based on L_{18} OA design plan, Chandrashekarappa et al. (2021) machined HCHCr D_2 steel material considering Ton, Ip and type of the tool material as the process variables and MRR, SR and TWR as the outputs. Graphite, copper and brass were used as the tool materials, distilled water and kerosene were utilized as the dielectric medium and the settings of Ton and Ip were maintained between 50 μs and 100 μs and 3 A and 9 A respectively. Weights of MRR, SR and TWR were estimated employing PCA and CRITIC methods. Both the optimization approaches, i.e., Taguchi-PCA-utility and Taguchi-CRITIC-utility had yielded the same combination of EDM parameters, i.e., distilled water as the dielectric, graphite as the tool material, Ip = 9 A and Ton = 50 μs as the optimal choice, providing the corresponding values of MRR, SR and TWR as 0.0632 g/min, 1.68 μm and 0.012 g/min respectively.

4.14 Multiple MCDM methods

It can be noticed from this literature review that some of the researchers have applied multiple MCDM methods for optimization of EDM processes. Those techniques have mainly been employed to validate the optimal parametric combination derived by one method against the other and it has been interestingly noticed that in most of the cases, they have provided the same intermix of EDM parameters. Table 8 shows applications of multiple MCDM methods considered for optimizing the EDM processes. From this table, it can be unveiled that the researchers (Das et al., 2018; Pradhan, 2018; Yuvaraj and Suresh, 2019; Kumar and Mondal, 2020; Kumar and

TABLE 7 GRA method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Ay et al. (2013)	L_{16} OA	Deionized water	Inconel 718	Ip (100–1,000 mA), Ton (3–50 µs)	Taper ratio (0.280), hole dilation (57 µm)	Regression analysis
Manivannan and Kumar (2013)	L_9 OA	IPOL spark oil	AISI D2 tool steel	Ip (5–15 A), Ton (20–75 µs), Toff (15–30 µs)	TWR (0.8840%), MRR (0.4750 g/min), SR (3.43 µm)	
Dewangan and Biswas (2013)	L_{27} OA	EDM oil	AISI P20 tool steel	Ip (2–8 A), Ton (100–500 µs), IEG (90–250 µs), work time (0.2–1 s), TL (0–1.4 s)	MRR (10.4700 mm³/min), TWR (0.01091 mm³/min)	
Gopalakrishnan et al. (2013)	L_{18} OA	Kerosene	Al 6063	Ip (16–32 A), Ton (2–8 µs), Toff (5–9 µs) Vg (40–60 V)	TWR (5.732%), MRR (0.2583 g/min), SR (12.243 µm)	
Muthuramalingam and Mohan (2013)	L_9 OA	Kerosene	AISI 202 steel	Ip (9–15 A), Vg (40–70 V), DF (40%–80%)	MRR (15.78 mm³/min), SR (6.42 µm)	
Pradhan (2013a)	CCD	EDM oil	AISI D2 tool steel	Ip (4–10 A), Ton (100–300 µs), Vg (40–60 V), DF (80%–90%)	MRR (32.551 mm³/min), TWR (0.036 mm³/min), ROC (0.215 µm)	PCA
Pradhan (2013b)	CCD	EDM oil	AISI D2 tool steel	Ip (1–9 A), Ton (50–100 µs), Vg (40–60 V), DF (80%–90%)	WLT (6.19 µm), SR (2.15 µm), SCD (0.0482 µm/µm²)	Regression analysis
Laxman and Raj (2014)	L_{27} OA	EDM Oil	Titanium alloy	Ip (9–15 A), Ton (10–50 µs), Toff (50–100 µs), TL (5–20 µs)	MRR (7.7 mg/min), TWR (0.20 mg/min)	
Palanisamy et al. (2014)	L_9 OA	Kerosene	Ti-6Al-4V	Ip (4–12 A), Ton (100–600 µs), Toff (20–75 µs)	TWR (5.2%), MRR (0.0097 g/min), SR (4.68 µm)	
Soepangkat et al. (2014)	L_{18} OA	Deionized water	AISI D2 tool steel	Ip (10–20 A), Ton (180–300 µs), Vg (30–60 V), DF (40%–60%)	MRR (39.52387 mm³/min), SR (5.37 µm)	Fuzzy logic
Mhatre et al. (2014)	L_{18} OA	IPOL spark erosion oil	Ti-6Al-4V	Ip (9–27 A), Ton (100–300 µs), Vg (40–60 V) DF (4%–12%)	MRR (0.00919 g/min), TWR (0.0021 g/min), SR (3.510 µm)	
Vikas and Kumar (2014)	L_{27} OA	Paraffin oil	EN 41	Ip (8–24 A), Ton (200–400 µs), Toff (2,100–2,300 µs), Vg (40–80 V)	SR (14.97 µm), Rq (18.57 µm), Rsk (0.54 µm), Rku (3.06 µm), Rsm (0.23 µm)	
Seelan and Rajesh (2014)	L_9 OA	EDM oil	Al alloy	Ip (4–8 A), Ton (5–8 µs), Toff (6–10 µs)	MRR (133.333 mm³/min), TWR (0.893 mm³/min), SR (8.717 µm)	
Kumar et al. (2014)	L_{27} OA	EDM oil	Al 6351	Ip (5–15 A), Ton (50–100 µs), Vg (40–50 V), DF (40%–80%)	TWR (0.25%), SR (4.54 µm), PE (2.13 kW)	
Tiwari et al. (2014)	L_9 OA	Kerosene	Carbon fiber epoxy composite	Ip (1–5 A), Ton (120–180 µs), Vg (20–60 V) DF (40%–60%)	MRR (0.000492 g/min), TWR (0.000023 g/min)	
Xess et al. (2014)	L_{16} OA	EDM oil	Ti-6A-4V	Ip (10–40 A), Ton (50–200 µs), DF (30%–60%) Vg (40–70 V)	MRR (4.68 mm³/min), SR (8.7 µm), OC (0.38 mm)	
Nayak and Routara (2014)	L_9 OA	Paraffin oil	Tungsten carbide	Ip (20–24 A), Ton (10–100 µs), Toff (10–20 µs)	MRR (0.5524 mm³/min), TWR (0.3521%), SR (1.8672 µm)	
Gaikwad et al. (2014)	L_{18} OA	Water, oil	Ti-6Al-4V	Ip (24–42 A), Ton (20–400 µs), DF (10%–12%) Vg (50–100 V), working time (5–15 s), retraction distance (1–2 mm), PF (0.3–1 kgf/cm²)	MRR (1 g/min), TWR (28.476%), SR (0.78471 µm)	
Kumar and Kumar (2014)	L_{18} OA	IPOL spark erosion oil	Al MMC	Ip (9–15 A), Ton (100–300 µs), Vg (45–65 V)	MRR (0.1210 g/min), TWR (0.0014%), SR (6.3 µm)	
Dewangan et al. (2015b)	CCD	EDM oil	AISI P20 tool steel	Ip (1–5 A), Ton (10–150 µs), work time (0.2–1 s), TL (0–1.5 s)	WLT (6.954 µm), SCD (0.0202 µm/µm²), SR (2.06 µm)	Fuzzy logic

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TABLE 7 (*Continued*) GRA method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Prabhu and Vinayagam (2015)	L_9 OA	Kerosene	AISI D_2 tool steel	Ip (2–8 A), Ton (1–5 µs), Vg (60–100 V)	MRR (0.535 g/min), SR (0.706 µm)	Fuzzy logic
Kolahan and Moghaddam (2015)	L_{36} OA	Kerosene	AISI 2312	Ip (2.5–7.5 A), Ton (10–75 µs), Toff (25–200 µs), DF (0.4–1.6), Vg (50–60 V)	MRR (0.352 g/min), TWR (0.00342 g/min), SR (0.669 µm)	
Radhika et al. (2015)	L_9 OA	Kerosene	Al-Si10 Mg alloy	Ip (10–30 A), Ton (120–420 µs), PF (100–200 kPa)	SR (3.376 µm), MRR (25.2340 g/h), TWR (0.0976 g/h)	
Priyadarshini and Pal (2015)	L_{25} OA	EDM oil	Ti-6Al-4V	Ip (10–50 A), pulse width (5–30 µs), Vg (6–10 V), DF (8–12)	MRR (1.324 mm^3/min), TWR (0.3271 mg/min), SR (0.986 µm)	
Singh et al. (2015)	L_9 OA	EDM oil	SS 304	Ip (8–16 A), Ton (50–150 µs), Toff (20–50 µs), Vg (40–60 V)	MRR (36.56 mm^3/min), TWR (19.28 mm^3/min)	
Mohanty and Rana (2015)	L_9 OA	Deionized water	High carbon steel	Ip (5–15 A), Ton (100–500 µs), Vg (30–50 V)	MRR (20.3604 mm^3/min), SR (4.5915 µm), TWR (1.3502 mm^3/min), ROC (4.3345 mm)	
Selvarajan et al. (2016)	L_{18} OA	EDM oil	Si_3N_4-TiN composite	Ton (6–15 µs), Ip (2–5 A), PF (15–17 kg/cm^2), Toff (10–22 µs)	MRR (0.0250 g/min), TWR (0.001 g/min), CIR (0.012 mm), CYL (0.015 mm), PER (0.210 mm)	
Marichamy et al. (2016)	L_9 OA	Kerosene	Duplex brass	Ton (100–200 µs), Ip (3–14 A), Vg (40–60 V)	TWR (0.843 mm^3/min), MRR (17.28 mm^3/min), SR (12.48 µm)	
Kolli and Adepu (2016)	L_9 OA	EDM oil + surfactant	Ti-6Al-4V	Ip (10–20 A), Ton (25–65 µs), Toff (24–48 µs), surfactant concentration (0.25–0.75 g/L)	MRR (2.213 mm^3/min), SR (2.98 µm)	
Mazarbhuiya et al. (2016)	L_8 OA	Hydrocarbon oil	Aluminium	Ip (8–16 A), Ton (463–1,010 µs), PF (5–10 kgf/cm^2)	MRR (12.11 mg/min), SR (22.3 µm)	
Rath (2017)	L_{27} OA	EDM oil	EN 19	Ton (1,000–3,000 µs), Ip (20–30 A), DF (8%–12%)	MRR (15.3483 mm^3/min), SR (6.9876 µm), TWR (0.0005 mm^3/min), OC (0.3 mm)	
Tamang et al. (2017)	L_9 OA	Deionized water	SS 304	Ton (100–200 µs), Ip (10–14 A), Vg (30–50 V)	OC (128.67 µm), TA (0.0089°)	DFA
Vijayanand and Ilangkumaran (2017)	L_9 OA	Kerosene	Monel 400	Ton (4–6 µs), Toff (2–4 µs), Ip (4–6 A)	MRR (0.01010 mm^3/min), TWR (0.07985 mm^3/min)	Fuzzy logic
Meena et al. (2017)	L_9 OA	Hydrocarbon oil	Titanium grade 2	Pulse width (0.5–2.0 µs), Ip (20–50 A), frequency (100–150 kHz)	MRR (0.006495 mm^3/min), TWR (0.005959 mm^3/min), OC (0.048 mm)	
Vinoth Kumar and Pradeep Kumar (2017)	L_{18} OA	IPOL spark erosion oil	AISI D_2 tool steel	Ton (100–300 µs), Ip (9–12 A), Vg (45–65 V)	MRR (0.1210 g/min), SR (6.5 µm), TWR (0.0014 g/min)	
Anand et al. (2017)	L_9 OA	Kerosene oil	HCHCr steel	Ton (50–250 µs), Ip (5–15 A), Vs. (10–30 V), Vg (85–115 V)	MRR (16.92 mm^3/min), SR (11.5 µm)	
Mishra and Routara (2017)	L_9 OA	Paraffin oil	EN 24	Ton (10–100 µs), Toff (10–20 µs), Ip (10–20 A), PF (0.25–0.75 kg/cm^2)	MRR (0.31992 mg/min), TWR (0.00555 mg/min)	
Selvarajan et al. (2017)	L_{25} OA	EDM oil	Si_3N_4-TiN composite	Ton (4–8 µs), Toff (8–12 µs), Ip (3–7 A), Vg (30–40 V), PF (14–18 kg/cm^2)	MRR (0.0163 g/min), SR (0.593 µm), TWR (0.0026 g/min), ROC (0.2965 mm), CIR (0.147 mm), CYL (0.197 mm), PER (0.181 mm), TA (6.824°)	Regression analysis
Reddy et al. (2018)	L_9 OA	EDM oil	SS304	Ton (50–150 µs), Toff (35–95 µs), Ip (8–24 A)	MRR (14.50 mm^3/min), SR (9.39 µm), TWR (0.78 mm^3/min)	
Dewan et al. (2018)	L_9 OA	EDM oil	Nimonic 90	Ton (2–10 µs), Toff (2–10 µs), Ip (10–30 A)	MRR (41.000 g/min), SR (0.4060 µm)	
Chauhan et al. (2018)	L_9 OA	Water	SS 304	Ton (10–30 µs), Toff (2–6 µs), Ip (1–5 A), PF (0.5–1.2 kg/cm^2)	MRR (0.001245378 mg/min), TWR (0.0000015 mg/min)	

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TABLE 7 (*Continued*) GRA method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
Gangil and Pradhan (2018b)	CCD	EDM oil	Ti-6Al-4V	Ton (50–100 µs), Ip (4–12 A), Vg (30–50 V), DF (14%–18%)	MRR (0.417 mm^3/min), SR (6.01 µm), TWR (0.105 mm^3/min)	PCA
Kumar et al. (2018)	L_9 OA	EDM oil	Ti-6Al-4V	Ton (100–200 µs), Ip (12–18 A), Vg (40–60 V)	MRR (0.046068089 g/min), SR (2.9 µm), Rz (17.8 µm), Rt (24.2 µm)	
Dastagiri et al. (2018)	L_9 OA	Water	SS316	Ton (100–300 µs), Toff (2–20 µs), Ip (3–35 A)	MRR (58.088 mm^3/min), SR (9.4 µm), TWR (11.1685 mm^3/min)	
Shukla and Dhakad (2018)	L_9 OA	EDM oil	Al alloy	Ton (50–150 µs), Ip (4–2 A), DF (5%–9%), RC (0–4.2 g)	MRR (58.405 mm^3/min), TWR (0.969 mm^3/min), ROC (0.195 mm), flatness (0.044 mm)	
Aravindan et al. (2018)	L_9 OA	Castrol Holo 401	SS 316	Ton (8–12 µs), Toff (6–10 µs), Ip (0.2–0.8 A)	MRR (0.0468 mm^3/min), SR (0.6253 µm), TWR (0.0131 mm^3/min)	
Gowthaman et al. (2018)	L_{27} OA	EDM oil	Monel	Ton (204–409 µs), Toff (2048–2,867 µs), Ip (9–15 A), Vg (80–150 V)	MRR (1.024 gm/s), SR (6.39 µm)	
Tharian et al. (2019)	L_9 OA	Deionized water	Al 7075	Ton (25–100 µs), Toff (25–100 µs), Ip (5–10 A)	MRR (1.92 g/min), SR (1.299 µm)	
Hanif et al. (2019)	BBD	Kerosene	AISI D_2 steel	Ip (9–15 A), Sg (2–6 mm), dielectric type (distilled water, kerosene, transformer oil)	MRR (17.23 mm^3/min), SR (3.86 µm)	
Moharana and Patro (2019)	BBD	Kerosene	EN 8	Ton (10–200 µs), Toff (10–50 µs), Ip (4–24 A), PF (0.25–0.75 kgf/cm^2)	MRR (0.4703 mm^3/min), SR (2.1029 µm), TWR (0.0005945 mm^3/min)	
Senthilkumar and Muralikannan (2019)	L_{27} OA	Kerosene	Al MMCs	Ton (50–100 µs), Ip (9–15 A), Vg (30–40 V)	MRR (0.3011 mm^3/min), SR (6.2667 µm), TWR (0.0313 mm^3/min)	
Sah and Gangil (2019)	L_9 OA	EDM oil	Carbon fiber nano composite	Ton (24–28 µs), Ip (6–10 A), Vg (60–80 V), DF (60%–90%)	MRR (0.00004308 g/min), TWR (0.411212 g/min)	
Matharou and Bhuyan (2020)	L_{16} OA	Kerosene- based EDM oil	Hybrid MMC	Ton (25–100 µs), Ip (3–12 A), DF (2%–8%), Sg (3–6 mm), tool material (Cu, Gr), DT (10–15 mm)	MRR (5.8746 mm^3/min), SR (4.09 µm), TWR (0.35749 mm^3/min)	PCA
Kumar and Dhanabalan (2020)	L_{18} OA	Kerosene	Inconel 718	Ton (200–600 µs), Toff (10–40 µs), Ip (4–12 A)	MRR (0.0022 g/min), TWR (0.016 g/min), squareness (89.67 mm), flatness (0.040 mm)	
Nguyen et al. (2020)	L_{25} OA	Deionized water	High Cr tool steel	Ton (18–75 µs), Toff (9–37 µs), Ip (1–5 A), Vg (30–70 V)	MRR (41.7 mg/min), SR (2.896 µm), MH (1,188.480 HV), WLT (22.453 µm)	
Kumar and Soota (2020)	BBD	EDM oil	Zircaloy	Ton (10–20 µs), Toff (4–8 µs), Ip (5–15 A)	MRR (0.209 × 10^{-3} mm^3/min), TWR (1.59 × 10^{-3} mm^3/min)	
Mazarbhuiya and Rahang (2020)	L_9 OA	EDM oil	Aluminium	Ton (100–400 µs), Ip (2–4 A), compact load (5–15 ton)	MRR (131.33 mg/min), SR (4.5 µm), TWR (620.13 mg/min)	
Sharma (2020)	BBD	EDM oil	Tungsten carbide	Ton (10–40 µs), Toff (2–8 µs), Ip (6–18 A)	MRR (2.4126 mm^3/min), SR (1.19 µm), MH (1346 HV)	
Phimoolchat and Muttamara (2020)	L_{27} OA	Kerosene	Al 2024	Ton (4–12 µs), Ip (6–14 A), Vo (80–220 V), DF (33%–75%)	MRR (35.116 mm^3/min), SR (4.975 µm), TWR (10.892 mm^3/min)	
Zeng et al. (2021b)	L_{18} OA	Kerosene	ZrO_2 ceramics	Ip (2–4 A), IH (0.4–1.2 A), PD (50–200 µs) EJI (2–4 s), Vs. (40–70 V)	MRR (0.2012 mm^3/min), SR (3.37 µm), TWR (0.0055 g/min)	AHP
Sharma et al. (2021)	L_{16} OA	EDM oil	Graphite iron	Ton (30–120 µs), Ip (32–44 A), IEG (0.011–0.014 mm)	MRR (187.005 mm^3/min), OC (0.0193 mm)	Fuzzy logic
Sahoo et al. (2021a)	BBD	Deionized water	Nitinol		MRR (0.0164 g/min), TWR (0.0.0064 g/min), TA (0.0097 radians)	

(Continued on following page)

TABLE 7 (*Continued*) GRA method.

Author(s)	Design plan	Dielectric	Material	EDM parameters	Responses	Other tools
				Ton (2–6 μs), Toff (5–9 μs), Ip (12–22 A), Vg (40–60 V), PF (50–100 kg/cm^2)		
Sahu and Mahapatra (2021)	L_{27} OA	EDM oil	Ti-4Al-6V	Ton (100–300 μs), Ip (20–30 A), Vg (20–30 V), DF (65%–85%), tool material (AlSi10Mg, Cu, Gr)	MRR (0.4440 mm^3/min), SR (6.5 μm), TWR (0.32 mm^3/min), SCD (0.011439 μm/μm^2), WLT (15.1050 μm), MH (519.37 VH)	FA, LSSVM
Fatatit and Kalyon (2021)	L_{18} OA	Kerosene	DIN 1.2767 steel	Ton (50–800 μs), Toff (50–800 μs), Ip (6–25 A)	MRR (25.24 mm^3/min), TWR (0.15 mm^3/min)	
Singh and Singh (2021)	L_{18} OA	Deionized water	Nimonic 75	Ton (120–200 μs), Toff (15–90 μs), Ip (6–12 A), Vd (40–50 V), TL (2–4 s), tool material (Cu, Br)	MRR (334.57 mg/min), SR (8.7 μm) TWR (0.7103 mg/min)	
Sivaraj et al. (2021)	L_9 OA	Kerosene	Al-TiC composite	Ton (50–100 μs), Ip (5–15 A), Vg (50–60 V)	MRR (0.3497 g/min), TWR (0.00204 g/min)	
Sahoo et al. (2021b)	CCD	EDM oil	Inconel 600	Ton (100–300 μs), Toff (60–100 μs), Ip (5–15 A)	MRR (2.671783 mm^3/min), SR (4.190333 μm), TWR (0.001116 mm^3/min)	RSM
Somasundaram and Kumar (2022)	L_{16} OA	Water	AZ31 Mg alloy	Ton (10–40 μs), Toff (5–8 μs), Ip (3–12 A), tool material (Cu, Br, Gr)	MRR (7.5512 mm^3/min), SR (3.2 μm), TWR (0.0042 gm/min), OC (0.0140 mm), TC (0.061 mm), CIR (0.0184 mm), CYL (0.0421 mm)	TOPSIS
Karmiris-Obratański et al. (2022)	L_{16} OA	Hydrocarbon fluid	CALMAX tool steel	Ton (12.8–100 μs), Vg (80–200 V), Ip (5–17 A)	MRR (7.979 mm^3/min), SR (6.13 μm), TWR (0.100 mm^3/min), WLT (6.35 μm)	
Jampana et al. (2022)	L_{16} OA	EDM oil	SS630	Ton (15–45 μs), Toff (20–90 μs), Ip (6–18 A), PF (2–8 MPa)	MRR (9.121 mm^3/min), SR (3.56 μm)	
Pragadish et al. (2022)	L_9 OA	Cardanol oil	Silicon steel	Vg (25–75V), green dielectric (0%–15%), coating thickness (0–2 μm)	MRR (9.69 mm^3/min), TWR (1.09 mm^3/min)	
Akgün (2022)	L_{27} OA	Kerosene	Monel K500	Ip (12–42 A), Ton (3–9 μs), Vg (50–100 V), tool material (Cu, Gr, W-Cu)	MRR (0.085 g/min), TWR (0.0075 g/min), SR (1.67 μm)	Regression analysis

Rai, 2020; Sahu and Mahapatra, 2020; Bhosale et al., 2021; Srinivasan et al., 2021b; Jana et al., 2021; Patnaik et al., 2022) have maximally preferred to employ both GRA and TOPSIS in identifying the optimal combinations of the EDM parameters. During machining of Si_3N_4-TiN ceramic material using an EDM process, Srinivasan et al. (2021b) applied both GRA and TOPSIS to achieve the same optimal intermix of EDM parameters as Ip = 10 A, Ton = 8 μs, Toff = 4 μs, PF = 20 kg/cm^2 and Vs. = 32 V to achieve the measured response values as MRR = 0.00584 g/min, SR = 1.41 μm, TWR = 0.00118 g/min, PER = 0.0321 mm and PAR = 0.0411 mm. The corresponding regression equations correlating the considered responses and EDM parameters were also formulated which had been subsequently optimized using TLBO algorithm. Prabhakar et al. (2021) proposed the combined application of MOORA and ELECTRE methods to develop an integrated MCDM tool to optimize the EDM operation on titanium alloy. The influences of various input variables, like Ton, Toff and Ip on MRR, SR and TWR were investigated and it was concluded that an optimal intermix of EDM parameters as Ton = 60 μs, Toff = 8 μs and Ip = 7 A would provide the enhanced performance of the said EDM process.

5 Results and discussion

The main objective of this review paper is to explore the applications of various MCDM techniques as multi-objective optimization tools to determine the most appropriate combinations of input parameters for having enhanced machining performance of EDM processes. The shortlisted research works are extensively studied to extract the relevant information with respect to experimental design plans employed, dielectrics used, work materials machined, input parameters and responses considered along with their settings/measured values, MCDM tools deployed and their applications along with other mathematical techniques. The results of these analyses are graphically portrayed in Figures 2–4. It can be noticed from Figure 2A that 82.5% the past researches have preferred to conduct EDM experiments based on Taguchi methodology (i.e., L_8, L_9, L_{16}, L_{18}, L_{21}, L_{25}, L_{27} and L_{36}) to examine the influences of different input parameters on the responses. This is because of its many advantageous features, like ability to provide robust design solutions with reduced experimental cost, inclusion of

TABLE 8 Multiple MCDM methods.

Author(s)	Design Plan	Dielectric	Material	EDM parameters	Responses	MCDM	Other tools
Kasdekar and Parashar (2015)	L_9 OA	Water	EN 353	Ip (9–25 A), Ton (10–87 µs), Toff (4–11 µs), concentration of dielectric (1–5 g/L)	MRR (30.63 mg/min), TWR (2.98 mg/min), SR (3.98 µm)	TOPSIS, WSM, WPM	EM
Das et al. (2018)	L_9 OA	Water	MDN 300 steel	Ton (25–65 µs), Toff (24–48 µs), Ip (10–20 A)	MRR (32.323 mm^3/min), SR (6.0668 µm), TWR (5.0482 mm^3/min)	GRA, TOPSIS	Fuzzy logic
Pradhan (2018)	CCD	EDM oil	AISI D2 tool steel	Ton (100–300 µs) Ip (4–10 A), Vg (40–60 V), DF (80%–90%)	MRR (32.551 mm^3/min), TWR (0.036 gm/min), ROC (0.215 µm)	TOPSIS, GRA	EM
Yuvaraj and Suresh (2019)	L_{18} OA	EDM oil	Inconel 718	Ton (100–200 µs), Toff (20–40 µs), Ip (10–14 A), Vg (30–50 V)	MRR (0.019137 mm^3/min), TWR (0.00261 g/min), OC (0.2419 mm), ROC (0.04839 mm)	TOPSIS, GRA	
Kumar and Rai (2020)	L_9 OA	Kerosene	Al 7050	Ton (50–150 µs), Toff (20–40 µs), Ip (6–10 A)	MRR (0.0338 g/min), SR (4.84122 µm) WLT (40.751 µm)	TOPSIS, GRA	
Kumar and Mondal (2020)	L_{27} OA	EDM oil	AISI M_2 steel	Ton (45–96 µs), Ip (2–7 A), Sg (4–6 mm)	MRR (0.006088 mm^3/min), SR (1.45 µm), TWR (0.035611 mm^3/min)	TOPSIS, GRA	
Sahu and Mahapatra (2020)	L_9 OA	EDM 30 oil	AISI 1040 steel	Ton (100–300 µs), Ip (10–30 A), tool material (AlSi10Mg, Cu, Br)	MRR (0.4525 mm^3/min), SR (4.6777 µm) SCD (0.013614 µm/µm^2), WLT (18.2403 µm), MH (547.57 VH)	TOPSIS, GRA	
Jana et al. (2021)	L_9 OA	Canola oil	AISI D_2 steel	Ip (6–8 A), Ton (300–500 µs), Vs. (40–60 V)	MRR (5.97 × 10^{-3} g/min), SR (1.8 µm), TWR (0.30 × 10^{-3} g/min)	TOPSIS, GRA	
Bhosale et al. (2021)	L_{18} OA	Kerosene	Ferrous clay matrix	Ton (400–600 µs), Ip (3–7 A), Vs. (48–50 V), RC (0%–5%)	MRR (0.1157 g/min), SR (3.66 µm), TWR (0.0167 g/min)	GRA, TOPSIS	
Dey et al. (2021)	CCD	Hydrocarbon oil	Al 6061-cenosphere	Ton (210–1,010 µs) Ip (6–10 A), RC (2%–6%), PF (0.2–0.6 MPa)	MRR (0.6843 g/min), SR (14.2872 µm), TWR (0.0019 g/min)	TOPSIS, VIKOR	AHP
Srinivasan et al. (2021b)	L_{25} OA	Deionized water	Si_3N_4-TiN ceramic	Ton (5–9 µs), Toff (2–10 µs), Vs. (28–36 V) Ip (4–12 A), PF (12–20 kg/cm^2)	MRR (0.00584 g/min), SR (1.41 µm), TWR (0.00118 g/min), PER (0.0321 mm), PAR (0.0411 mm)	GRA, TOPSIS	TLBO
Prabhakar et al. (2021)	L_{25} OA	EDM oil	Ti-4Al-6V	Ton (15–75 µs), Toff (2–10 µs), Ip (7–35 A)	MRR (0.1 mm^3/min), SR (0.847 µm) TWR (0.0016 mm^3/min)	MOORA, ELECTRE	
Patnaik et al. (2022)	L_9 OA	EDM oil	Inconel 718	Ton (250–1,000 µs), Vg (4–8 V), Ip (20–40 A)	MRR (25.4297 mm^3/min), SR (2.98233 µm), TWR (0.27960 mm^3/min)	TOPSIS, GRA, PSI	

both qualitative and qualitative variables, easy mathematical steps, availability of user-friendly software, *etc.* Among various Taguchi's OAs, L_9 OA has been maximally utilized (39.4%), followed by L_{18} OA (13.9%) and L_{27} (13.1%) OA design plans. It is interestingly noticed that in the past studies, maximum number of EDM experiments has been carried out considering three parameters set at three different operating levels which have led to selection L_9 OA as the most suitable design plan based on the computed degrees of freedom. Besides OAs, CCD (10.2%) and BBD (7.3%) have also been employed which would lead to development of the corresponding polynomial regression equations correlating EDM parameters and responses. Those equations have later been optimized using GA (2), NSGA-II (1), TLBO (2), MOPSO (1), QPSO (1), GP (1), FA (1) and CS (1) algorithms in the continuous solution space. The numerical value in the parenthesis indicates the number of occurrences of those techniques in the reviewed articles for EDM processes optimization.

Figure 2B provide information with respect to different types of dielectrics used by the past researchers. EDM oil (EDM-30, EDM SAE 40, EDM SE0501, EDM SAE 450, D323, HD-1, HD-11, *etc.*) has been the mostly utilized dielectric (43.6%), followed by deionized water (12.1%) and plain water (7.9%). To achieve sustainable and

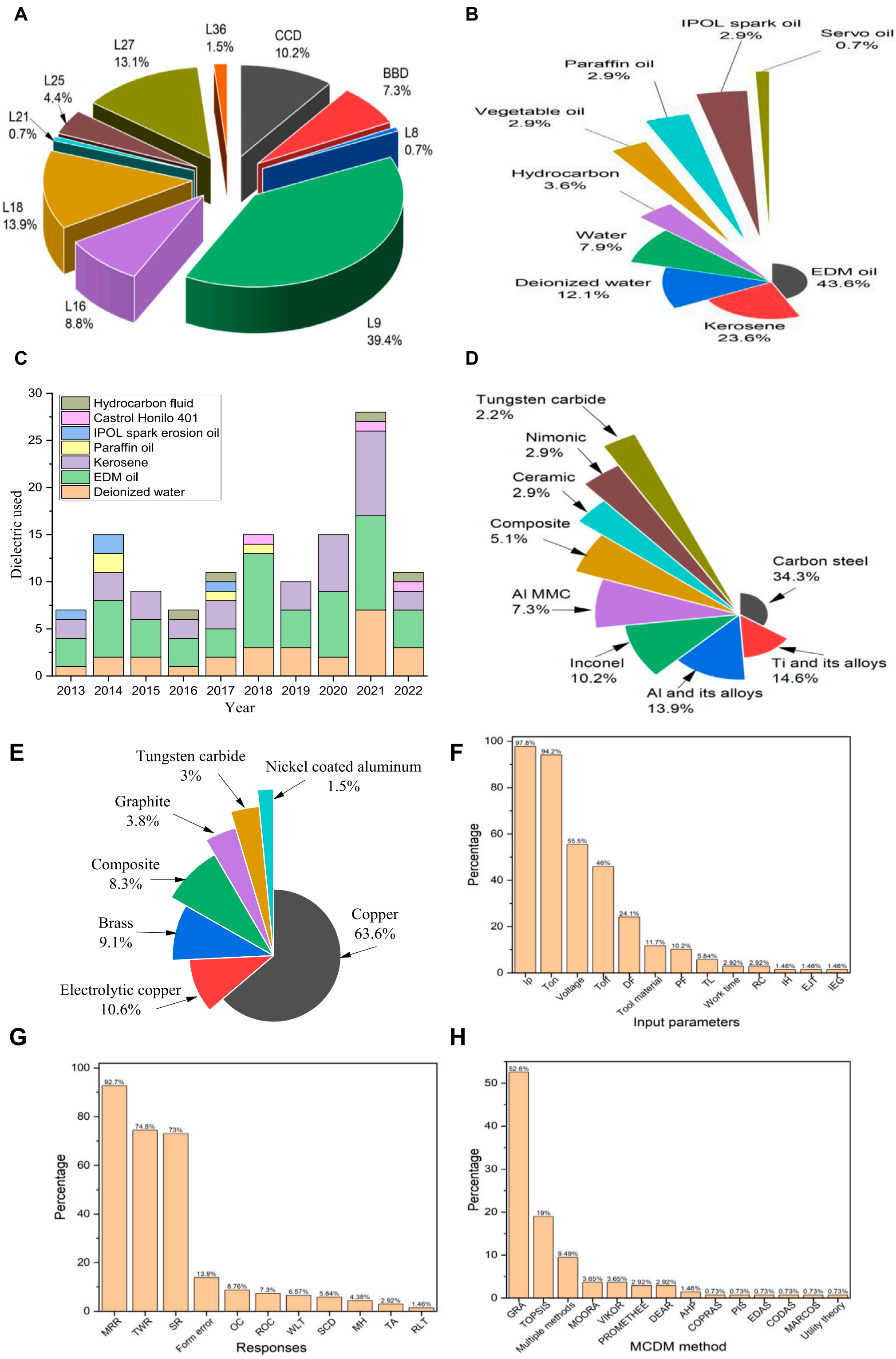

FIGURE 2
Graphical representation of the reviewed paper in terms of **(A)** design plan used **(B)** dielectric medium **(C)** trend of dielectric usage over the years **(D)** material machined **(E)** tool material **(F)** process parameter considered **(G)** response studied and **(H)** MCDM tools employed by the researchers.

dry machining environment while avoiding the perilous effects of EDM oil, it is noticed that deionized water and plain water have emerged out as user-friendly and less hazardous dielectric fluids during EDM operations (Figure 2C). The EDM process is extremely suitable to generate complex shape geometries in many of the hard-to-cut engineering materials having higher strength-to-weight ratio. Figure 2D shows the applications of EDM processes in machining of some of the major work materials, such as medium and high carbon

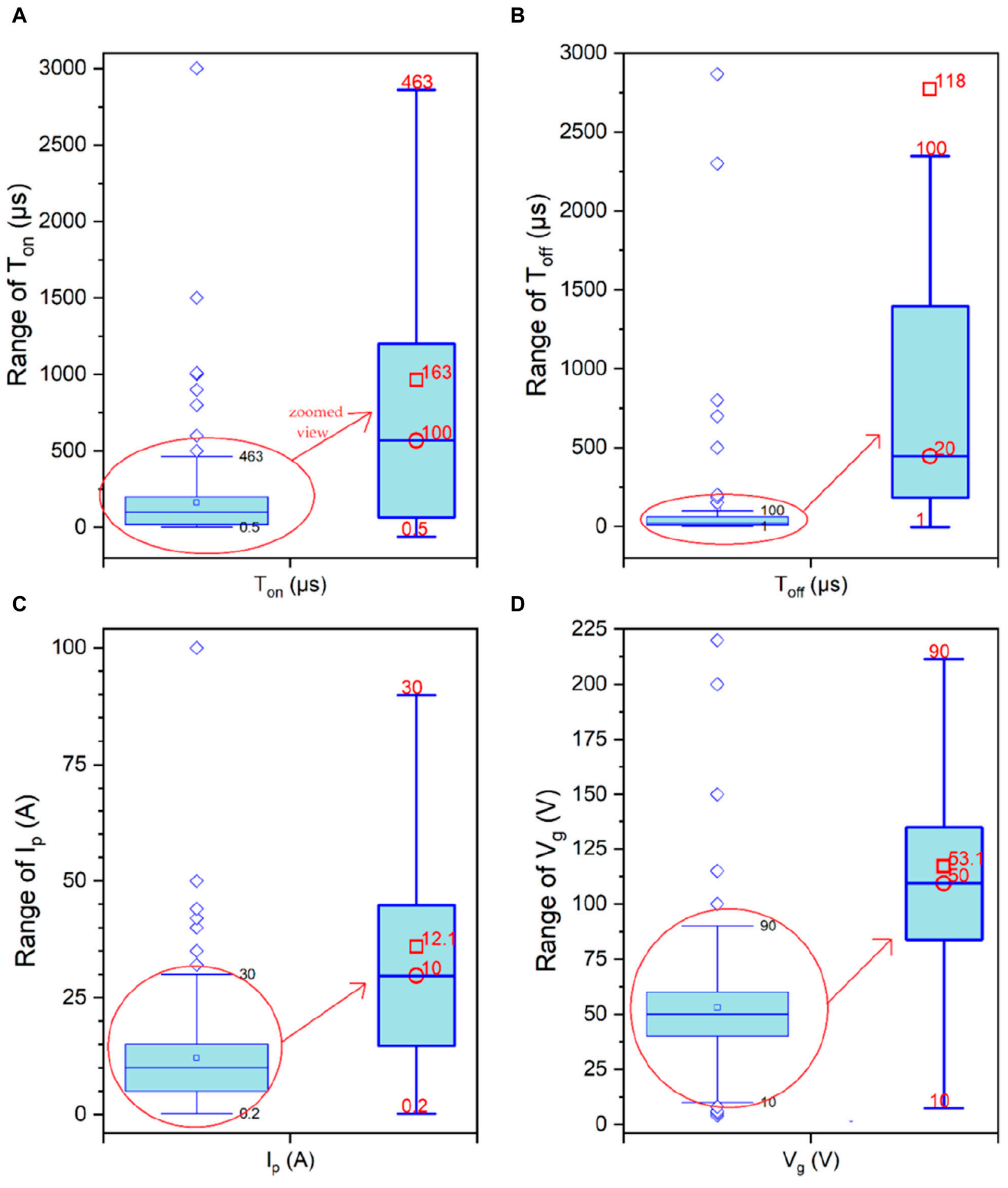

FIGURE 3
Ranges of main EDM parameters. **(A)** Pulse-on time **(B)** pulse-off time **(C)** paeak current **(D)** gap voltage.

steels (34.3%) (making of shafts, crankshafts, axles, gears, couplings, forgings, *etc.*), titanium and its alloys (14.6%) (used in airplanes, missiles and rockets), aluminium and its alloys (13.9%) (used in electric and electronic industries, making of automotive and aerospace body structures, solar equipment), Inconel (10.2%) (making of propeller blades, propulsion motors, wire rope, sheathing for underwater communication cables), aluminium MMCs (7.3%) (huge applications in defence, aerospace, automotive and aviation industries), other composites (5.1%) (used in chemical, paper, oil and gas industries, water treatment plants), ceramics (2.9%) (making of bio-implants, body armours, spark plugs, fiber optics, race car brakes, chemical sensors), Nimonic

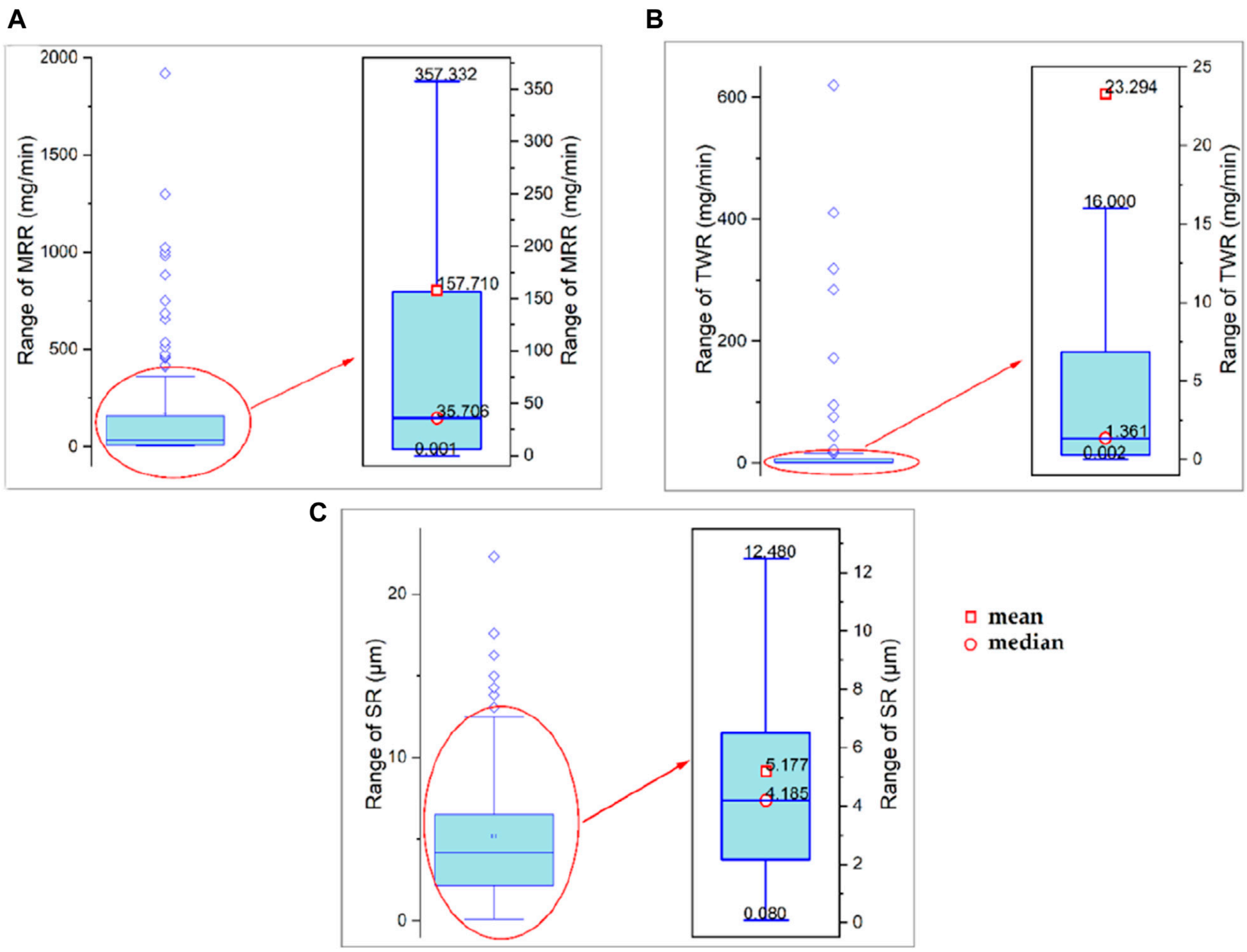

FIGURE 4
Ranges of main responses. **(A)** material removal rate **(B)** tool wear rate **(C)** surface roughness.

(2.9%) (for gas turbine components, nuclear boiler tube supports, automobile exhaust valves) and tungsten carbide (2.2%) (mainly used as cutting tool material for various machining operations). Other work materials, like magnesium and its alloys, Zircaloy, Monel, brass, copper and Nitinol have also been occasionally machined using EDM processes, but are not shown in Figure 2D due to their least number of occurrences (≤2) in the reviewed articles.

Figure 2E illustrates the trend of tool material usage in EDM research. Copper stands out as the most commonly used tool material, being featured in 63.6% papers. This prevalence is likely due to copper's excellent electrical conductivity and thermal properties, making it an effective electrode material for the EDM process. Electrolytic copper was used in 10.6% papers, is a refined version of copper that usually offers higher purity and, consequently, better performance in EDM. Brass was also used in 9.1% papers, is also a favorable choice due to its good machining properties and cost-effectiveness. Composite tool materials, used in 8.3% papers, indicate an interest in exploring the benefits of composite electrodes, such as improved wear resistance or specialized machining capabilities, which can be tailored by combining different materials. Graphite, though less frequently used, appearing in only 3.8% papers, offers advantages such as higher melting points and the ability to achieve finer finishes. Its lower popularity could be due to its brittleness and the challenges associated with handling and machining graphite electrodes. Tungsten carbide, mentioned in 3% papers, is known for its hardness and high wear resistance, making it suitable for precision machining, although its use is less due to higher material costs. Nickel-coated aluminum found use only in 1.5% papers, suggesting that it may be a relatively new area of exploration in EDM tool materials, possibly offering a combination of the lightweight properties of aluminum with the superior surface characteristics of a nickel coating.

The performance of EDM processes with respect to MRR, SR (average surface roughness value, Ra), TWR, form errors (flatness, squareness, CYL, CIR, PAR and PER), OC, ROC, *etc.*, is noticed to be significantly affected by the considered input parameters. Thus, it is highly recommended to operate the EDM processes while setting those parameters at their optimal levels. The major input parameters taken into account by the past researchers during EDM of diverse work materials are exhibited in Figure 2F which reveals that Ip has been the most important parameter (97.8%), followed by Ton (94.2%), voltage (55.5%), Toff (46%), DF (24.1%), type of the tool material (11.7%), PF (10.2%) *etc.* On the other hand,

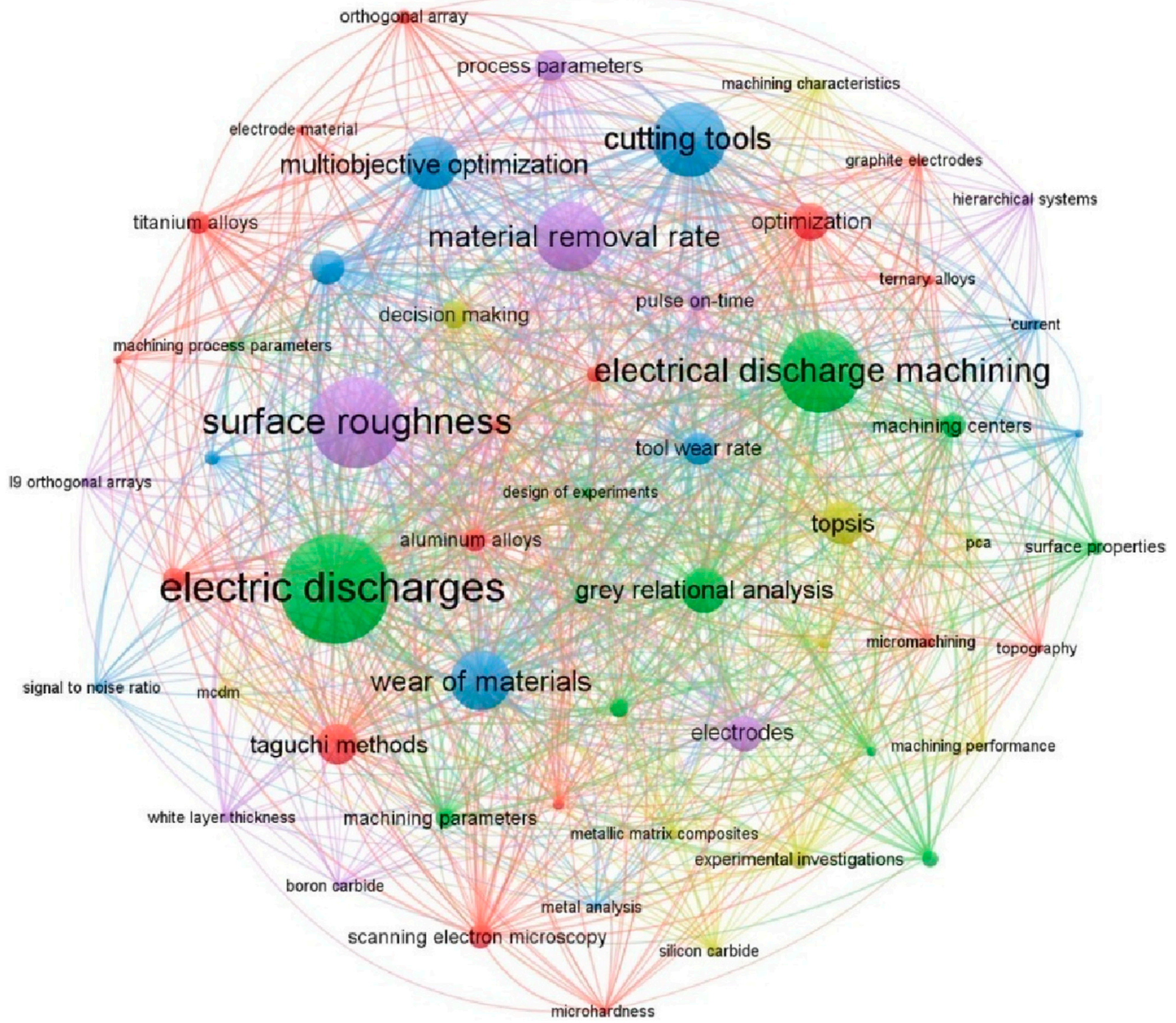

FIGURE 5
Co-citations of different keywords in the surveyed research articles.

Figure 2G provides information about some of the most important responses measured to evaluate the machining performance of EDM processes. MRR has been maximally considered (92.7%), which has been followed by TWR (74.5%), SR (73%), form errors (13.9%), OC (8.76%), ROC (7.3%), WLT (6.57%), SCD (5.84%), MH (4.38%), TA (2.92%) and RLT (1.46%) according to their descending importance to represent performance of the EDM processes. In all the reviewed articles, the value of SR has mainly been measured in terms of Ra (average surface roughness). Besides Ra, other roughness parameters, like root mean square roughness (Rq), skewness of surface profile (Rsk), kurtosis of surface profile (Rku), mean width of roughness profile (Rsm) and ten-point surface roughness (Rz) have also been occasionally considered to represent surface quality of the machined components. But, the correlations between those roughness parameters have never been evaluated. There are also some unimportant EDM parameters, like C, GC, Sg, RC, DT, *etc.*, and responses, such as PFE, fractal dimension, RS, SEC, N, MC, taper ratio, PE, TC, *etc.*, considered by the past researchers in their experimental studies which are not included while developing Figures 2F, G due to their least number of occurrences in the reviewed articles.

Figure 2H depicts the quantum of different MCDM tools deployed for optimization of EDM processes in the reviewed research articles. The GRA technique has found maximum applications (52.6%), followed by TOPSIS (9%), MOORA (3.65%), VIKOR (3.65%), PROMETHEE (2.92%) and DEAR (2.92%) methods. Other MCDM methods, such as AHP, COPRAS, PIS, EDAS, CODAS, MARCOS and utility theory have also been occasionally utilized for the same purpose. The high popularity of GRA is perhaps due to its simplicity and efficiency in handling uncertainty and incomplete data. GRA integrates smoothly with the Taguchi method and simplifies multivariate analysis by converting multiple performance measures into a single composite score. Further, GRA does not require the weighting of criteria which reduces the computational load for researchers. Although the researchers have preferred to assign equal importance to the responses under consideration during optimization of EDM processes using different MCDM tools mainly to reduce the computation complexity, several subjective techniques, like AHP (13) and Simo's weighting method (1) and objective techniques, like PCA (7), EM (4), SDV (1), WPCA (1) and CRITIC (1) have been employed for estimating the relative importance of different responses. To deal with uncertainty involved during allotting criteria weights, fuzzy set theory (4) has also been combined with MCDM methods. Integration of fuzzy logic with MCDM methods (7) has helped the researchers to develop the corresponding "If'-Then" rules to explore the relationships between EDM parameters and responses.

Although the operating level of each of the EDM parameters largely depends on the type of the work material and feature to be machined, interaction between the work and tool materials and manufacturer and model of a particular EDM setup; based on the reviewed articles, an attempt is put forward in Figure 3 to portray the settings of four main EDM parameters, i.e., Ton, Toff, Ip and Vg, as considered by various past researchers, in the form of box plots. It is interesting to notice that those settings are widely varying, leading to large number of outliers towards higher levels of all the considered parameters. For Ton parameter, the lower and upper whisker values of the developed box plot are 0.5 µs and 463 µs respectively; while the corresponding mean and median values are 163 µs and 100 µs respectively (excluding the outliers). Similarly, the lower and upper whiskers, mean and median values for Toff, Ip and Vg can be obtained. It can be noted that for Toff, the mean of the box plot is well above the upper whisker indicating that a few studies have considered extreme high values for Toff during experimentation as compared to bulk of other studies. Thus, the mean value of the process parameter range in such cases is not a true representation of Toff considered by the past research community. Thus, it can be concluded from Figure 3 that the future researchers should attempt to set the corresponding values of Ton, Toff, Ip and Vg as 100 µs, 20 µs, 10 A and 50 V (all median values) respectively for having the best performance of an EDM process. It would eventually relieve the operators to conduct pilot runs or rely on trial-and-error approach for having the idea regarding the initial settings of different EDM parameters prior to any real-time experiment, thereby saving machining cost and time.

In EDM process, different physical properties of the work material, machining time, material of the tool and operating levels of the input parameters under consideration significantly influence the achieved responses values. In Figure 4, values of three main responses, i.e., MRR, TWR and SR attained by the earlier researchers at the derived optimal intermixes of the considered EDM parameters are depicted in the form of box plots. While developing the box plots for MRR and TWR, their volumetric measured values are converted into corresponding gravimetric values and their unit is kept as mg/min. Those response values also widely vary depending on the type of the work material machined, tool material used and settings of the EDM parameters. For MRR, the values of lower and upper whiskers, mean and median are observed to be 0.001 mg/min, 357.332 mg/min, 157.710 mg/min and 35.706 mg/min respectively (excluding the outliers). On the other hand, those values for TWR are 0.002 mg/min, 23.294 mg/min, 16.000 mg/min and 1.361 mg/min respectively. In case of SR, lower and upper whiskers, mean and median values are obtained as 0.080 µm, 12.480 µm, 5.177 µm and 4.185 µm respectively. Thus, irrespective of the work and tool materials and input parameter settings, the achievable MRR, TWR and SR would be 35.706 mg/min, 1.361 mg/min and 4.185 µm respectively (considering their median values).

The co-citations of different keywords as considered in the reviewed articles with the focal keyword "Optimization of EDM process using MCDM methods" are plotted in Figure 5. From this figure, it can be interestingly unveiled that "Electrical discharges," "Surface roughness," "Material removal rate," "Cutting tools," "Multi-objective optimization," "Wear of materials," "Grey relational analysis," "TOPSIS" and "Taguchi methods" are strongly related when different MCDM methods have been employed for optimizing the performance of EDM processes. Co-existence of other keywords, such as "Process parameters," "Optimization," "Tool wear rate," "Electrodes," "MCDM," "L9 orthogonal arrays," "Decision making," "Current," "Pulse-on time," "Aluminium alloys," "Titanium alloys" etc., also closely matches with the observations of this review paper.

6 Conclusions and future directions

Based on the information extracted after comprehensively reviewing 137 research articles published during 2013–2022 and available in the SCOPUS database, the following conclusions can be drawn:

a) Keeping in mind the widespread applications of EDM processes in many of the modern-day industries to generate complex shape features on diverse difficult-to-cut work materials, their optimization using MCDM methods appears as a topic of immense interest among the research community.
b) The major advantage of MCDM-based optimization of EDM processes lies in the fact that in most of the cases, the derived optimal combinations of the input parameters would be among the conducted experimental runs, relieving the machinists to perform additional experiments.
c) Taguchi's L_9 OA plan has been maximally employed by the past researchers to carry out EDM experiments. On the other hand, EDM oil has been the most preferred dielectric fluid and medium and high carbon steels have been mostly machined using EDM processes. With respect to input and output parameters, peak current has been the most important EDM parameter and MRR has been maximally considered to characterize the performance of EDM processes.
d) Due to its uncomplicated computational steps and independency of criteria weighting technique, GRA has appeared to be the most popular multi-objective optimization tool to determine the optimal parametric combinations of EDM processes. On the other hand, the earlier researchers have preferred application of AHP to measure weights of different responses under consideration.
e) With respect to four most important EDM parameters, i.e., Ton, Toff, Ip and Vg, the future researchers are advised to conduct EDM experiments while setting their corresponding operating values at 100 µs, 20 µs, 10 A and 50 V respectively.

f) Irrespective of the work and tool materials and ranges of the input parameters, the achievable values of the three most important responses, i.e., MRR, TWR and SR would be 35.706 mg/min, 1.361 mg/min and 4.185 μm respectively.
g) It would act as a valuable data repository to explore the stochastic behaviour of EDM processes and guide the future researchers in setting the operating levels of the main input parameters, relieving them to conduct pilot experiments while saving experimental cost and time.
h) "Optimization of EDM process using MCDM methods" is strongly interlinked with "Electrical discharges," "Surface roughness," "Material removal rate," "Cutting tools," "Multi-objective optimization," "Wear of materials," "Grey relational analysis," "TOPSIS" and "Taguchi methods."

This review on the applications of MCDM techniques for parametric optimization of EDM processes proposes the following future research directions:

a) Applications of various metaheuristics for optimizing EDM processes may be explored.
b) Further review may be conducted on MCDM techniques and metaheuristics deployed to derive the optimal performance of other traditional as well as non-traditional machining processes.
c) The scope of other newly developed but yet to be popular MCDM tools, like combined compromise solution (CoCoSo), multi-attributive ideal-real comparative analysis (MAIRCA), multi-attributive border approximation area comparison (MABAC) *etc.*, may be exploited to optimize EDM processes.
d) It is advised to estimate the relative importance of the responses using objective weighting methods, like CRITIC, method based on the removal effects of criteria (MEREC) *etc.*, to derive more pragmatic solutions.
e) Integration of MCDM methods with fuzzy set, intuitionistic fuzzy set, hesitant fuzzy set, neutrosophic fuzzy set *etc.*, is highly encouraged involving multiple decision makers to qualitatively evaluate significance of the responses in uncertain group decision making environment.
f) The extracted information with respect to process parameter settings and achieved response values may be treated as the inputs to any of the machine learning algorithms to design and develop the corresponding predictive models.
g) Future research should explore the integration of machine learning with MCDM techniques to enhance predictive accuracy and process optimization.
h) Additionally, investigating environmentally friendly EDM processes aligns with global sustainability goals, presenting a critical avenue for further studies.

The major limitations of this paper are consideration of only MCDM techniques for optimizing EDM processes as a review topic, exclusion of conference papers and book chapters from the scope of review, omitting the derived optimal values of EDM parameters from further analysis (due to lack of exact information) and dependency on only SCOPUS database.

Author contributions

DP: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Validation, Writing–original draft, Writing–review and editing. KK: Conceptualization, Funding acquisition, Methodology, Visualization, Writing–review and editing. SC: Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing–original draft, Writing–review and editing. RČ: Conceptualization, Funding acquisition, Project administration, Resources, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Glossary

AHP	Analytic Hierarchy Process
C	Capacitance
Cent	Circularity at entry
CIR	Circularity
COPRAS	COmplex PRoportional ASsessment
CS	Cuckoo Search
DF	Duty Factor
DT	Tool Diameter
EDM	Electrical Discharge Machining
EJT	Electrode jumping-up time
EM	Entropy Method
GA	Genetic Algorithm
GP	Genetic Programming
GRG	Grey Relational Grade
IH	Auxiliary current with high voltage
LSSVM	Least Square Support Vector Machine
MC	Machining Cost
MH	Micro-hardness
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
MRR	Material Removal Rate
N	Noise
OA	Orthogonal Array
PAR	Parallelism
PD	Pulse Duration
PF	Flushing Pressure
PROMETHEE	Preference Ranking Organization METHod for Enrichment Evaluation
QPSO	Quantum-behaved Particle Swarm Optimization
RC	Percentage of Reinforcement
ROC	Radial Overcut
RSM	Response Surface Methodology
SDV	Standard Deviation
Sg	Spark Gap
SS	Stainless Steel
TC	Taper Cut
TLBO	Teaching Learning-based Optimization
Ton	Pulse-on time
TWR	Tool Wear Rate
Vg	Gap voltage
Vo	Open voltage
WLT	White Layer Thickness
WPM	Weighted Product Model

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BBD	Box-Behnken Design
CCD	Central Composite Design
Cexi	Circularity at exit
CODAS	COmbinative Distanced-based Assessment
CRITIC	CRiteria Importance Through Intercriteria Correlation
CYL	Cylindricity
DEAR	Data Envelopment Analysis Ranking
DFA	Desirability Function Approach
EDAS	Evaluation based on Distance from Average Solution
EJI	Interval of electrode jumping
ELECTRE	ELimination Et Choice Translating REality
FA	Firefly Algorithm
GC	Gap Control
GRA	Grey Relational Analysis
IEG	Inter-electrode Gap
Ip	Peak Current
MARCOS	Measurement Alternatives and Ranking according to COmpromise Solution
MCDM	Multi-Criteria Decision Making
MMC	Metal Matrix Composite
MOPSO	Multi-objective Particle Swarm Optimization
MW	Mean Weight
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
OC	Overcut
PCA	Principal Component Analysis
PE	Process Energy
PER	Perpendicularity
PFE	Plasma Flushing Efficiency
PSI	Preference Selection Index
RLT	Recast Layer Thickness
RS	Residual Stress
SCD	Surface Crack Density
SEC	Specific Energy Consumption
SR	Surface Roughness
TA	Taper Angle
TL	Tool Lift Time
Toff	Pulse-off Time
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
Vd	Discharge Voltage
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
Vs.	Servo Voltage
WPCA	Weighted Principal Component Analysis
WSM	Weighted Sum Model