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REVIEW PAPER

Parametric optimization of non-traditional machining processes using multi-criteria decision making techniques: literature review and future directions

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Abstract
Continuous urge for generation of complex intricate features on harder and tougher materials with close dimensional tolerance and superior surface quality has led to the development of non-traditional machining (NTM) processes. Unlike the conventional machining processes, the NTM processes employ energy in various forms or their combinations for removal of material from the workpiece. As these processes are quite capital-intensive, their performance needs to be optimized. In this direction, applications of various multi-criteria decision making (MCDM) techniques have already become popular. This paper provides a comprehensive review of the present literature on the applications of MCDM techniques for parametric optimization of NTM processes. Among all the NTM processes, electrochemical machining (ECM), electrical discharge machining (EDM), wire electrical discharge machining (WEDM), abrasive water jet machining (AWJM), laser beam machining (LBM), ultrasonic machining (USM), and plasma arc machining (PAM) are considered in this paper due to their widespread acceptance in modern manufacturing industries. The essence of all the reviewed articles would help the process engineers in identifying the most suitable experimental design plan, work material, process parameters and responses, MCDM tools, criteria weight measurement techniques, and hybrid models for parametric optimization of NTM processes. Future directions are also included to explore the feasibility of newer MCDM tools to have more pragmatic solutions.

Keywords NTM process · MCDM · Optimization · Parameter · Response

Abbreviations

AHP	Analytic hierarchy process
AJM	Abrasive jet machining
ANFIS	Adaptive neuro fuzzy inference system
ANN	Artificial neural network
ARAS	Additive ratio assessment
AWJM	Abrasive water jet machining
BBD	Box–Behnken design
CCD	Central composite design
CoCoSo	Combined compromise solution
CODAS	Combinative distance-based assessment
COPRAS	Complex proportional assessment
CRITIC	Criteria importance through intercriteria correlation
CSA	Cuckoo search algorithm
DEMATEL	Decision making trial and evaluation laboratory
DFA	Desirability function approach
DoE	Design of experiments
ECM	Electro-chemical machining
EDAS	Evaluation based on distance from average solution
EDM	Electrical discharge machining
EWR	Electrode wear rate
FEM	Finite element method
GA	Genetic algorithm
GRA	Grey relational analysis

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GRNN	General regression neural network
GWO	Grey wolf optimizer
HAZ	Heat affected zone
KW	Kerf width
LBM	Laser beam machining
MABAC	Multi-attributive border approximation area comparison
MARCOS	Measurement alternatives and ranking according to compromise solution
MCDM	Multi-criteria decision making
MMC	Metal matrix composite
MOGA	Multi-objective genetic algorithm
MOORA	Multi-objective optimization on the basis of ratio analysis
MRR	Material removal rate
MRSN	Multiple response signal-to-noise
NTM	Non-traditional machining
OA	Orthogonal array
OC	Overcut
OCRA	Operational competitiveness rating analysis
PAM	Plasma arc machining
PCA	Principal component analysis
PROMETHEE	Preference ranking organization method for enrichment evaluation
PSI	Preference selection index
Ra	Average surface roughness
Rku	Kurtosis of surface roughness distribution
ROC	Radial overcut
ROV	Range of value
Rq	Root-mean-square roughness
Rsk	Skewness of surface roughness distribution
Rsm	Mean width of profile elements
Rz	Ten-point surface roughness
SAW	Simple additive weighting
SDV	Standard deviation
SIR	Superiority inferiority ranking
SR	Surface roughness
SS	Stainless steel
SVM	Support vector machine
TLBO	Teaching–learning-based optimization
TODIM	TOmada de Decisao Interativa Multicriterio
TOPSIS	Technique for order of preference by similarity to ideal solution
TWR	Tool wear rate
USM	Ultrasonic machining
UT	Utility theory
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted aggregated sum product assessment
WEDM	Wire electrical discharge machining
WJM	Water jet machining
WPCA	Weighted principal component analysis
WPM	Weighted product method
WSM	Weighted sum method
WSN	Weighted signal-to-noise

1 Introduction

In conventional machining processes, material is usually removed by shearing action where the shear force is provided by a single- or multi-point cutting tool kept in contact with the workpiece. In those processes, tool material is required to be harder than the workpiece for smooth cutting action. But, there are certain machining situations wherein the conventional machining processes cannot be able to deliver the required degree of dimensional accuracy or sometimes they cannot even machine certain materials. For example, long holes with small diameters are difficult to generate by the conventional drilling operation because of a potential buckling due to high slenderness ratio of the drill bit (Youssef and El-Hofy 2020). It is also a well-known fact that an increase in work material hardness reduces the economic cutting capability of the conventional machining processes. The advanced engineering materials, like ferrous alloys, titanium, nickel, aluminum, cobalt and their alloys, Nimonics, ceramics, composites, etc. possess some typical mechanical properties, such as high strength-to-weight ratio, excessive hardness, high toughness, high strength temperature resistance, etc. which make them unsuitable to be machined by the conventional material removal processes (El-Hofy 2005). These materials have already found wide-ranging applications in diverse technologically advanced industries, like aerospace, nuclear, defence, automobile, etc. To fulfill such requirements, newer material removal processes have been developed in the form of NTM processes which can be commercially utilized to machine different hard-to-cut materials. Unlike the conventional machining processes, they employ energy in the form of thermal, chemical, electrical, mechanical or a combination of them to remove material from the workpiece (Pandey and Shan 1980). In these processes, the tool does not make any direct contact with the workpiece and mechanism of material removal is not necessarily shearing. They are favored because of their capability to provide excellent surface finish with higher dimensional accuracy, minimum tool wear, and possibility of automation, miniaturization, etc. They are now being successfully employed to machine and fabricate micro as well as nano-components (Bhattacharyya and Doloi 2020). But, these processes also have some disadvantages, like higher initial setup cost and energy consumption, requirement of skilled manpower, low MRR, not suitable for bulk production, etc.

In today's highly competitive manufacturing environment, process optimization plays a key role in reducing manufacturing cost, achieving better product quality, enhancing process performance with reduction of human error, and promoting consistent operation. It also helps in reducing the operator's/machinist's involvement and dependency of the data handbooks in identifying the optimal set of process parameters. Lack of awareness of the optimal intermix of various process parameters may lead to several machining inconsistencies. As the machining processes involve multiple conflicting objectives (like maximization of MRR and minimization of SR, maximization of machining rate and minimization of energy consumption, etc.), it is always preferred to deploy multi-objective optimization techniques which can identify the most suitable combinations of the process parameters resulting in simultaneous optimization of the responses under consideration.

Like other machining processes, in NTM processes, attainment of the desired response values is also significantly influenced by the proper setting or tuning of the considered input parameters. An improperly selected parametric combination may lead to consequences, like short circuit, workpiece deformation, damage of tool, etc. Bhattacharyya and Sorkhel (1999) pointed out that in an ECM process, the target values of MRR and OC could only be achieved at an optimal combination of electrolyte concentration, applied voltage, inter-electrode gap and electrolyte flow rate. On the other hand, Muthuramalingam and Mohan (2015) studied the effects of pulse shape and discharge energy on attaining the most desirable values of MRR, SR, and EWR in an EDM process. Many of the NTM processes are capital-intensive, consume high specific energy, have extremely low MRR, and high tooling and operating cost. Hence, for efficient deployment of these processes and explore their maximum machining performance, careful selection of the corresponding input parameters has become essential. Involvement of large number of input parameters and conflicting responses, and their possible interactions also make parametric optimization of the NTM processes more complex.

The MCDM techniques are those mathematical tools which help in identifying the best alternative from a set of feasible solutions in the presence of conflicting criteria. They have already become popular among the decision making community due to their simplicity and uncomplicated computational steps. Application of any of the MCDM techniques requires a decision matrix having a set of alternatives and evaluation criteria. An experimental design plan with different parametric combinations and responses for any of the machining processes closely resembles a decision matrix. Thus, MCDM techniques have appeared to be viable tools in solving parametric optimization problems of diverse machining processes (Sidhu et al. 2018; Asjad and Talib 2018). The present literature is flooded with successful applications of different MCDM techniques in determining the optimal intermixes of various NTM process parameters leading to better response values. In this paper, more than 200 research articles (most of them have been published during the last 10 years) on parametric optimization of ECM, EDM, WEDM, AWJM, LBM, PAM, and USM processes (due to their wide acceptability in modern-day manufacturing industries) using MCDM tools are critically analyzed in succinct tabular forms. Special attention is provided on identification of the experimental design plan deployed, material machined, process parameters and responses considered, and MCDM tool employed. Attempts are also put forward to extract information with respect to integration of those MCDM tools with other mathematical techniques (criteria weight measurement, fuzzy theory, etc.). This review paper would be an asset to the machinists as well as researchers for optimization of NTM processes. The essence of this paper would help the process engineers/machine operators in first searching out the most suitable design plan before any real-time experiment based on the number of NTM parameters and their operating levels. It would guide in selecting the appropriate work material to be machined focusing on the requirements of the present-day manufacturing industries. For each NTM process, the most significant input parameters affecting the responses under consideration can be identified and the relevant quality characteristics of the machined components can be shortlisted fulfilling the requirements of all the stakeholders. It would help in providing guidance with respect to employment of suitable techniques for quantitatively estimating the importance of the responses and optimization of the NTM processes. This paper is structured as follows: Section 2 briefly describes the working principles of some of the NTM processes adopted by the past researchers for their parametric optimization. Section 3 presents a concise review of the most popular MCDM techniques. Reviews on the applications of different MCDM methods for parametric optimization of the considered NTM processes are presented in succinct tabular forms in Sect. 4. Outcomes of this review paper are summarized in Sect. 5 and conclusions are drawn in Sect. 6 along with the future directions.

2 Classification of NTM processes

As already mentioned, the NTM processes employ different energies in their direct forms or their combinations for material removal. Thus, it is always advisable to classify them based on the source of energy, i.e. mechanical, thermal, chemical and electrochemical, and hybrid, as shown in Fig. 1. Mechanical processes involve erosion of work material using a high velocity stream of fluid or abrasive particles. In thermal processes, electrical energy is converted into thermal energy

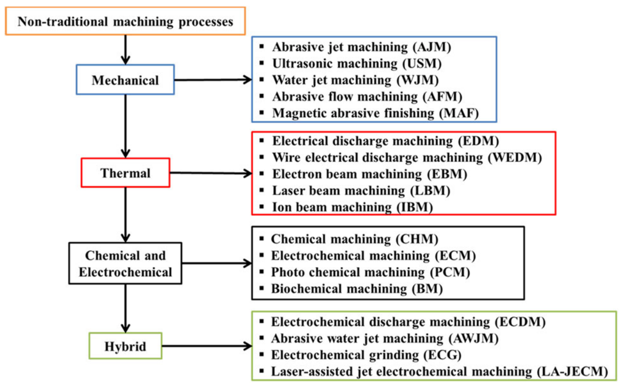

Fig. 1 Classification of NTM processes

which is responsible for material removal from the workpiece by vaporization or fusion. Chemical processes utilize chemicals to act as etchants for material removal while other portions of the workpiece are covered by a suitable mask, whereas, electrochemical dissolution of the workpiece leads to material removal in ECM processes. In hybrid processes, two or more NTM processes are synergically combined with an aim to achieve better machining performance than their constituent processes. For example, AJM and WJM processes are combined together to develop AWJM process where a water jet mixed with abrasive particles is injected at an extremely high speed on to the workpiece surface leading to material removal due to mechanical actions of both water and abrasives.

2.1 ECM process

The basic principle of material removal in ECM is same as the process of electrolysis. Here, the tool acts as a cathode and the workpiece acts as an anode. Low voltage high current DC flows through them through an electrolyte solution which flows between the inter-electrode gap (Yuan et al. 2021). Material removal takes place as a result of anode losing ions which are carried away by the pressurized electrolyte. During the machining operation, the tool is guided towards the workpiece without touching it. Due to electrolytic action, material is dissolved from the workpiece with the tool forming the desired shape on the workpiece surface. The machined feature would be an exact mirror image of the tool. This process is widely employed in aerospace, automotive and medical equipment industries because of its high level of accuracy. The main benefit of this process is high MRR as well as precision machining of only electrically conductive materials. During ECM, the workpiece is not subjected to any kind of thermal and mechanical stresses which is considered as one of the deciding factors to choose ECM over the other NTM processes.

2.2 EDM process

The material removal mechanism of EDM process is based on the principle of thermo-electric phenomenon where the electrical energy is converted into thermal energy. A series of sparks is thus generated yielding high temperature resulting in melting and vaporization of the work material (Ho and Newman 2003). The evaporated metal and some portion of the molten material are then flushed away from the machining zone by a dielectric fluid. In this process, both the tool and the workpiece should be electrically conductive, and a minimum gap needs to be maintained between them. It is one of the most popular NTM processes being widely employed by the aerospace, automotive, mold, and tool and die making industries. This process is mainly utilized to machine hard conductive materials which are quite difficult to machine using the conventional machining processes with high dimensional accuracy and excellent surface finish (Hasçalık and Çaydaş 2007).

2.3 WEDM process

The working principle of WEDM process is quite similar to that of EDM process with respect to material removal mechanism. In this process, a thin strand of wire, typically made of brass, is continuously fed through the workpiece which is entirely submerged in a dielectric fluid (Xu 2012). The wire is automatically supplied from a spool, and is guided by two wire guides held at the top and bottom of the workpiece to keep the wire in tension. The movements of these guides are regulated by a computer numerical control mechanism. Unlike EDM, in WEDM process, the wire acts as an electrode and the material removal takes place due to generation of sparks. The dielectric fluid used in WEDM helps to rinse out the debris from the machining zone. This process can cut materials as thick as 300 mm, and is capable of generating intricate geometries on diverse hard and difficult-to-machine materials, like MMCs, carbides, ceramics, etc. (Alduroobi et al. 2020). Due to high precision in cutting, it is widely used in tool and die making, aerospace, and automotive industries (Shivade and Shinde 2014).

2.4 AWJM process

The AWJM is one of the hybrid machining processes, combining the material removal principles of both AJM and WJM processes. It is a cold machining process in which abrasives are proportionately mixed with water to perform the material removal operation by plastic deformation, erosion, and fracture of the workpiece. In this process, the available pressure energy of water is transformed into kinetic energy by allowing it to pass through a small nozzle to perform the required machining operation. Some portion of the impulsive force of water is also transferred as kinetic energy to the abrasive particles, thereby rapidly increasing their velocity to help in material removal (Muthuramalingam et al. 2018). Besides being a carrier for the abrasives, water also acts as a cooling agent and flushes away the eroded particles from the machining zone. It also prevents the abrasives from spreading away after exit from the nozzle. Besides machining SS, MMCs, titanium, Inconel, brass, etc., it is extremely suitable for non-conductive materials, which have found large applications in automotive, nuclear, aerospace, oil, medical, and construction industries (Azmir et al. 2009).

2.5 LBM process

In LBM process, material removal takes place using thermal energy through melting, vaporization, and degradation of chemical bonds of the work material. A high energy density laser beam (e.g. CO_2, Nd:YAG, etc.) is focused on the workpiece surface in a very narrow area by a lens which is subsequently absorbed by the work material to be transformed into a molten, vaporized or chemically changed state due to impingement of photons into the workpiece. A flow of high pressure assist gas jet then helps to eject the transformed material from the machining zone (Meijer 2004). Due to its various unique characteristics, like no tool wear, no built-up edge formation, no residual stress, no vibration, etc., laser cutting process is capable of machining a wide range of engineering materials (metals and non-metals), having high brittleness, and low thermal diffusivity and conductivity properties. This process is being effectively employed for cutting, drilling, marking, welding, grooving, and micro-machining operations (Shivakoti et al. 2021).

2.6 PAM process

This NTM process was primarily developed in the mid 1950s to cut SS and aluminum alloys. Plasma is the fourth and the most highly energized state of matter (Xu et al. 2002). In this process, an inert gas is blown with high speed out from a nozzle and at the same time, electric arc is generated through the gas to the workpiece surface leading to formation of plasma. The high-temperature plasma arc has sufficient energy to melt or vaporize the surface being cut and move very fast to flow the molten metal away from the cutting zone (Patel et al. 2018). As compared to LBM process, PAM has a larger spot size, making it suitable in the milling process. It has the advantages to cut non-conductive materials, less maintenance cost and can be easily automated. It has been extremely popular in shipbuilding and process technology industries.

2.7 USM process

It is an example of mechanical type of NTM process, mainly employed to machine hard and brittle materials. The material removal process consists of a shaped tool, high frequency mechanical vibrator, and abrasive slurry. The tool is prepared according to the preferred shape to be generated on the workpiece surface (Thoe et al. 1998). The tool is mounted on a tool cone which usually vibrates with a frequency of 20 kHz and amplitude of 0.013–0.1 mm on the work surface. The material is removed from the workpiece through hammering of abrasive particles on the work surface with the help of the vibrating tool. As the tool vibrates in the downward stoke, it hits the abrasive particles which as a result attain kinetic energy and strike the workpiece surface with higher force sufficient enough for material erosion and removal. Due to erosion of material in small quantities, it has very low MRR (Kumar 2013), but it is capable of generating intricate holes/cavities on brittle and hard materials with excellent surface finish.

3 MCDM techniques

In this section, for description of the MCDM techniques mainly applied by the past researchers for parametric optimization of different NTM processes, the decision problem is stated as an $m \times n$ matrix, called the decision/evaluation matrix, where m and n denote the number of alternatives and number of criteria, respectively. In manufacturing environment, the design plan deployed for conducting the experiments resembles a typical decision matrix, with each row representing an alternative experimental trial (combination of different settings of the input parameters) and each column symbolizing a criterion (response/process output). Almost all the MCDM methods have two common initial steps, i.e. (a) normalization of the decision matrix to assure that all of its elements are on a non-dimensional and similar scale, and (b) development of the corresponding weighted normalized decision matrix. This weight normalized decision matrix is formulated after multiplying the elements of the normalized decision matrix by the criteria weights. Thus, the weight (relative importance) assigned to each criterion under consideration plays an important role in arriving at the final decision. However, it should be noted that some MCDM methods have in-built criteria weight calculation step, while for most of the MCDM techniques, criteria weights are externally provided. After these two steps, each MCDM method adopts its inherent algorithm to compute a 'performance score', which is essentially a non-dimensional number that allows unbiased comparison of the candidate alternatives on a single scale. Based on the considered algorithm and operational

Table 1 Features of some MCDM methods commonly employed for parametric optimization of NTM processes

MCDM	Type	Weight allocation	Number of steps	Terminology for performance score	Performance score type
WPM (Miller and Starr 1969)	Elementary	External	3	Preference score	Maximization
WSM (also called SAW) (Miller and Starr 1969)	Elementary	External	3	Preference score	Maximization
WASPAS (Zavadskas et al. 2012; Chakraborty and Zavadskas 2014)	Elementary	External	6	Joint generalized criterion	Maximization
AHP (Saaty 1980)	Pair-wise comparison	In-built	3	Preference score	Maximization
MOORA (Brauers et al. 2008)	Elementary	External	4	Assessment value	Maximization
TOPSIS (Behzadian et al. 2012)	Distance-based	External	7	Closeness coefficient	Maximization
VIKOR (Opricovic and Tzeng 2004)	Distance-based	External	5	Q	Minimization
PROMOTHEE (Brans and Vincke 1985)	Outranking	External	7	Multi-criteria preference index	Maximization
COPRAS (Kaklauskas et al. 2006)	Unique synthesizing	External	7	Performance index	Maximization
OCRA (Parkan and Wu 1997)	Unique synthesizing	External	5	Performance rating	Maximization
ARAS (Zavadskas and Turskis 2010)	Unique synthesizing	External	5	Optimality function	Maximization
EDAS (Keshavarz et al. 2015)	Distance-based	External	7	Appraisal score	Maximization
PSI (Maniya and Bhatt 2010)	Unique synthesizing	In-built	7	Preference selection index	Maximization
TODIM (Gomes and Rangel 2009)	Dominance-based	External	5	Dominance degree	Maximization
ROV (Madić et al. 2016)	Elementary	External	3	Average utility function	Maximization
SIR (Xu 2001)	Dominance-based	External	7	Net flow values	Maximization
Modified similarity index (Safari et al. 2013)	Distance-based	External	6	Performance index	Maximization
GRA (Sreenivasulu and Rao 2013)	Unique synthesizing	In-built	7	Grey relational grade	Maximization
MABAC (Pamučar and Ćirović 2015)	Distance-based	External	6	S_i	Maximization
MARCOS (Stević et al. 2020)	Unique synthesizing	External	7	Utility function	Maximization
CoCoSo (Yazdani et al. 2019)	Unique synthesizing	External	5	k_i	Maximization
CODAS (Ghorabaee et al. 2016)	Distance-based	External	8	Assessment score	Maximization

procedure, the MCDM methods can be broadly categorized as elemental approaches, pair-wise comparison-based approaches, unique synthesizing approaches, distance-based approaches, dominance-based approaches and outranking approaches. Elementary methods aim in reducing the intricate decision making problem into singular basis for selection of an alternative. In pair-wise comparison approaches, all the criteria are first pair-wise compared to evaluate their weights. Thereafter, the alternatives are pair-wise compared with respect to each of the criteria to estimate their relative performance. The relative performance of the alternatives and criteria weights are finally aggregated together to rank the alternatives. Unique synthesizing approaches employ some special mathematical and analytical techniques in the modeling and execution phase. Distance-based approaches depend on ideal, anti-ideal, and reference points to derive a preference order of the alternatives. In dominance-based approaches, the degree by which one alternative dominates another alternative or is being dominated by other alternative with respect to a particular criterion is calculated. These dominance degrees are aggregated together to aid in final ranking of the alternatives. The outranking approaches employ a series of pair-wise comparisons of the alternatives with respect to each criterion to frame an outranking relation indicating the degree of dominance of one alternative over the other. Most of the MCDM methods seek to maximize this performance score, i.e. a higher value corresponds to a better solution. However, a very few MCDM methods, like VIKOR work on the minimization philosophy, where a lower value of the performance score corresponds to a better solution. It is worthwhile to mention here that the term 'performance score' is considered in a more generic way and the actual terminology for each method is explained in Table 1.

It has already been mentioned that assignment of relative weights to the criteria (responses in case of NTM processes) significantly influences the solution of any of the MCDM methods with respect to the ranking of the alternatives. These weights can be allotted to the responses in different ways, e.g. equal, subjective, objective or combination of subjective and objective weights. To ease out the calculation steps involved in MCDM, the decision makers usually prefer to assign equal importance to all the criteria. The AHP is a popular subjective method of weight calculation based on pair-wise comparison of criteria. But, it is occasionally influenced by the judgments of the decision makers, has a strict hierarchical structure (the criteria are independent) and suffers from the problem of rank reversal. The past researchers also employed entropy, SDV, and CRITIC methods as effective objective tools while assigning relative importance to different responses during experiments. All these methods estimate the criteria weights based on randomness of the data itself. Entropy method (Kumar et al. 2021) calculates the weights using the information content in the criteria values of the alternatives. This uncertain information (entropy) is computed using probability theory. If a criterion has the same value for each of the alternatives, it would not provide any information to differentiate the alternatives. On the other hand, a criterion with varying values for the alternatives has high information content, being more capable in comparing the alternatives. The SDV method estimates the standard deviation for each criterion and its normalized value is treated as the criterion weight. On the other hand, in CRITIC method (Diakoulaki et al. 1995), criteria weights depend on the standard deviations of the normalized criteria values and correlation coefficients between all pairs of the considered criteria. The details of different criteria weight measurement techniques can be available in Chakraborty et al. (2023).

4 Parametric optimization of NTM processes using MCDM techniques

4.1 ECM process

In ECM process, electrolytic dissolution is responsible for removal of material from the workpiece and the machined component would be a mirror copy of the tool (electrode). The dissolved material is rinsed out from the machining zone with the help of pressurized electrolyte flow. Low voltage high current DC is applied between the electrode and workpiece resulting in anodic dissolution. During material removal, the tool is guided towards the workpiece without making a direct contact. Bhattacharyya and Sorkhel (1999) observed that while keeping other parameters constant, MRR would increase nonlinearly with increasing values of electrolyte concentration, electrolyte flow rate, and applied voltage. However, their higher values had detrimental effects on OC. It can be revealed from Table 2 that the past researchers thus mainly considered applied voltage, electrolyte concentration and its flow rate, feed rate, inter-electrode gap, duty cycle (pulse-on time + pulse-off time), duty ratio (pulse-on time/duty cycle), etc. as the predominant ECM parameters affecting the responses. It is noticed from this table that almost all the ECM experiments were conducted based on Taguchi's OAs. Selection of an appropriate OA principally depends of the number of input parameters and their operating levels. With respect to work materials machined, ECM operations were mainly performed on those materials (like various grades of steel and SS, titanium and aluminum alloys, Inconel, Hastelloy, Al MMCs, etc.) which are usually difficult-to-cut by the conventional machining processes. The performance (productivity) of any of the machining processes is measured with respect to MRR and surface quality of the machined components is evaluated using Ra value. Besides measuring MRR and Ra for an ECM process while machining EN 31 steel material, Das et al. (2014a) also determined values of Rq, Rsk, Rku, and Rsm as the other surface characteristics. But, the correlations between those surface characteristics were not explored. It is worthwhile to mention here that some of those surface properties may be correlated. The optimal settings of electrolyte concentration, feed rate, voltage, and inter-electrode gap were later determined using GRA technique. During any of the NTM operations, quality of the machined holes is usually measured with respect to ROC which is the difference between hole diameter and electrode diameter, divided by two. On the other hand, while generating cavities, pockets, channels, etc., OC is treated as the metric for dimensional

Table 2 Optimization of ECM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Chakradhar and Venu Gopal (2011)	L_9 OA	EN 31 steel	Electrolyte concentration, feed rate, applied voltage	MRR, OC, cylindricity, Ra	GRA	
Santhi et al. (2013)	CCD	Ti–6Al–4V	Electrolyte concentration, current, applied voltage, feed rate	MRR, Ra	TOPSIS	DFA, fuzzy theory
Thanigaivelan and Arunachalam (2013)	L_{18} OA	AISI 304	Tool tip shape, voltage, pulse-on time, electrolyte concentration	Machining rate, OC	GRA	
Das et al. (2014a)	L_{27} OA	EN 31 steel	Electrolyte concentration, voltage, feed rate, inter-electrode gap	MRR, Ra, Rq, Rsk, Rku, Rsm	GRA	
Manikandan et al. (2015)	L_9 OA	Ti–6Al–4V	Feed rate, electrolyte flow rate, electrolyte concentration	MRR, ROC	GRA	
Mohanty et al. (2015)	L_9 OA	Inconel 825	Electrolyte concentration, voltage, feed rate	MRR, Ra	TOPSIS	Fuzzy theory
Singh et al. (2015)	L_9 OA	Inconel 825	Voltage, concentration, tool feed	MRR, Ra, ROC	GRA	PCA
Khan and Maity (2016a)	L_{18} OA, L_{27} OA	AISI 304, Al MMC	Tool tip shape, voltage, pulse-on time, electrolyte concentration, feed rate, percentage of reinforcement	MRR, Ra, machining rate, OC	MOORA	
Geethapriyan et al. (2016)	L_9 OA	Inconel 718	Applied voltage, electrolyte concentration, micro-tool feed rate, duty ratio	MRR, Ra, ROC	GRA	
Manikandan et al. (2017)	L_{27} OA	Inconel 625	Feed rate, electrolyte flow rate, electrolyte concentration	MRR, Ra, ROC, circularity, perpendicularity	GRA	
Pillai et al. (2017)	L_9 OA	Nimonic 75 alloy	Voltage, feed rate, duty cycle	MRR, ROC, conicity	TOPSIS	
Agrawal et al. (2018)	L_{16} OA	AA6082, AA6082 MMC	Voltage, feed rate, electrolyte concentration, type of the electrode	MRR, electrolyte coating thickness	GRA	PCA
Chakraborty et al. (2018)	L_{27} OA	LM6 Al/B4C composite	Applied voltage, electrode feed rate, electrolyte concentration, reinforcement content	MRR, Ra, ROC	GRA	Fuzzy logic

Table 2 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Soundarrajan and Thanigaivelan (2018)	L_{18} OA	Cu	Electrolyte concentration, machining voltage, duty cycle, electrolyte temperature	MRR, ROC	TOPSIS, GRA	
Gobinath and Hariharan (2018)	L_{27} OA	Hastelloy	Type of the electrolyte, voltage, feed rate	Taper angle, ROC	TOPSIS	
Geethapriyan et al. (2018)	L_9 OA	Ti–6Al–4V	Applied voltage, micro-tool feed rate, electrolyte concentration, duty cycle	MRR, Ra, OC	GRA	
Geethapriyan et al. (2019)	L_9 OA	Inconel 718	Voltage, feed rate, electrolyte concentration, duty ratio	MRR, Ra, ROC	TOPSIS	
Pradeep et al. (2019)	L_{27} OA	AISI 304	Voltage, duty cycle, electrolyte concentration	MRR, ROC, taper angle	TOPSIS	
Maniraj and Thanigaivelan (2019)	L_{18} OA	Al6061 MMC	Voltage, duty cycle, electrolyte concentration, % of composition	MRR, ROC	TOPSIS	
Mouliprasanth et al. (2019)	L_9 OA	AISI 304	Voltage, feed rate, duty ratio	MRR, Ra	TOPSIS	
Krishnan et al. (2020)	L_{16} OA	AISI 304	Voltage, duty ratio, rotational speed, feed rate, electrolyte concentration	MRR, taper angle, Ra	VIKOR, TOPSIS	
Chandrasekhar and Prasad (2020)	L_{27} OA	AA6061–TiB_2	Voltage, current, electrolyte concentration	MRR, delamination, ROC	VIKOR	Entropy method
Panda et al. (2020)	L_{18} OA	EN-19 chromoly steel	Voltage, tool feed rate, signal	MRR, Ra	MOORA, TOPSIS	

deviation. Circularity, cylindricity, perpendicularity, delamination, taper angle, etc., were also considered by the past researchers for measuring hole quality during ECM operation.

Table 2 unveils that almost all the past researchers applied either GRA or TOPSIS for optimization of the ECM processes. The popularity of these MCDM techniques may be due to their extremely simple and easily understandable calculation steps. Khan and Maity (2016a), and Chandrasekhar and Prasad (2020), respectively, employed MOORA and VIKOR methods for the same purpose. Soundarrajan and Thanigaivelan (2018) contrasted the multi-objective optimization performance of TOPSIS and GRA methods, and concluded that GRA would be a more preferred technique achieving 35.24% improvement in the preference grade as compared to 17.54% improvement attained in TOPSIS. On the other hand, Krishnan et al. (2020) interestingly noticed that the applications of both VIKOR and TOPSIS methods would provide the same combination of voltage, duty ratio, feed rate, electrolyte concentration, and tool rotational speed for achieving improved values of MRR, Ra, and taper angle. With respect to the relative importance assigned to the responses, the past researchers mostly preferred to allocate equal weights simply to reduce the computational burden. Chandrasekhar and Prasad (2020) estimated those weights employing entropy method, whereas, Singh et al. (2015) and Agrawal et al. (2018) applied PCA technique for the same purpose. The PCA is a powerful mathematical tool for data dimensionality reduction, and estimation of the proportionate contribution of the responses in decision making based on eigenvector and eigenvalues.

To resolve the ambiguity during allocation of relative weights to the responses, Mohanty et al. (2015) integrated fuzzy theory with TOPSIS in an attempt to identify the optimal intermix of voltage, feed rate and electrolyte concentration while achieving the most desired MRR and Ra values. Trapezoidal fuzzy numbers were assigned to both the responses to determine their significance. Santhi et al. (2013) first performed ECM experiments using a CCD plan, and applied DFA to transform both the MRR and Ra values into a global knit quality index. Fuzzy set theory along with trapezoidal membership function was later utilized to convert the input parameters and responses into fuzzy scales. Finally, TOPSIS was adopted to optimize the considered process based on the closeness coefficients. Chakraborty et al. (2018) proposed the application of grey-fuzzy logic approach as an effective multi-objective optimization tool for an ECM process. Besides identifying the optimal parametric combination, it also helped in developing simple 'If–Then' rules to investigate the effects of feed rate, voltage, electrolyte concentration and reinforcement content on MRR, ROC, and Ra. It was noticed that the proposed approach would outperform TOPSIS with respect to the predicted values of grey-fuzzy relational grade.

4.2 EDM process

Among all the NTM processes, EDM is the most important one, extensively used in various modern-day industries, mainly for making tools and dies. It is a thermo-electric process where material removal takes place under high frequency controlled pulses generated in the dielectric fluid between the tool and workpiece. A plasma channel developed in the spark gap is maintained between the tool and workpiece. Continuous bombardment of ions and electrons, raising the temperature around 8000°-12,000 °C in the small gap, causes vaporization and erosion of the work material. Although it has extremely low MRR, but it can machine components with satisfactory surface finish. As it is a thermo-electric process, tool (electrode) wear, formation of HAZ, white (recast) layer, surface crack, residual stress, change in the micro-structural properties of the workpiece, etc., are inevitable which adversely affect the geometrical accuracy of the machined components. Table 2 presents some of the recent research works carried out on optimization of the EDM processes.

It can be revealed from Table 2 that most of the past researchers adopted Taguchi's OA for conducting the experiments; and preferred to machine various grades of steel and SS, aluminum MMCs, aluminum, Nimonic, titanium and their alloys, ceramic composites, Inconel, etc., due to their poor machinability properties, but having immense potentialities as advanced engineering materials. Pulse-on time, pulse-off time, discharge current, gap voltage, flushing pressure of the dielectric, etc., as the process parameters; and MRR, Ra, EWR/TWR/tool wear ratio, surface crack density, white layer thickness, micro-hardness, etc., as the responses were treated with maximum importance during EDM operations. Although GRA and TOPSIS were the two most popular approaches for EDM process optimization, but the applications of other MCDM tools, like SAW, WPM, WASPAS, MOORA, VIKOR, PROMETHEE, ARAS, COPRAS and similarity index method were also occasionally found.

Sivapirakasam et al. (2011), Senthil et al. (2014), Tiwary et al. (2014), Dewangan et al. (2015a), Roy and Dutta (2019), and Viswanth et al. (2020) intergated TOPSIS with fuzzy set theory for assigning relative importance to the responses under uncertain environment, and later optimized the EDM processes under consideration. On the other hand, Dewangan et al. (2015b), and Singh and Sharma (2018) proposed the combined application of GRA and fuzzy logic to frame 'If–Then' clauses to study the influences of various EDM parameters on the responses leading to process optimization. Singh and Sharma (2018) also employed ANFIS as a prediction tool to envisage the response values for an EDM process. Using DoE, Chakraborty et al. (2019) developed TOPSIS-based metamodels to optimize the performance of an EDM process. Huu (2020) estimated the subjective criteria weights using AHP and applied similarity index method as a multi-objective optimization tool for a powder-mixed EDM process. Similarly, while machining ceramic composites, Chaudhury and Samantaray (2020) first determined the relative importance of the responses using WPCA approach, and later optimized the EDM process using MOORA method.

Some of the researchers also endeavored to integrate metaheuristic algorithms with MCDM techniques for optimization of the EDM processes. Prabhu and Vinayagam (2016) first applied TOPSIS to identify the best combination of pulse current, pulse duration, and pulse voltage during EDM of AISI D2 tool steel material, and later validated the derived solutions with the help of developed regression equations which were subsequently solved using GA technique. Based on a CCD plan with 20 experiments, Sharma et al. (2020) developed two second-order polynomial equations for electrical discharge drilling rate and EWR. The GRA technique was employed to calculate the corresponding grey relational grades for all the experimental trials which were again employed to formulate a regression model. Finally, TLBO algorithm was utilized to solve the developed model to identify the optimal intermix of EDM process parameters. Shastri and Mohanty (2021) developed a regression model correlating the net outranking flow of PROMETHEE and EDM process parameters which was subsequently optimized with the help of CSA. A combination of discharge current = 3 A, voltage = 60 V, pulse-on time = 100 µs, duty factor = 85% and copper electrode would provide the optimal values of the responses under consideration.

Despite its several advantages, EDM is a hazardous process, releasing large amount of harmful solid and liquid wastes along with expulsion of toxic gases, thus polluting the environment (Sivapirakasam et al. 2011). These harmful and toxic substances may cause severe health hazards due to inward breath, ingestion or skin contact. Nowadays, green-EDM has emerged out as a suitable alternative of EDM process with minimum use of dielectric fluid, energy consumption, and emission of toxic gases. Sivapirakasam et al. (2011) optimized a green-EDM process using TOPSIS while machining high carbon high chromium (HCHCr) tool steel material. Using the same dataset of Sivapirakasam et al. (2011), Jagadish (2015, 2016) employed GRA technique to determine the ideal settings of pulse duration, peak current, flushing pressure, and dielectric level to minimize the hazardous effects of EDM process along with minimum tool wear and process energy (Table 3). The corresponding criteria weights were calculated using entropy method and PCA, respectively. While developing a causal diagram for a green-EDM process, Das and Chakraborty (2020a) applied DEMATEL to segregate all the responses into corresponding cause and effect groups, and optimized the process using SIR method. It was observed that the adopted approach would provide better results as compared to TOPSIS and same results as grey-AHP method.

4.3 WEDM process

Unlike EDM process, a thin wire (usually made of brass, tungsten or molybdenum with diameter 0.05–0.30 mm) is utilized in WEDM as an electrode to convert electrical energy into thermal energy to cut intricate 2- and 3-dimensional profiles on various harder and tougher materials due to spark erosion (Rao et al. 2020). In this process, material is eroded ahead of the wire, and there is no direct contact between the wire and workpiece. Due to high accuracy level and good surface finish, it has found its major applications in manufacturing of extrusion dies, stamping dies and prototype components. Pulse-on time, pulse-off time, discharge current, gap voltage, pulse frequency, wire feed rate, wire tension, dielectric pressure, etc., are the main input parameters for this process. On the other hand, besides MRR and Ra, KW is treated as the most important measure of dimensional deviation of the machined components. Its value is estimated after adding the wire diameter to 2 × 'wire-workpiece gap distance' (Selvam and Kumar 2017). While machining Hastelloy-C-276 work material using a brass wire, Selvam and Kumar (2017) observed that KW would increase with increasing values of pulse-on time and pulse-off time, whereas, higher values of pulse current, gap voltage, and wire tension would result in lower KW.

A concise review of different MCDM methods applied by the past researchers for optimizing WEDM processes is presented in Table 4. Gauri and Chakraborty (2010) adopted four multi-objective optimization techniques in the form of GRA, MRSN, WSN, and VIKOR, and concluded that WSN would supersede others in optimizing the WEDM process. Azhiri et al. (2014) and Kumar et al. (2019b) determined the optimal combinations of the WEDM process parameters using GRA technique, and later employed ANFIS models to accurately predict the corresponding responses. Similarly, besides process optimization, the applications of fuzzy logic in studying the relationships between WEDM process parameters and responses can be found in Majumder and Maity (2018a, b), Das et al. (2019), Guha et al. (2021). Majumder and Maity (2018a, b) also deployed GRNN as a predictive tool for the responses during WEDM of Nitinol shape memory alloy. Diyaley et al. (2017) optimized a WEDM process using PSI and TOPSIS methods, and noticed that both the MCDM techniques would provide the same combination of pulse-on time, pulse-off time, servo voltage, and wire tension. Similarly, Patel and Maniya (2019) applied MOORA, GRA, TOPSIS, ARAS, and OCRA methods for parametric optimization of a WEDM process, and observed that those

Table 3 Optimization of EDM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Lin and Lin (2002)	L_{18} OA	SKD11 alloy steel	Workpiece polarity, pulse-on time, duty factor, open discharge voltage, discharge current, dielectric fluid	MRR, Ra, electrode wear ratio	GRA	
Singh et al. (2004)	L_{27} OA	Al MMC	Current, pulse-on time, flushing pressure	MRR, TWR, taper, ROC, Ra	GRA	
Donaivi et al. (2008)	L_{27} OA	SKD11 tool steel	Discharge current, pulse-on time, discharge voltage, duty factor	MRR, electrode wear ratio, Ra	GRA	
Jung and Kwon (2010)	L_{18} OA	AISI 304	Input voltage, capacitance, resistance, feed rate, spindle speed	Time, electrode, entrance clearance, exit clearance, number of shorts	GRA	
Sivapirakasam et al. (2011)	L_9 OA	HCHCr steel	Peak current, pulse duration, dielectric level, flushing pressure	Process time, relative tool wear ratio, process energy, concentration of aerosol, dielectric consumption	TOPSIS	Fuzzy theory
Natarajan and Arunachalam (2011)	L_9 OA	AISI 304	Pulse-on time, discharge current, gap voltage	MRR, TWR, ROC	GRA	
Singh and Yeh (2012)	L_{18} OA	Al alloy	Pulse current, pulse-on time, duty cycle, gap voltage, time interval of tool lift, abrasive powder concentration, abrasive particle size	TWR, Ra, MRR	GRA	
Meena and Azad (2012)	L_{18} OA	Ti–6Al–4V	Voltage, frequency, current, pulse width	MRR, TWR, OC	GRA	
Pradhan (2013)	CCD	AISI D2 tool steel	Pulse current, pulse duration, duty cycle, discharge voltage	MRR, TWR, ROC	GRA	PCA
Raghuraman et al. (2013)	L_9 OA	Mild steel IS 2026	Discharge current, pulse-on time, pulse-off time	MRR, TWR, Ra	GRA	
Muthuramalingam and Mohan (2013)	L_9 OA	AISI 202	Gap voltage, peak current, duty factor	MRR, Ra	GRA	
Senthil et al. (2014)	L_{18} OA	Al–$CuTiB_2$ MMC	Discharge current, pulse-on time, pulse-off time	MRR, TWR, Ra	TOPSIS	Fuzzy theory
Muthuramalingam and Mohan (2014)	L_{27} OA	AISI 202	Gap voltage, discharge current, duty factor	MRR, EWR, Ra	GRA	

Table 3 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Mhatre et al. (2014)	L_{18} OA	Ti–6Al–4V	Duty cycle, pulse current, pulse-on time, electrode type, gap voltage	MRR, EWR, Ra	GRA	
Kumar et al. (2014)	L_{27} OA	Al 6351 alloy	Pulse current, pulse-on time, pulse duty factor, gap voltage	Electrode wear ratio, Ra, power consumption	GRA	
Bhuyan et al. (2014)	CCD	Al MMC	Peak current, pulse-on time, flushing pressure	MRR, TWR, ROC, Ra	TOPSIS	Entropy method
Tiwari et al. (2014)	L_9 OA	Carbon fiber epoxy polymer	Peak current, gap voltage, pulse-on time, duty cycle	MRR, TWR	GRA	
Kumar and Kumar (2014)	L_{18} OA	Al MMC	Electrode environment, discharge current, pulse-on time, gap voltage	MRR, EWR, Ra	GRA	
Tiwary et al. (2014)	CCD	Ti–6Al–4V	Peak current, pulse-on time, gap voltage, flushing pressure	MRR, TWR, OC, taper	TOPSIS	Fuzzy theory
Tang and Du (2014)	L_9 OA	Ti–6Al–4V	Discharge current, gap voltage, lifting height, polarity, pulse duty factor	EWR, MRR, Ra	GRA	
Dewangan et al. (2015a)	CCD	AISI P20 tool steel	Pulse current, pulse-on time, tool-work time, tool-lift time	White layer thickness, surface crack density, Ra, ROC	TOPSIS	Fuzzy theory
Jagadish (2015)	L_9 OA	HCHCr steel	Peak current, pulse duration, dielectric level, flushing pressure	Process time, relative tool wear ratio, process energy, concentration of aerosol, dielectric consumption	GRA	Entropy method
Chakraborty et al. (2015)	L_{27} OA	Al MMC	Discharge current, pulse-on time, duty cycle, flushing pressure, % of SiC, mesh size	MRR, TWR, Ra, circularity	WASPAS	
Talla et al. (2015)	L_{18} OA	Al MMC	Powder concentration, peak current, pulse-on time, duty cycle	MRR, Ra	GRA	PCA
Dewangan et al. (2015b)	CCD	AISI P20 tool steel	Discharge current, pulse-on time, tool-work time, tool-lift time	White layer thickness, surface crack density, Ra	GRA	Fuzzy logic

Table 3 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Kasdekar and Parashar (2015)	L_9 OA	EN-353	Discharge current, pulse-on time, pulse-off time, dielectric field	MRR, TWR, Ra	SAW, WPM, TOPSIS	Entropy method
Selvarajan et al. (2015)	L_{18} OA	$MoSi_2$–SiC composite	Current, pulse-on time, pulse-off time, spark gap, dielectric pressure	MRR, EWR, circularity, cylindricity, perpendicularity	GRA	
Lin et al. (2015)	L_9 OA	Ti–6Al–4V	Current, pulse-on time, pulse-off time, gap voltage	Electrode depletion, MRR, overcut	GRA	
Khanna et al. (2015)	L_{27} OA	Al 7075	Pulse-on time, pulse-off time, flushing pressure	MRR, TWR	GRA	
Jagadish (2016)	L_9 OA	HCHCr steel	Peak current, pulse duration, dielectric level, flushing pressure	Process time, relative tool wear ratio, process energy, concentration of aerosol, dielectric consumption	GRA	PCA
Manivannan and Kumar (2016)	L_{27} OA	AISI 304	Feed rate, current, pulse-on time, gap voltage	MRR, EWR, ROC, taper angle, circularity	TOPSIS	
Khan and Maity (2016a)	L_{27} OA	EN 41 steel	Pulse-on time, pulse-off time, discharge current, voltage	Ra, Rq, Rsk, Rku, Rsm	MOORA	
Tripathy and Tripathy (2016)	L_{27} OA	H-11 die steel	Powder concentration, peak current, pulse-on time, duty cycle, gap voltage	MRR, TWR, EWR, Ra	GRA, TOPSIS	
Prabhu and Vinayagam (2016)	L_9 OA	AISI D2 tool steel	Pulse current, pulse duration, pulse voltage	Ra, fractal dimension, MRR	TOPSIS	AHP, GA
Bhuyan and Routara (2016)	CCD	Al alloy	Pulse-on time, peak current, flushing pressure	MRR, TWR, ROC, Ra	VIKOR	Entropy method
Priyadarshini and Pal (2016)	L_9 OA	Ti–6Al–4V	Pulse duration, duty factor, peak current, gap voltage	MRR, TWR, Ra	GRA	PCA
Selvarajan et al. (2016)	L_{18} OA	Si_3N_4–TiN ceramic composite	Current, pulse-on time, pulse-off time, dielectric flushing pressure	MRR, TWR, circularity, cylindricity, perpendicularity	GRA	
Pragadish and Pradeep Kumar (2016)	L_{27} OA	AISI D2 tool steel	Discharge current, pulse-on time, voltage, pressure, tool rotational speed	MRR, Ra	GRA	
Kalayarasan and Murali (2016)	L_9 OA	Ceramic composite	Pulse-on time, pulse-off time, dielectric pressure, discharge current	MRR, EWR	GRA, TOPSIS	

Table 3 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Bhaumik and Maity (2016)	L_{18} OA	AISI 304	Peak current, pulse-on time, gap voltage, duty cycle	MRR, TWR	GRA	
Manivannan and Pradeep Kumar (2017)	L_{27} OA	AISI 304	Current, pulse-on time, pulse-off time, gap voltage	MRR, TWR, Ra, taper angle, circularity	TOPSIS	
Tripathy and Tripathy (2017)	L_{27} OA	H-11 die steel	Powder concentration, peak current, pulse-on time, duty cycle, gap voltage	MRR, TWR, EWR, Ra	GRA, TOPSIS	
Raj and Prabhu (2017)	L_9 OA	AISI D2 tool steel	Pulse-on time, pulse-off time, pulse current	MRR, EWR, Ra	TOPSIS	
Meena et al. (2017)	L_9 OA	Ti alloy	Current, pulse frequency, pulse-on time	MRR, EWR, ROC	GRA	
Pradhan (2018)	CCD	AISI D2 steel	Discharge current, pulse-on time, duty cycle, voltage	MRR, TWR, ROC	GRA, TOPSIS	Entropy method
Sidhu et al. (2018)	L_{18} OA	Al MMC	Electrode material, current, pulse-on time, dielectric medium	MRR, Ra, residual stress	MOORA	AHP
Singh and Sharma (2018)	L_{27} OA	WC alloy	Pulse-on time, dielectric level, current intensity, flushing pressure	MRR, TWR, aerosol concentration, dielectric consumption	GRA	Fuzzy logic, ANFIS
Chakraborty et al. (2019)	CCD	Inconel 718	Open circuit voltage, peak current, pulse-on time, duty factor, flushing pressure	MRR, EWR, Ra, surface crack density, white layer thickness, micro-hardness	TOPSIS	DoE
Kumar et al. (2019a)	L_9 OA	Al7050	Pulse current, pulse-on time, pulse-off time	MRR, Ra, depth of cut	ARAS	AHP
Huu et al. (2019)	L_9 OA	SKD61 die steel	Current, pulse-on time, pulse-off time, vibration frequency	MRR, TWR, Ra	MOORA	
Paul et al. (2019)	CCD	Inconel 800	Pulse-on time, pulse-off time, pulse current	MRR, Ra	MOORA	PCA
Roy and Dutta (2019)	L_9 OA	AISI 304	Pulse-on time, duty cycle, discharge current, gap voltage	MRR, tool wear ratio, tool overcut	AHP, TOPSIS	Fuzzy theory
Kumar and Rai (2019)	L_{16} OA	AA7050	Pulse current, pulse-on time, pulse-off time	MRR, Ra, TWR	ARAS, GRA	

Table 3 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Patel and Pradhan (2019)	L_9 OA	Al7075	Weight percentage, pulse current, discharge voltage, pulse duration	MRR, TWR, Ra, ROC	Correlation coefficient, SDV	
Bhowmik et al. (2019a)	L_9 OA	Ti–6Al–4V	Discharge current, pulse width, gap voltage, lifting height	MRR, Ra, TWR	GRA	Entropy method
Huo et al. (2019)	L_9 OA	AISI 304	Open circuit voltage, peak current, duty factor, tool electrode	Ra, recast layer thickness, residual stress	TOPSIS	
Hanif et al. (2019)	BBD	AISI D2 steel	Discharge current, dielectric type, spark gap, electrode polarity	MRR, Ra	GRA	
Payal et al. (2019)	L_{36} OA	Inconel 825	Electrode material, gap voltage, pulse-on time, duty cycle, tool-lift time, discharge current, type of the dielectric	MRR, TWR, Ra	GRA	PCA
Nguyen et al. (2020)	L_{27} OA	HCHCr steel	Peak current, gap voltage, pulse-on time, pulse-off time	MRR, Ra, micro-hardness, white layer thickness	GRA	
Viswanth et al. (2020)	L_{27} OA	AISI 2507	Pulse-on time, pulse-off time, peak current, voltage, inter-electrode gap	MRR, EWR, Ra	TOPSIS	Fuzzy theory
Singaravel et al. (2020)	L_9 OA	AISI D2 die steel	Dielectric fluid, current, pulse-on time	MRR, TWR, Ra	VIKOR	
Huu (2020)	L_{27} OA	SKD11 die steel	Workpiece material, electrode material, electrode polarity, pulse-on time, pulse-off time, current, powder concentration	MRR, TWR, Ra, hardness, surface crack density, white layer thickness	Similarity index method	AHP
Sharma et al. (2020)	CCD	Titanium Grade-2	Peak current, pulse-on time, pulse-off time	Drilling rate, EWR	GRA	TLBO
Chaudhury and Samantaray (2020)	L_{27} OA	SiC ceramic composite	Peak current, gap voltage, pulse-on time, duty cycle, polarity	MRR, plasma flushing efficiency, Ra, recast layer thickness	MOORA	WPCA
Das and Chakraborty (2020a)	L_9 OA	HCHCr steel	Peak current, pulse duration, dielectric level, flushing pressure	Process time, relative tool wear ratio, process energy, concentration of aerosol, dielectric consumption	SIR	DEMATEL

Table 3 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Srikanth et al. (2021)	L_9 OA	Ti–6Al–4V	Current, pulse-on time, pulse-off time, type of the electrode	MRR, TWR	MOORA	
Sharsar et al. (2021)	L_9 OA	HCHCr steel	Peak current, pulse duration, dielectric level, flushing pressure	Process time, relative tool wear ratio, process energy, concentration of aerosol, dielectric consumption	COPRAS, TOPSIS	Entropy
Srinivasan et al. (2021)	L_{21} OA	Ceramic composite	Current, spark gap voltage, pulse-on time, pulse-off time	MRR, Ra	GRA	
Bhosale et al. (2021)	L_{18} OA	Ferrous clay composite	% of clay, current, pulse-on time, voltage	EWR, MRR, Ra	GRA, TOPSIS	
Zeng et al. (2021)	L_{18} OA	Al_2O_3 ceramic	Adhesive foil, peak current, auxiliary current with high voltage, pulse duration, electrode jumping-up time, servo reference voltage	EWR, MRR, Ra	TOPSIS	AHP
Shastri and Mohanty (2021)	BBD	Nimonic C263 superalloy	Voltage, discharge current, pulse-on time, duty factor, electrode material	Specific energy consumption, machining noise, MRR, EWR, Ra, OC	PROMETHEE	AHP, CSA
Debnath and Ghosh (2021)	CCD	Al—4.5% Cu—SiC	Current, pulse-on time, pulse-off time	MRR, TWR, SR	MOORA	AHP
Bhattacharjee et al. (2022)	CCD	Al MMC	Pulse-on time, peak current, % of reinforcement	MRR, TWR, Ra	PROMETHEE	
Pandiyan et al. (2022)	L_{27} OA	Al MMC	Current, pulse-on time, gap voltage	MRR, TWR, circularity, cylindricity	CODAS	Entropy

Table 4 Optimization of WEDM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Chiang and Chang (2006)	L_{18} OA	Al 6061 alloy	Cutting radius, pulse-on time, pulse-off time, arc-on time, arc-off time, servo voltage, wire feed rate, water flow	MRR, Ra	GRA	
Gauri and Chakraborty (2010)	L_{18} OA, L_{27} OA	Al6061 alloy	Cutting radius of workpiece, on time of discharging, off time of discharging, arc-on time of discharging, arc-off time of discharging, servo voltage, wire feed, water flow, discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow rate	Ra, cutting removal rate, MRR, KW	GRA, VIKOR	MRSN, WSN
Datta and Mahapatra (2010)	L_{27} OA	D2 tool steel	Discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow rate	MRR, Ra, KW	GRA	
Somashekhar et al. (2011)	L_9 OA	Al	Gap voltage, capacitance, feed rate	MRR, OC, Ra	GRA	
Jangra et al. (2012)	L_{18} OA	WC—5.3% Co composite	Taper angle, peak current, pulse-on time, pulse-off time, wire tension, dielectric flow rate	MRR, Ra, angular error, ROC	GRA	Entropy method
Gadakh (2012)	L_8 OA, L_9 OA, CCD	Incoloy 800, Al 6061 MMC	Gap voltage, pulse-on time, pulse-off time, wire feed rate, applied current, wire tension	MRR, Ra, KW	TOPSIS	
Rajyalakshmi and Venkata Ramaiah (2013)	L_{36} OA	Inconel 825	Pulse-on time, pulse-off time, corner servo, flushing pressure, wire feed rate, wire tension, spark gap voltage, servo feed	MRR, Ra, spark gap	GRA	
Nayak and Mahapatra (2013)	L_{27} OA	D2 tool steel	Discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow rate	MRR, Ra, KW	TOPSIS	AHP

Table 4 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Durairaj et al. (2013)	L_{16} OA	AISI 304	Gap voltage, wire feed, pulse-on time, pulse-off time	Ra, KW	GRA	
Shivade and Shinde (2014)	L_{9} OA	D3 tool steel	Pulse-on time, pulse-off time, peak current, wire speed	MRR, dimensional deviation, gap current, machining time	GRA	
Goswami and Kumar (2014)	L_{27} OA	Nimonic 80A alloy	Pulse-on time, pulse-off time, spark gap set voltage, peak current, wire feed, wire tension	MRR, wire wear ratio	GRA	
Khan et al. (2014)	L_{9} OA	AISI 304	Pulse-on time, pulse-off time, current	Ra, KW	GRA	
Mathew et al. (2014)	L_{27} OA	AISI 304	Pulse-on time, pulse-off time, servo voltage wire feed, wire tension, dielectric pressure	MRR, Ra, dimensional deviation	GRA	
Saedon et al. (2014)	L_{9} OA	Ti–6Al–4V	Pulse-off time, peak current, wire tension, wire feed	Ra, cutting rate, MRR	GRA	
Azhiri et al. (2014)	L_{27} OA	Al alloy	Pulse-on time, pulse-off time, gap voltage, discharge current, wire tension, wire feed	Cutting velocity, Ra	GRA	ANFIS
Anand Babu and Venkataramaiah (2015)	L_{18} OA	Al6061 alloy	Wire type, pulse-on time, pulse-off time, wire feed rate, sensitivity	Cutting speed, MRR, Ra, dimensional deviation	TOPSIS	AHP
Chakraborty et al. (2015)	L_{31} OA	Brass CuZn377	Peak current, duty factor, wire tension, water pressure	MRR, wear ratio, Ra	WASPAS	
Bobbili et al. (2015)	L_{18} OA	Al alloy	Pulse-on time, pulse-off time, peak current, spark voltage	MRR, Ra, gap current	GRA	
Lal et al. (2015)	L_{27} OA	Al7075 alloy	Pulse-on time, pulse-off time, current, wire drum speed	Ra, KW	GRA	
Ramamurthy et al. (2015)	L_{27} OA	Ti–6Al–4V	Pulse-on time, pulse-off time, servo voltage, wire tension, electrode type	MRR, Ra, KW	GRA	

Table 4 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Saha and Mondal (2016)	L_{25} OA	Hardfacing materials	Pulse-on time, Pulse-off time, servo voltage, wire tension, wire feed rate	MRR, machining time, Ra	GRA	PCA
Khan and Maity (2016a)	L_{27} OA	D2 tool steel	Discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow rate	MRR, Ra, cutting width	MOORA	
Majumder et al. (2017)	CCD	Inconel 800	Pulse-on time, pulse-off time, pulsed current, servo voltage	Cutting time, Ra	GRA	PCA
Diyaley et al. (2017)	L_9 OA	EN 31 tool steel	Pulse-on time, pulse-off time, servo voltage, wire tension	Ra, MRR	PSI, TOPSIS	
Majumder and Maity (2017)	L_{27} OA	Titanium Grade 6	Pulse-on time, pulse-off time, wire feed, wire tension	Cutting speed, KW, Ra	MOORA	PCA
Santhanakumar et al. (2017)	L_{16} OA	Ti 6–4 alloy	Gap voltage, capacitance, feed rate, wire tension	Ra, KW, MRR	TOPSIS	
Majumder and Maity (2018a)	L_{27} OA	Ni–Ti shape memory alloy	Pulse-on time, discharge current, wire feed, wire tension, flushing pressure	Ra, Rq, Rz, micro-hardness	VIKOR	Fuzzy logic, GRNN
Mohapatra and Sahoo (2018)	L_{16} OA	Inconel 718	Pulse-on time, pulse-off time, wire tension	MRR, KW	TOPSIS	
Rao and Venkaiah (2018)	CCD	Nimonic-263 super alloy	Peak current, pulse-on time, pulse-off time, servo voltage	MRR, Ra	GRA, VIKOR, TOPSIS	
Patel and Maniya (2018)	L_{27} OA	Al alloy	Wire material, pulse-on time, pulse-off time, peak current, wire diameter, wire tension, wire feed rate	MRR, Ra, cutting velocity	WSM	AHP
Muniappan et al. (2018)	L_{27} OA	Magnesium AZ91 alloy	Pulse-on duration, pulse-off duration, peak pulse current, gap voltage, wire feed, wire tension	KW, cutting speed	MOORA	
Reddy and Reddy (2018)	L_{27} OA	Ni 718 super alloy	Pulse-on time, spark gap, wire feed, wire tension, flushing pressure, servo speed, peak current	Ra, MRR, dimensional deviation	TOPSIS	Neutrosophic sets

Table 4 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Kumar et al. (2018)	CCD	High speed steel (HSS) M2	Pulse-on time, pulse-off time, peak current, wire feed	MRR, Ra, KW	GRA	
Majumder and Maity (2018b)	L_{27} OA	Nitinol	Pulse-on time, discharge current, wire feed, wire tension, flushing pressure	Ra, Rq, Rz, micro-hardness	MOORA	Fuzzy logic, GRNN
Kumar and Dhanabalan (2019)	L_9 OA	Die steel grade D3	Gap voltage, wire speed, gap current, duty factor	MRR, cutting speed, machining time, Ra	GRA	Fuzzy logic
Patel and Maniya (2019)	L_{27} OA	Al MMCs	Wire material, wire diameter, pulse-on time, pulse-off time, peak current, wire tension, wire feed rate	MRR, Ra, cutting velocity	OCRA, TOPSIS, ARAS, MOORA, GRA	AHP
Kavimani et al. (2019)	L_{27} OA	AZ31 Mg alloy	Pulse-on time, pulse-off time, wire feed rate	MRR, Ra	GRA	
Ram Prasad et al. (2019)	L_{27} OA	Ti–6Al–4V	Peak current, pulse-on time, servo voltage, pulse-off time	MRR, Ra, dimensional deviation	TOPSIS	AHP
Das et al. (2019)	L_9 OA	EN 31 steel	Servo voltage, wire tension, pulse-on time, pulse-off time	MRR, Ra	GRA	Fuzzy logic
Chakraborty et al. (2019)	L_{18} OA	Al6061	Wire type, pulse-on time, pulse-off time, wire feed rate, sensitivity	Cutting speed, MRR, Ra, dimensional deviation	TOPSIS	DoE
Sahoo et al. (2019)	L_9 OA	HCHCr steel	Pulse-on time, pulse-off time, wire feed, servo voltage	Cutting speed, MRR, KW, Ra	TOPSIS	
Kumar et al. (2019b)	L_{18} OA	Ti–6Al–4V	Peak current, taper angle, pulse-on time, pulse-off time, dielectric fluid flow rate	MRR, Ra	GRA	ANFIS
Kumar and Narasimhamu (2020a)	L_{18} OA	Inconel 750	Wire feed rate, pulse-on-time, pulse-off-time, water pressure	Cutting speed, Ra	TOPSIS	GWO
Majumder et al. (2020)	L_9 OA	Inconel 718	Pulse-on time, pulse-off time, pulsed current, servo voltage	Cutting rate, Ra, machining time	MOORA	

Table 4 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Thangaraj et al. (2020)	L_{27} OA	Ti–6Al–4V	Pulse-on time, pulse-off time, servo voltage, wire electrode, wire tension	White layer thickness, wire wear ratio, micro-hardness	GRA	
Harish et al. (2020)	L_{27} OA	HCHCr tool steel	Pulse-on time, current, pulse-off time, spark gap voltage, wire runoff time, wire tension	MRR, TWR, Ra, KW	TOPSIS	
Thejasree et al. (2021)	L_{27} OA	Inconel 718	Pulse-on time, pulse-off time, peak current	MRR, Ra, OC	GRA	
Guha et al. (2021)	L_9 OA	AISI 4140	Pulse-on time, pulse-off time, wire tension	KW, MRR, dimensional deviation, Ra, delamination factor	GRA	Fuzzy logic
Tudu et al. (2021)	L_9 OA	Ti–6Al–4V	Peak current, wire speed, pulse-on time, pulse-off time, wire feed, wire tension	MRR, Ra	WASPAS	MOGA
Fuse et al. (2021)	CCD	Ti–6Al–4V	Pulse-on time, pulse-off time, current	Cutting speed, MRR, Ra	AHP, TOPSIS	Fuzzy theory
Sen et al. (2021)	L_{18} OA	Incoloy 800	Pulse-on time, pulse-off time, peak current, spark gap voltage	Machining time, cutting velocity, MRR, KW, power consumption	AHP, ARAS	Trapezoidal interval type-2 fuzzy number
Chaudhary et al. (2021)	L_{16} OA	Nimonic alloy	Current, pulse-on time, pulse-off time, wire tension, dielectric fluids	Dimensional deviations	TOPSIS	Entropy method
Kumar et al. (2022)	L_{27} OA	AISI 316L steel	Wire feed rate, pulse-on time, pulse-off time, voltage, peak current	SR, KW	GRA	
Abhilash and Chakradhar (2022)	L_{18} OA	Incoloy 718	Pulse-on time, pulse-off time, servo voltage, wire feed rate, wire type	Cutting speed, SR, surface flatness	GRA, TOPSIS	Entropy method
Sreeraj et al. (2022)	L_{27} OA	AA6351/Rutile composite	Peak current, applied voltage, wire feed rate	KW, Rz	MOORA, TOPSIS	PCA
Biswas et al. (2022)	L_{27} OA	SS304, SS316	Pulse-on time, pulse-off-time, arc-on time, arc-off time, wire feed, servo voltage	MRR, KW, OC, Ra	TOPSIS	ANN

Table 5 Optimization of AWJM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Tozan (2011)		Ti alloy	Traverse speed, abrasive mass flow rate, angle of attack, depth of cut, cost, process time	Ra	AHP	Fuzzy theory
Deris et al. (2013)	L_{27} OA	Al7075	Traverse speed, water jet pressure, stand-off distance, abrasive grit size, abrasive flow rate	Ra	GRA	SVM
Singh and Chaturvedi (2014)	L_{16} OA	AISI 304	Traverse speed, stand-off distance, abrasive flow rate, water pressure	MRR, Ra	GRA	
Satyanarayana and Srikar (2014)	L_{27} OA	Inconel 718	Abrasive flow rate, pressure, stand-off distance	MRR, KW	GRA	
Naresh Babu and Muthukrishnan (2015)	L_{18} OA	Corian aurora	Mesh size, nozzle diameter, abrasive flow rate, water pressure, stand-off distance, feed rate	Ra, kerf angle	GRA	
Chaturvedi and Singh (2015)	L_{16} OA	AISI 304	Transverse speed, stand-off distance, abrasive flow rate, water pressure	Ra, MRR	VIKOR	
Yuvaraj and Pradeep Kumar (2015)	L_{27} OA	AA5083–H32 Al alloy	Water jet pressure, traverse rate, abrasive flow rate, stand-off distance	Depth of penetration, cutting rate, Ra, taper cut ratio, KW	TOPSIS	
Ghosh et al. (2015)	L_{31} OA	Si_3N_4 ceramic	Water pressure, abrasive flow rate, traverse speed, stand-off distance	MRR, KW, Ra	GRA	
Santhanakumar et al. (2015)	L_{27} OA	Ceramic	Abrasive grain size, abrasive flow rate, nozzle-workpiece stand-off, water pressure, jet traverse rate	Ra, taper angle	GRA	
Khan and Maity (2016a)	L_9 OA, L_{27} OA	Borosilicate glass, soda-lime glass	Stand-off distance, feed rate, air temperature, water pressure, abrasive flow rate, traverse speed	MRR, Ra, depth of cut	MOORA	
Khan and Maity (2016b)	L_{27} OA, L_9 OA	Inconel 718, soda-lime glass	Abrasive flow rate, pressure, stand-off distance, feed rate, air temperature	MRR, KW, Ra	TOPSIS	

Table 5 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Santhanakumar et al. (2016)	L_{18} OA	Al alloy	Water pressure, traverse speed, abrasive flow rate, stand-off distance	Striation zone (length and angle), Ra	GRA	
Kalirasu et al. (2017)	L_{27} OA	Jute/polyester composites	hydraulic pressure, feed rate, stand-off distance	Ra, kerf taper angle	MOORA	
Chakraborty et al. (2018)	L_{18} OA	Inconel 617	Water pressure, stand-off distance, abrasive flow volume, table feed	MRR, circularity, cylindricity, perpendicularity, parallelism	GRA	Fuzzy logic
Yuvaraj and Pradeep Kumar (2018)	L_{27} OA	AA5083–H32 Al alloy	Water jet pressure, abrasive mesh size, jet impingement angle	Depth of penetration, cutting rate, KW, kerf taper ratio, Ra	TOPSIS	Fuzzy theory
Gutturthi and Chinta (2018)	CCD	Inconel 601	Traverse speed, stand-off distance, abrasive flow rate	MRR, Ra, KW	GRA	
Rao et al. (2019)	CCD		Pressure, stand-off distance, abrasive flow rate, traverse speed,	KW, Ra, taper angle, depth of penetration	PROMETHEE	Jaya algorithm
Bhowmik et al. (2019b)	L_9 OA	Polymer composite	Work pressure, nozzle speed, abrasive grain size, stand-off distance	MRR, Ra, taper angle	TOPSIS	
Prajapati and Patel (2019)	L_{27} OA	Al 5083	Traverse speed, stand-off distance, abrasive flow rate	MRR, Ra, KW	MOORA, TOPSIS	AHP
Patel et al. (2020)	L_{27} OA	Polymer matrix composites	Abrasive grain size, working pressure, stand-off distance, nozzle speed, abrasive mass flow rate	Ra, MRR, process time	MOORA, GRA, TOPSIS	PCA
Kumar et al. (2020)	L_9 OA	GFRP composites	Water jet pressure, stand-off distance, abrasive mass flow rate, traverse speed	MRR, Ra, KW, kerf angle	GRA	Fuzzy logic
Samson et al. (2020)	L_9 OA	Inconel 718	Pressure, stand-off distance, abrasive flow rate	Roundness, taper angle, MRR, Ra	VIKOR	
Reddy et al. (2020)	L_{27} OA	Inconel 625	Stand-off distance, traverse speed, sand flow rate	MRR, Ra, KW	WASPAS, MOORA	Entropy method
Das and Chakraborty (2021)	L_9 OA	Inconel 617	Water jet pressure, stand-off distance, abrasive mass flow rate	Drill rate, OC, circularity, taper, Ra	EDAS	Grey correlation method

Table 6 Optimization of LBM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Çaydaş and Hasçalık (2008)	L_{16} OA	St-37 steel	Power, cutting speed	Ra, top kerf, HAZ	GRA	
Rao and Yadava (2009)	L_{27} OA	SUPERNI 718	Oxygen pressure, pulse width, pulse frequency, cutting speed	KW, kerf taper, kerf deviation	GRA	Entropy method
Mishra and Yadava (2013)	L_9 OA	Al	Pulse width, pulse frequency, peak power, workpiece thickness	MRR, HAZ, taper angle	GRA	PCA, ANN, FEM
Kibria et al. (2013)	L_9 OA	Alumina ceramics	Laser beam average power, pulse frequency, workpiece rotational speed, feed rate	Ra, depth deviation	GRA	
Madić et al. (2014)	L_{27} OA	AISI 304	Laser power, cutting speed, assist gas pressure, focus position	Depth of separation line, drag line separation, burr height	GRA	
Chakraborty et al. (2015)	L_9 OA	SUPERNI 718	Oxygen pressure, pulse width, pulse frequency, cutting speed	KW, kerf deviation, kerf taper	WASPAS	
Madić et al. (2015a)	L_{27} OA	SS	Laser power, cutting speed, assist gas pressure, focus position	Burr height, drag line separation, depth of separation line, Ra, cut perpendicularity	WASPAS	AHP
Madić et al. (2015b)	L_{27} OA	AISI 304	Power, cutting speed, assist gas pressure, focus position	RA, KW, burr height	ROV	
Adalarasan et al. (2015)	L_{18} OA	Al MMC	Laser beam power, cutting velocity, gas pressure, pulsing frequency	Ra, KW, cut edge slope	GRA	

Table 6 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Priyadarshini et al. (2015)	L_{25} OA	High carbon steel Domex C67	Pulse width, number of pulses, assist gas flow rate, supply pressure	HAZ, circularity, MRR	GRA	Fuzzy logic
Khan and Maity (2016a)	L_{27} OA	Al MMC, AISI 304	Pulse power, pulse frequency, assist gas pressure, pulse width, laser power, cutting speed, assist gas pressure, focus position	KW, kerf deviation, kerf taper, burr height, drag line separation, depth of separation line	MOORA	
Khan and Maity (2016b)	L_9 OA, L_{27} OA	Ni-based superalloy, AISI 304	Assist gas pressure, pulse width, pulse frequency, cutting speed, laser power, cutting speed, focus position	KW, kerf deviation, kerf taper, burr height, drag line separation, depth of separation line	TOPSIS	
Madic et al. (2016)	L_9 OA	$AlMg_3$	Laser power, cutting speed, assist gas pressure, focus position	Cut perpendicularity, KW, Ra	WASPAS, OCRA	AHP
Priyadarshini et al. (2017)	L_{25} OA	High carbon steel	Pulse width, number of pulses, assist gas flow rate, assist gas flow rate	HAZ, circularity, MRR	TOPSIS	Fuzzy theory
Madić et al. (2017)	L_{27} OA	AISI 304 SS	Cutting speed, assist gas pressure, laser power, focal position	Ra, HAZ, KW, MRR	PSI	
Parthiban et al. (2018)	L_8 OA	Ni superalloy C263	Inclination angle, laser scanning speed, number of passes	Ra, surface crack density	TOPSIS	
Joshi and Sharma (2018)	BBD	Al 6061-T6 alloy	Lamp current, pulse width, pulse frequency, cutting speed	Kerf taper, HAZ	GRA	Fuzzy logic
Das et al. (2018)	L_9 OA	Ni-based superalloy	Assist gas pressure, pulse width, pulse frequency, cutting speed kerf width, kerf deviation and kerf taper	KW, kerf deviation, kerf taper	GRA	Fuzzy logic

Table 6 (continued)

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Sivaprasad and Haq (2019)	CCD	Hastelloy-X, Inconel-HX	Power, pulse width, pulse frequency, gas pressure	MRR, circularity, diametrical error	Similarity index method	Entropy method
Biswas et al. (2019)	CCD	Gamma-titanium aluminide	Lamp current, Pulse frequency, Air pressure, workpiece thickness	Circularity at entry, circularity at exit, hole taper	TOPSIS	Fuzzy theory
Gautam and Mishra (2019)	CCD	Kevlar-29/Basalt	Lamp current, pulse width, pulse frequency, compressed air pressure, cutting speed	KW, kerf deviation, kerf taper	GRA	GA
Kannan et al. (2020)	L_9 OA	Al7475 MMC	Laser power, scanning speed	Dimensional deviation	TOPSIS	
Das and Chakraborty (2020b)	L_9 OA	SUPERNI 718, Al6061 MMC	Gas pressure, pulse width, pulse frequency, cutting speed, laser beam power	KW, kerf deviation, kerf taper, Ra, cut edge slope	SIR	
Mishra et al. (2020a)	Box-Behnken design	Kevlar-29 composites	Pulse width, gas pressure, lamp current, stand-off distance, cutting speed	KW	GRA	
Chengal Reddy et al. (2020)	L_{27} OA	Hastelloy C276	Scanning speed, pulse intensity, pulse frequency, pulse duration	Ra, milling depth	TOPSIS	
Mishra et al. (2020b)	CCD	Basalt–glass–Kevlar-29 composite	Lamp current, pulse width, stand-off distance, compressed air pressure, cutting speed	Kerf deviation	GRA	

Table 7 Parametric optimization of USM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Chakravorty et al. (2013)	L_{18} OA	Co-based super alloy, tungsten carbide	Tool material, abrasive slurry material, slurry concentration, grit size, power rating	MRR, TWR, Ra	GRA	WSN, MRSN, UT
Chakraborty et al. (2015)	L_{27} OA	Al-based ceramic	Workpiece material, tool material, grit size, power rating, slurry concentration	Hole oversize, out-of-roundness, conicity	WASPAS	
Kataria et al. (2016)	L_{36} OA	WC–Co composite	Cobalt content, workpiece thickness, tool profile, tool material, abrasive grit size, power rating	MRR, TWR	GRA	
Khan and Maity (2016a)	L_{18} OA	Co-based super alloy	Tool material, abrasive slurry, slurry concentration, grit size, power ratio	MRR, TWR	MOORA	
Chakraborty et al. (2018)	L_{8} OA	titanium (ASTM Grade-I)	Tool material, abrasive type, grit size, power rating	MRR, TWR, Ra	GRA	Fuzzy logic
Bhowmik et al. (2019)	L_{9} OA	Zirconia composite	Slurry concentration, feed rate, power	MRR, taper angle, OC	TOPSIS	Fuzzy theory
Biswas et al. (2019)	L_{9} OA	Zirconia composite	Slurry concentration, power, feed rate	MRR, taper angle, OC	MOORA	
Bania et al. (2021a)	L_{16} OA	Reinforced epoxy hybrid composite	Abrasive grit size, abrasive flow rate, power rating, slurry concentration	MRR, TWR, OC	EDAS	CRITIC
Bania and Maity (2021b)	L_{16} OA	Reinforced epoxy hybrid composite	Abrasive grit size, abrasive flow rate, power rating, slurry concentration	MRR, TWR, OC	TODIM	CRITIC
Banerjee et al. (2022)	CCD	Zirconia	Grit size, slurry concentration, power rating, feed rate	MRR, Ra	TOPSIS	AHP

preference ranking methods would lead to varied intermixes of the input parameters for different aluminum MMCs.

Reddy and Reddy (2018) and Sen et al. (2021), respectively, adopted neutrosophic fuzzy number and trapezoidal interval type-2 fuzzy number for criteria weight measurement under uncertain environment, and pointed out that their integration with MCDM techniques would provide more pragmatic solutions. For a WEDM process, Kumar and Narasimhamu (2020) first employed TOPSIS to compute the closeness coefficients of all the experimental trials which were subsequently utilized to formulate a regression equation. The GWO was finally applied to optimize the developed equation along with determination of the optimal settings of pulse-on time, pulse-off time, wire feed rate, and water pressure. Tudu et al. (2021) presented the application of WASPAS and MOGA techniques for optimizing a WEDM process, and observed that both the approaches would provide almost comparable results for MRR and Ra.

Table 8 Optimization of PAM processes using MCDM techniques

Author(s)	Design plan	Material	Process parameters	Responses	MCDM	Other tool(s)
Das et al. (2014b)	L_{27} OA	EN 31 steel	Arc gas pressure, arc current, torch light	MRR, Ra, Rq, Rsk, Rku, Rsm	GRA	
Maity and Bagal (2015)	CCD	AISI 316	Feed rate, current, voltage, torch height	Kerf, chamfer, dross, Ra, MRR	GRA	PCA
Renangi et al. (2015)	L_{18} OA	SS 420	Cutting current, cutting speed, torch height	Ra, MRR	GRA	
Khan and Maity (2016a)	L_{27} OA	EN 31 steel	Arc gas pressure, arc current, torch light	MRR, Ra, Rq, Rsk, Rku, Rsm	MOORA	
Khan and Maity (2016b)	CCD	AISI 316	Feed rate, current, voltage, torch height	MRR, Ra, chamfer, dross, kerf	TOPSIS	
Chakraborty et al. (2018)	L_{27} OA	SUPERNI 718	Assist gas pressure, pulse width, pulse frequency, cutting speed	KW, kerf deviation, kerf taper	GRA	Fuzzy logic
Muhamedagic et al. (2018)	L_9 OA	X5CrNi18-10 SS	Cutting speed, plasma gas pressure	Ra, cut perpendicularity, KW	TOPSIS	
Ananthakumar et al. (2019)	BBD	Monel 400 superalloy	Cutting speed, gas pressure, arc current, stand-off distance	MRR, kerf taper, HAZ	TOPSIS	
Hamdy et al. (2019)	L_{27} OA	Mild steel	Cutting speed, arc current, stand-off distance	Kerf taper, dross, Ra, MRR	MOORA	SDV, GA
Hema and Ganesan (2020)	L_{18} OA	SS 304 alloy	Arc voltage, cutting speed, stand-off distance, plasma offset	Ra, MRR, kerf ratio	GRA	

4.4 AWJM process

The AWJM is a hybrid NTM process in which the working principles of AJM and WJM are synergically integrated to remove material mainly from brittle materials (glass and ceramics). In this process, abrasive particles, like SiC, B_4C, etc., proportionately mixed with water, are passed through a small nozzle and ejected on to the workpiece surface causing removal of material due to erosive action. Thus, various features of the abrasive as well as nozzle, like abrasive grain size, abrasive flow rate, water pressure, nozzle diameter, stand-off distance, etc., play significant roles in attaining the desired properties of the work materials. From Table 5, which presents a literature survey on optimization of AWJM processes using MCDM techniques, it can be noticed that most of the researchers utilized this process for machining of ceramics and composite materials.

Tozan (2011) and Yuvaraj and Pradeep Kumar (2018) considered the application of fuzzy theory along with the MCDM techniques while assigning relative importance to the responses under consideration. It was concluded that the integrated approach could effectively resolve the ambiguity and uncertainty involved in the group decision making scenario. Deris et al. (2013) hybridized GRA and SVM to develop a predictive model for an AWJM process. It was postulated that the proposed model would provide better results as compared to GRA which was only applied to identify the significant process parameters affecting the responses. Rao et al. (2019) optimized the input parameters of an AWJM process using Jaya algorithm and its posteriori version. It was observed that the derived optimal solutions would outperform those as obtained by other metaheuristics, like particle swarm optimization, CSA, simulated annealing, firefly algorithm, blackhole algorithm, and bio-geography-based optimization techniques. Finally, PROMETHEE was implemented to single out the best solution from the set of the Pareto-optimal solutions developed using the multi-objective version of Jaya algorithm. In a recent paper, Das and Chakraborty (2021) integrated grey correlational method with EDAS to solve the parametric optimization problem of an AWJM process.

4.5 LBM process

The LBM process employs a high intensity laser beam, focused on to the workpiece surface to a very small spot with the help of a lens. Due to extremely high temperature at the narrow zone on the surface, material removal takes place through melting and/or vaporization of the work material, leaving a crater on the incident area of the beam. The molten material is blown away from the machining zone with the help of air, oxygen, nitrogen or argon, which also helps in minimizing the HAZ. It has several advantages, like higher cutting speed, high degree of flexibility and automation, lower level of noise, etc. Micro-holes with better KW, smaller HAZ and accurate cut edge profile can be easily generated using this process. It can also machine brittle materials.

Based on the working principle of this process, it can be revealed that the researchers should be interested to control dimensional accuracy of the machined components while setting the optimal values of laser beam power, pulse width, pulse frequency, focus position, cutting speed, and pressure and flow rate of the assist gas during LBM operation. While assigning relative importance to the considered responses using suitable linguistic variables, Priyadarshini et al. (2017), and Biswas et al. (2019) combined fuzzy theory with TOPSIS for parametric optimization of LBM processes. In the similar direction, fuzzy logic was hybridized with GRA to frame fuzzy rules to investigate the effects of varying LBM process parameters on the responses and also to search out the ideal settings of those parameters (Priyadarshini et al. 2015; Joshi and Sharma 2018; Das et al. 2018). Madic et al. (2016) first applied AHP to determine weights of KW, Ra, and perpendicularity, and later optimized an LBM process using WASPAS and OCRA methods. The applications of both the MCDM approaches had identified the same parametric intermix of the said process. The same research group also applied PSI method to optimize an LBM process (Madić et al. 2017). Sivaprasad and Haq (2019) and Das and Chakraborty (2020b), respectively, employed similarity index and SIR methods to determine the ideal combinations of different input parameters leading to optimization of LBM processes. While machining Kevlar-29 and Basalt materials using LBM process, Gautam and Mishra (2019) applied GRA to compute the grey relational grades of all the experimental trials which were subsequently utilized to develop a nonlinear model taking into account the considered process parameters. Finally, GA was employed to solve the model along with determination of the optimal parametric intermix. Integrating FEM and ANN, Mishra and Yadava (2013) developed a prediction model for a laser beam percussion drilling process. At first, FEM-based thermal models for the process were developed, considering temperature-dependent thermal properties, optical properties and phase change phenomena of aluminum. The ANN was then trained using the input and output data based on the FEM model. Finally, the said process was optimized using GRA and PCA techniques. The adopted multi-objective optimization tool was able to maximize MRR with reduced values of taper angle and HAZ. A concise review on the applications of MCDM methods for optimizing LBM processes is provided in Table 6.

4.6 USM process

During USM operation, material is removed from the workpiece surface with the help of low amplitude and high frequency vibration of a tool in the presence of abrasive particles. The material removal takes place due to abrasion of the abrasive-loaded liquid slurry circulating between the workpiece and the tool vibrating perpendicular to the workpiece at an ultrasonic frequency. It differs from the other NTM processes as minimum amount of heat is generated during the machining operation. It can also effectively machine brittle materials. To expedite the performance of USM process, type, size of the abrasive and its concentration, power rating, abrasive flow rate, etc., are identified to play important roles.

Chakravorty et al. (2013) applied four techniques, i.e. GRA, WSN, MRSN, and UT for simultaneous optimization of MRR, Ra, and TWR during machining of cobalt-based superalloy and tungsten carbide work materials. It was noticed that WSN having simple computational steps would provide the best intermix of the considered USM parameters. The relative importance of MRR, TWR, and OC was first estimated by Bania et al. (2021a) using CRITIC method, and EDAS method as an MCDM tool was later adopted to optimize the USM process. Similarly, Bania et al. (2021b) determined weights of the responses using CRITIC, and adopted TODIM method to search out the best combination of abrasive flow rate, power rating, abrasive grit size, and slurry concentration which would simultaneously maximize MRR, and minimize TWR and OC. Table 7 enlists the MCDM techniques adopted by the past researchers for optimizing USM processes.

4.7 PAM process

In PAM process, material is removed by directing a high velocity jet of high-temperature ionized gas on to the workpiece, causing melting and vaporization of the material. This ionized gas is known as plasma. It can effectively machine thick hard and brittle materials, and has a faster machining rate while providing good dimensional accuracy. The applications of different MCDM techniques for parametric optimization of PAM processes are presented in Table 8.

Maity and Bagal (2015) integrated GRA with PCA to study the effects of current, voltage, feed rate, and torch height while optimizing MRR, Ra, dross, kerf and chamfer during machining of AISI 316 SS work material using PAM process. Hamdy et al. (2019) first determined the relative importance of Ra, MRR, kerf taper, and dross using SDV method. The MOORA method was later adopted to convert the multiple responses into a single performance index which

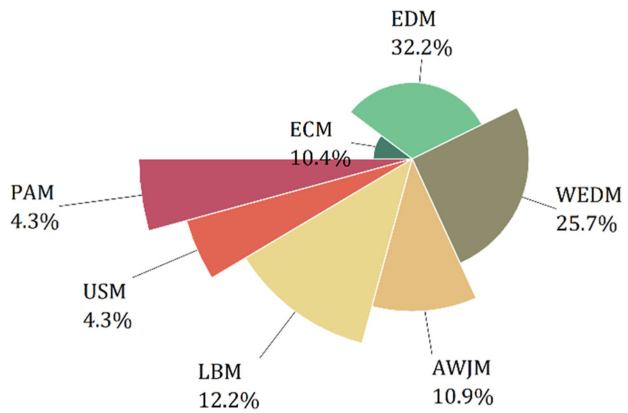

Fig. 2 NTM processes considered for parametric optimization

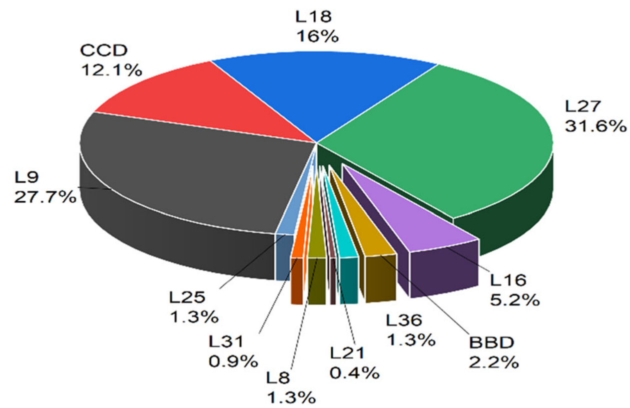

Fig. 3 Experimental design plans deployed for parametric optimization of the NTM processes

was subsequently modelled using GA. The derived solutions would help in studying the effects of PAM parameters on the responses and determining the ideal parametric intermix of the said process.

5 Summary

This paper reviews more than 200 research articles mainly published during the last ten years on the applications of different MCDM techniques for optimizing ECM, EDM, WEDM, AWJM, LBM, USM, and PAM processes. It can be revealed from Fig. 2 that EDM and WEDM processes contribute 32.2% and 25.7%, respectively, to the total number of articles reviewed. The immense popularity of these two NTM processes may be due to their potentiality to generate complex and intricate shape features on various conductive and non-conductive advanced engineering materials used in modern-day automobile, molding, tool and die making industries. This review paper also extracts valuable information with respect to the design plans deployed for conducting the required experiments, materials machined, process parameters and responses considered, and MCDM methods applied for optimizing the said NTM processes. Figure 3 exhibits that among different experimental design plans, L_9 (27.7%), L_{18} (16.0%) and L_{27} (31.6%) are maximally considered while conducting experiments leading to optimization of the NTM processes. Perhaps the main reason for huge popularity of OAs (L_9, L_{18}, L_{27}, etc.) lies in their simplicity. The OAs, which are developed with a fraction of full factorial array, maintain independency between various factors evaluated. They are also extremely potent tools for pilot analysis as the number of factors evaluated can often be increased without increasing the number of tests to be carried out. For example, considering a three-level design, an L_9 OA can be employed for constructing a DoE of 2, 3, and 4 number of factors. Thus,

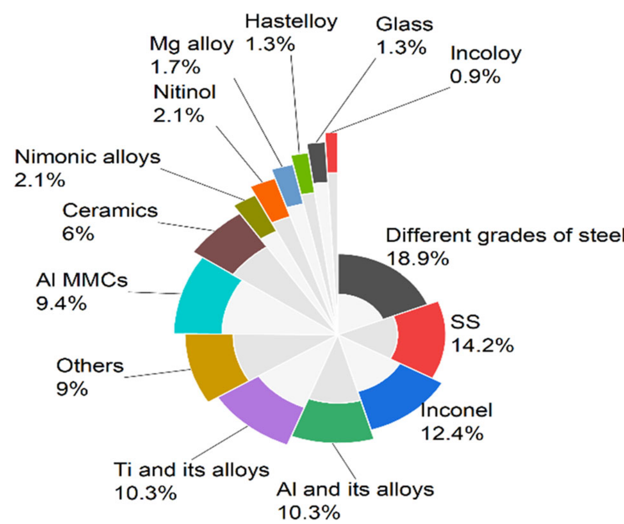

Fig. 4 Types of work materials machined using the NTM processes

they can be effectively utilized to study machining characteristics of the NTM processes with minimum number of experimental trials. Figure 3 also reveals that CCD (12.1%) and BBD (2.2%) plans are also employed mainly to develop the corresponding metametals correlating the NTM process parameters and responses.

From Fig. 4, which shows various work materials machined by the NTM processes, it can be unveiled that different grades of steel and SS, aluminum, Nimonic, and titanium and their alloys, Inconel, MMCs and ceramics are maximally machined due to their wide-ranging industrial applications. These harder and tougher materials with poor machinability properties cannot be machined by the conventional material removal processes. Besides these work materials, different ceramic-based composites, WC alloy, hardfacing materials, polymer composites, etc. are also machined which are combined together in 'Others' category

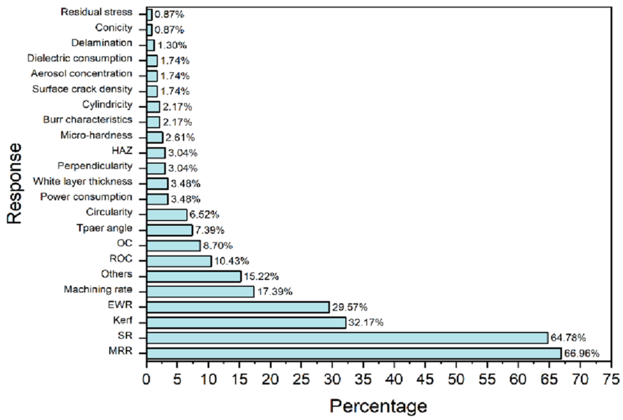

Fig. 5 Responses considered during optimization of the NTM processes

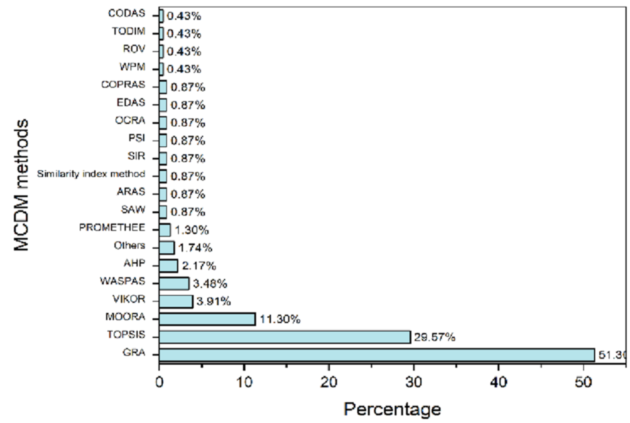

Fig. 6 MCDM tools employed for parametric optimization of the NTM processes

in Fig. 4. With respect to the input parameters, applied voltage, feed rate, inter-electrode gap, electrolyte concentration, and its flow rate for ECM process; pulse-on time, pulse-off time, discharge voltage and current, dielectric type, and its flushing pressure for EDM process; and pulse-on time, pulse-off time, peak current, wire feed rate and tension for WEDM process are mainly treated with utmost importance by the researchers. On the other hand, abrasive size and its flow rate, traverse speed, and stand-off distance; laser power, cutting speed, focus position, and assist gas pressure; power rating, abrasive slurry material, size, concentration and flow rate, and feed rate; and arc current, torch height, cutting speed, and arc gas pressure are considered as the main input parameters for AWJM, LBM, USM, and PAM processes, respectively.

It can be noticed from Fig. 5 that MRR has the maximum importance among the researchers as the response, followed by SR (consisting of Ra, Rku, Rq, Rsk, Rsm, and Rz), kerf characteristics and EWR. As the primary objective of any of the machining processes is to remove material from a given workpiece, MRR is always treated as the main metric to quantify production rate and machining efficiency. To reduce friction, heat generation, consumption of energy, material loss due to wear, degradation of metallurgical properties, etc., it is always desired to have a smooth machined surface which is often defined by various surface characteristics (mainly in the form of Ra value). During generating intricate shape geometries on various work materials using WEDM, AWJM, LBM, and PAM processes, dimension deviations are usually characterized by different kerf features (KW, kerf deviation, and kerf taper angle). Furthermore, EWR represents tool (electrode) wear during the machining operation which is proportional to more tool consumption leading to higher machining cost.

Figure 6 reveals that GRA (51.30%) and TOPSIS (29.57%) are the two most popular MCDM tools deployed by the researchers for optimizing of the considered NTM processes. The extreme popularity of GRA lies in its simple calculation steps, ability to deal with incomplete information and in-built criteria weight estimation. In this method, after translating the performance scores of all the candidate alternatives into a comparability sequence, a reference sequence is framed. The difference between the reference sequence and every comparability sequence is then estimated in terms of grey relational grade which is finally employed to rank the alternatives. The TOPSIS identifies the best alternative which is positioned nearest to the ideal solution and farthest from the anti-ideal solution. Besides GRA and TOPSIS, applications of other MCDM tools, like MOORA, VIKOR, WASPAS, AHP, SAW, ARAS, EDAS, SIR, PSI, PROMETHEE, OCRA, COPRAS, etc., are also found for optimizing the NTM processes. It is also observed that in most of the cases, equal weights are assigned to the criteria (responses) mainly to ease out the related calculation steps. When it is required to allocate objective weights to the responses, entropy method, CRITIC and PCA are occasionally applied. Fuzzy set theory, fuzzy logic, neutrosophic fuzzy set and interval type-2 fuzzy number are also integrated with many of the MCDM techniques to resolve the problem of subjective weight allocation to the responses under uncertain decision making environment. Based on the calculated performance scores of the MCDM tools, attempts are also put forward to develop the corresponding metamodels which are subsequently solved using different metaheuristics, like GA, GWO, CSA, TLBO, etc., leading to determination of the optimal combinations of the NTM process parameters in continuous solution space.

6 Conclusions

This review of research articles published on parametric optimization of ECM, EDM, WEDM, AWJM, LBM, USM, and PAM processes using different MCDM tools draws the following conclusions:

(a) Among the experimental design plans, the researchers preferred Taguchi's L_9 (27.7%), L_{18} (16.0%), and L_{27} (31.6%) OAs mainly due to their easier calculation steps and availability of user-friendly software (like MINITAB, Design Expert, etc.). They are also capable of dealing with both quantitative and qualitative input parameters and responses.
(b) The harder, tougher, and brittle materials having poor machinability properties are usually machined employing the NTM processes with generation of complex and intricate shape features with minimum dimensional deviation and satisfactory surface finish.
(c) The MRR is the most important response (66.96%), followed by SR (64.78%), kerf characteristics (32.17%), and EWR (29.57%).
(d) Among the MCDM tools, GRA has found maximum applications (51.30%), followed by TOPSIS (29.57%) for optimizing the considered NTM processes.
(e) To ease out the computational steps, equal importance is usually allocated to the responses.
(f) The applications of fuzzy set theory and its different variants are sometimes found while assigning subjective weights to the responses under uncertain decision making environment.

This review paper also proposes the following future research directions:

(a) The application potentialities of MCDM techniques for optimization of other NTM processes, like AJM, WJM, electrochemical discharge machining, electrochemical grinding, electrochemical honing, etc., need to be explored.
(b) More emphasis needs to be focused on the applications of CCD/BBD-like design plans to identify the optimal parametric combinations of the NTM processes in continuous solution space.
(c) The interaction effects between the NTM process parameters may be explored with subsequent development of the corresponding linear graphs related to different OAs.
(d) In GRA, influences of the changing values of the distinguishing coefficient on the derived optimal solutions should be investigated.
(e) More preference should be provided on criteria weight determination using objective methods. In this direction, application of simultaneous estimation of criteria and alternatives (SECA) method is highly recommended.
(f) Other new but yet to be popular MCDM tools, like CoCoSo, MABAC, MARCOS, compromise ranking of alternatives from distance to ideal solution (CRADIS), etc., can be employed to derive the optimal intermixes of the NTM process parameters.
(g) It should be interesting to study the effects of changing criteria weights on the optimal parametric settings through sensitivity analysis (Mukhametzyanov and Pamučar 2018).
(h) The MCDM tools can be effectively hybridized with various metaheuristic algorithms leading to optimization of NTM processes.
(i) Development of a decision support system is highly demanded to alleviate the calculation steps of MCDM tools which would guide the concerned process engineers in identifying the most suitable parametric combinations with the help of a graphical user interface (Chakraborty and Kumar 2021).

The limitations of this review paper are as follows. Applications of MCDM tools for optimization of ECM, EDM, WEDM, AWJM, LBM, USM, and PAM processes are only considered in this paper. Further review may be conducted to highlight the applications of MCDM tools for optimizing other NTM processes, like electrochemical discharge machining, electrochemical grinding, AJM, WJM, electron beam machining, chemical machining, etc. Metaheuristics-based optimization of various NTM processes may be a topic of another review work. It also does not endeavor to extract values of the optimal settings as well as achieved response values of the NTM processes. Extraction of this information would greatly help the process engineers in conducting the pilot runs to study the significant effects of the input parameters on the responses.

Declarations

Conflict of interest The authors declare no competing interests.

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