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Review

Parameters Optimization of Electrical Discharge Machining Process Using Swarm Intelligence: A Review

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Abstract: Electrical discharge machining (EDM) can use soft tool electrodes to process hard workpieces to achieve "soft against hard", because it directly uses electrical energy and thermal energy to remove metal materials. Then, it can generate complex features on harder materials and meet the requirements of excellent surface quality. Since EDM involves many process parameters, including electrical parameters, non-electrical parameters, and materials properties, it is essential to optimize its process parameters to obtain good performance. In this direction, the application of the swarm intelligence (SI) technique has become popular. In this paper, the existing literature is comprehensively reviewed, and the application of the SI technique in the optimization of EDM process parameters is summarized. Sinker-EDM (SEDM), wire-EDM (WEDM), and micro-EDM (MEDM) with various hybrid techniques are among the EDM methods considered in this study because of their broad adoption in industrial sections. The fundamental nature of all review articles will assist engineers/workers in determining the process parameters and processing performance, the SI algorithm, and the optimal technique by which to obtain the desired process parameters. In addition, discussions from the perspectives of the similarity, individuality, and complementarity of various SI algorithms are proposed, and necessary outlooks are predicted, which provides references for the high performance of the EDM processes in the future.

Keywords: EDM process; SI; optimization; parameter; performance

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1. Introduction

The tool electrode and the workpiece are submerged in the dielectric during electrical discharge machining (EDM), and they are linked to the two poles of the pulse power source. A large amount of heat energy is concentrated in the tiny discharge channel, the temperature may be as high as 10,000 °C, and the pressure also sharply changes [1–3]. Therefore, at this time, a small amount of metal material on the surface of the workpiece in the discharge area will immediately melt, vaporize, and explode into the working fluid. The material removal in the electric discharge is realized by the electric heating in the discharge process, and the conductivity and thermal properties of the material have a significant impact on its machinability. Therefore, low-rigidity workpieces may be machined and micro-machined particularly well using the EDM technique. In addition, it is particularly suitable for machining a workpiece with a complex surface, because the tool electrode shape can be copied to the workpiece. Since EDM involves many process parameters, including electrical parameters, non-electrical parameters, and material properties, it is essential to optimize its process parameters to obtain good performance [4]. In this direction, the application of the swarm intelligence (SI) technique has become popular.

Ant colonies, bird flocking, bee colonies, eagle hunting, grazing, fish colonies, bacterial development, etc., are all examples of SI in nature. SI is derived from research on the collective behavior of social insects such as ants and bees. A swarm intelligence system is often made up of a collection of simple agents or clusters that interact one with another and with surroundings. Swarm intelligence has been formally proposed as a theory and has steadily caught the attention of a significant number of researchers since Dorigo [5] put forward the Ant Colony Optimization (ACO) hypothesis in 1991, starting a research movement. Kennedy et al. [6] presented the Particle Swarm Optimization (PSO) in 1995. Since then, research on swarm intelligence has rapidly developed, and relevant technologies can be applied in various fields, such as aerospace [7,8], precision medicine [9], and advanced manufacturing [10,11].

This review focuses on the progress in parameters optimization of the EDM process using swarm intelligence. First, the principle of different swarm intelligence techniques is critically reviewed in Section 2, including the ACO, the PSO, the genetic algorithm (GA), the Artificial Bee Colony (ABC), the Glowworm Swarm Optimization (GSO), the Cuckoo Search Algorithm (CSA), the Differential Evolution Algorithm (DEA), and others. Second, the application of the swarm intelligence technique in the optimization of EDM process parameters is summarized, and the sinker-EDM (SEDM), wire-EDM (WEDM), and micro-EDM (MEDM) with various hybrid techniques are reviewed in Sections 3, 4, and 5, respectively. Third, discussions from the perspectives of similarity, individuality, and complementarity of various SI algorithms characteristics are proposed. Finally, necessary outlooks (involving limitations and challenges) are predicted, which provide references for the high performance of the EDM processes in the future.

2. Principal of Swarm Intelligence

2.1. ACO

Ants seek food sources, and there are numerous routes to the food source. As they select a way, they emit a pheromone. This pheromone's concentration decreases as time passes. As a result, the number of ants with shorter paths will grow, as will the pheromone content. The ants will take the path with the most pheromones. With the passage of time, the number of ants using shorter paths will increase. Then, corresponding is the best answer to the problem to be solved [5,12]. The ACO algorithm is a probabilistic technique for determining the best path. It was originally intended to solve the problem of the traveling salesman (TSP). Currently, the ACO algorithm has been continuously improved and gradually built with a mature algorithm framework, becoming one of the most promising algorithms in the field of combinatorial optimization [12,13]. Its application extends to all aspects of optimization problems, such as the assignment problem, the vehicle routing problem, the graph coloring problem, the job-shop scheduling problem, and the network routing problem [12–15].

2.2. PSO

PSO is a group behavior that mimics the predation process of birds and fish, and is a branch of evolutionary computation [6]. A single particle is an individual of a group of birds or fish. It describes the members of the group as individuals without mass or volume, and it is also convenient to describe its speed and acceleration state [6,16]. PSO utilizes three simple behaviors of separation, alignment, and cohesion to describe the population, and moves the individuals in the population to a good region according to their adaptability to the environment, thus guiding the particles to find the global optimal solution. It is worth noting that the GA does not include the "crossover" and "mutation" operations [17]. It seeks the global optimum by following the currently searched optimal value. Compared with other modern optimization methods, the PSO algorithm has an obvious feature in that it requires few parameters to be adjusted and has a fast convergence speed [18]. It has become a key topic in the field of modern optimization methods. The PSO algorithm has now been widely used in optimization problems in various engineering fields [19,20].

2.3. GA

The strong adapt and thrive in nature, whereas the weak typically perish. The GA search optimization algorithm mimics the idea of "survival of the fittest" by basing itself on the mechanism of natural selection [21,22]. The GA is a group-based technique where participants score each other based on how suitable their answers are. The technique uses mathematics and computer simulation to change the problem-solving process into a process such as the crossing, reproduction, and mutation of chromosomal genes in biological evolution [23,24]. In comparison to certain conventional optimization techniques, they may frequently produce better optimization outcomes more rapidly when handling complicated combinatorial optimization issues [23,25,26]. Consequently, the GA has been widely applied in combinatorial optimization, signal processing, artificial life, machine learning, adaptive control, and other fields.

2.4. ABC

A single bee's behavior is quite basic, yet the social group it belongs to exhibits extraordinarily sophisticated behavior. The actual bee population can efficiently gather nectar from flowers (food sources) in settings. They may also adjust to environmental changes at the same time. An optimization technique called the ABC algorithm is put forth by emulating bee behavior [27,28]. The population's overall optimal value is eventually highlighted by the local optimization behavior of individual artificial bees. A novel swarm intelligence algorithm is the ABC algorithm. It merely requires a comparison of the benefits and disadvantages of the problem and has quick convergence; it does not require extensive knowledge of the topic. The algorithm is considered as simple to code as the PSO and the DEA [29,30].

2.5. GSO

The GSO algorithm is a new multi-modal function optimization technology of swarm intelligence proposed by Krishnanad and Ghose [30,31]. The GSO algorithm is memoryless and does not need global and gradient information. It has the characteristics of a fast calculation speed, fewer adjustment parameters, and easy implementation. In the process of population evolution, each iteration consists of five parts: the population initialization stage, the fluorescein update stage, the mobile probability calculation stage, the location update stage, and the neighborhood range update stage. After several years of development, the GSO algorithm has good application prospects in the optimization process of continuous space and some production scheduling.

2.6. CSA

The cuckoo has a unique breeding pattern in nature as a nest parasite bird. Nest parasitism is the practice of using other birds' nests to hatch their own eggs. To increase egg survival, the parasite birds destroy or conceal the host's eggs. If the host discovers the egg, the host will either find a new nest or kill the egg. Because this is a natural selection process, the quality of nest selection has a direct impact on the survival rate of the following generation. The CSA is a method for solving optimization problems by imitating the parasitic brood of a particular species of cuckoo [32–34]. Compared with other methods, the CS algorithm has the advantages of a multi-modal objective function and requires less parameters to be fine-tuned [35–38].

2.7. DEA

The DEA is a population-based algorithm based on the genetic annealing technique. It is comparable to a genetic algorithm due to the employment of similar operators (mutation, crossover, and selection) [39,40]. The primary distinction between the DEA and the GA is the ability to build superior solutions. The DEA is dependent on mutation, whereas the GA is dependent on crossover. In the DEA, regardless of their fitness value, all solutions in the population have the same chance of being chosen as parents. This is the primary operational distinction between the DEA and the GA. Although the DEA offers advantages in terms of improving local search ability and preserving population diversity, its convergence can be gradual and unpredictable [4,41].

2.8. Others

There are also other interesting evolutionary algorithms, such as genetic programming (GP), evolutionary programming (EP), evolutionary strategy (ES), the firefly algorithm (FA), the bat algorithm (BA), and the grey wolf optimizer (GWO) [42–45]. GP is another evolutionary algorithm, involving a process similar to the genetic algorithm [46]. The ES algorithm, using the same method as the GA and DE, is another optimization method. However, it uses an adaptive mutation rate [47]. Initialization, mutation, and evaluation are comparable processes in both the EP and GA. The EP does not employ a crossover operation to produce offspring, which is the primary distinction between it and the GA [45,48]. The FA was influenced by how fireflies interact with one another by flashing their lights. The BA algorithm is another recently introduced optimization technology inspired by the feeding behavior of bats. It is very similar to the PSO and consists of speed and position equations [45]. The GWO achieves the goal of optimization based on the mechanism of wolf group cooperation by simulating the predatory behavior of gray wolf groups [49,50].

3. Sinker-EDM

3.1. Brief Introduction for Sinker-EDM

Sinker EDM is performed in a liquid media, with the machine tool's automated feed adjustment unit accurately controlling the spark to treat conductive materials [51]. Sinker EDM works by eroding conductive materials via a sequence of spatially discrete high-frequency discharges (sparks) between the tool and the workpiece [52,53]. Figure 1 depicts the four stages of EDM. When a high pulse is delivered between these two electrodes (attaining the breakdown voltage of the medium in the gap), the dielectric insulation strength is destroyed at the weakest spot. Because the energy is highly short and concentrated, the instantaneous high temperature in the machining surface partly melts, vaporizes, and evaporates the metal on the two electrodes' surfaces. Under the action of the explosive force, the partially melted and vaporized metal is propelled into the working fluid, cooled into minute metal particles, and is swiftly washed away from the working area, producing a small crater on the surface of the two electrodes. The dielectric insulation strength will recover after the initial discharge and await the next discharge. Therefore, sinker EDM involves many process parameters, including electrical parameters (discharge current, pulse width, pulse frequency, gap voltage, etc.), non-electrical parameters (dielectric fluid, scouring mode, pressure, etc.), and material thermal properties. Therefore, it is essential to optimize its process parameters to obtain the required performance, such as the material removal rate (MRR), Ra, the tool relative wear rate, machining accuracy, etc.

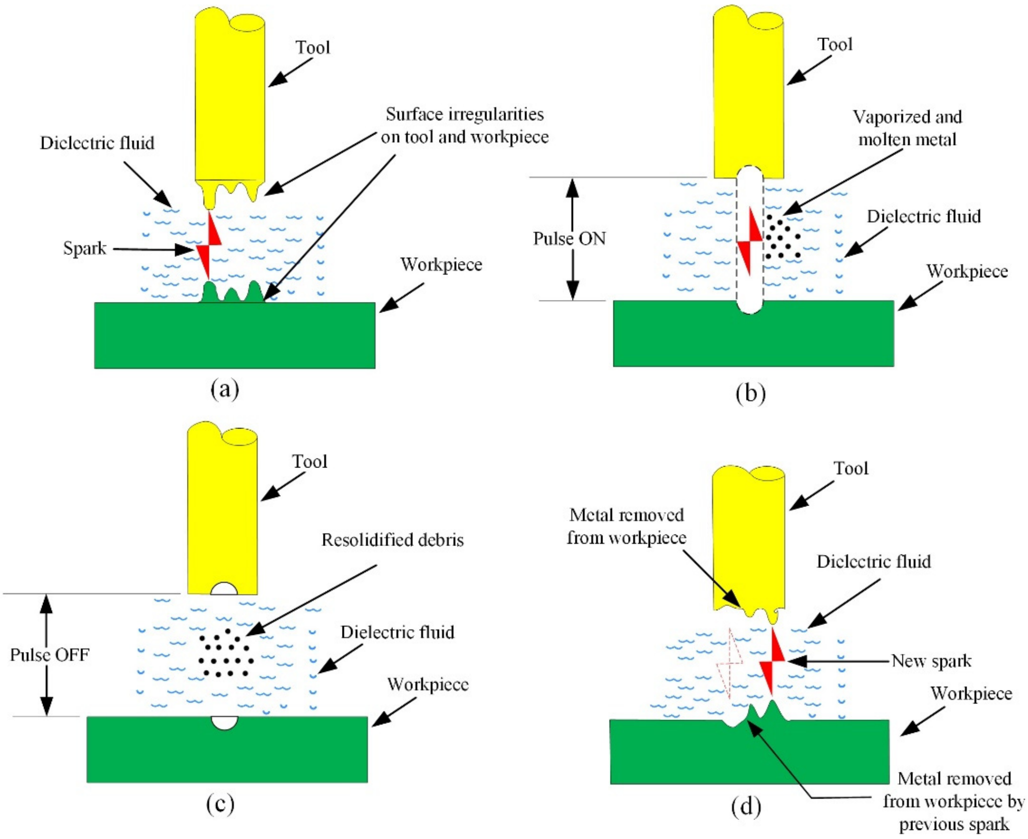


Figure 1. Four stages of the process of EDM; (**a**) spark beginning stage, (**b**) melting and vaporization stage, (**c**) removing debris stage, and (**d**) recovery stage.

3.2. Single-Objective Optimization

ACO is a popular optimization technique that has been used for optimization problem-solving. Mondal et al. [54] investigated the optimization of EDM process parameters using the ACO algorithm while cutting AISI 304 stainless steel. The findings revealed that, after 50 iterations, the highest MRR of 9.232 (mm^3/min) was attained, and at the end of all iterations, the optimal solution was found. The PSO technique is one of the most advanced evolutionary computational intelligence-based optimization methodologies for optimizing real-world multimodal problems. Aich and Banerjee [55] determined the desired process parameters combination of the maximum MRR and the minimum Ra through the PSO algorithm, with an average searching time of 4.334 s. The EDM processing optimization proposed by Saffaran et al. [56] was highly effective, and the error of single-objective and multi-objective optimization was less than 4% and 7%, respectively. Tzeng and Chen [57] optimized the EDM process using the GA approach while machining SKD 11, and discovered that GA had better prediction than RSM. Mahanta et al. [58] carried out GA-based optimization to produce high-quality jobs with low power consumption in the process of EDM. Mukherjee and Chakraborty [59] compared the optimization performance of the EDM process by using various swarm intelligence algorithms, and found that the performance of the ABC algorithm was better that of the ACO or GA algorithms. Zainal et al. [60] employed linear regression and the GSO method to conduct an integrated assessment of surface roughness in the EDM process. Furthermore, the minimal Ra of 2.03 μm could be searched for by the proposed method. Shen et al. [61] proposed an improved beta-distributing cuckoo search (IBCS) algorithm, and utilized this proposed IBCS to obtain the single-objective optimization (Ra) in the EDM process. The results demonstrated that the number of iterations of the IBCS algorithm (eight iterations) was half of that of the BCS algorithm (seventeen iterations). The DEA method was also used in the parameter optimization of the EDM process [62], and the optimization performance could be acceptable. As for the GP algorithm, its effect in terms of EDM parameter optimization was also better than the traditional response surface method (RSM), and the previous study showed that it had better and more accurate estimation [63]. The ES method could be used in the EDM process optimization of machining Inconel 718 alloy [64]. For different materials, such as die steel [65], Al-SiCp [66], FA was applied in the EDM process for optimizing the process parameters to obtain the desired machining performance.

For the hybrid-EDM process, the single-objective optimization can also be performed by various swarm intelligence techniques. A continuous ACO method was used to select the best magnetic-field-assisted-EDM (MF-EDM) process parameters for maximum MRR and specified surface roughness (SR) by Teimouri and Baseri [67]. The optimal input values (process parameters) for different desired SR were obtained, and the variation of SR and MRR were heavily dependent on discharge energy fluctuation. Singh et al. [68] proposed an intelligent hybrid approach, using the PSO algorithm, to obtain a desired prediction of gas-assisted EDM (GA-EDM) performance. The results showed that the improved PSO algorithm was effective for the G-EDM performance estimation. Rouniyar and Shandilya [69] performed the optimization of process parameters in magnetic field assisted powder mixed EDM (MFAPM-EDM) for cutting Al 6061, and compared the optimized performance of GA method with others. Danish et al. [70] used the GWO approach to optimize the hydroxyapatite powder mixed electric discharge machining (HPM-EDM) process in order to improve modified surface characteristics, such as the recast layer thickness (RLT), of 316L stainless steel. The test demonstrated that the gray wolf optimizer’s predicted solution sets are very accurate, with less than 10% inaccuracy. As listed below, the comparison of various swarm intelligence techniques for parameters optimization in the sinker-EDM process is depicted in Table 1.

Table 1. Comparison of various swarm intelligence techniques for parameters optimization in the sinker-EDM process.

Techniques	Year, Authors, Process	Parameters	Performance	Findings	Shortcomings or Limitation
ACO	2014, Teimouri and Baseri [67], MF-EDM	Magnetic field intensity (Fi), rotational speed of electrode (Rs), and discharge energy (Ee)	MRR and SR	With the help of the ACO algorithm, the magnetic field assisted rotary EDM process can also be successfully optimized.	It is not compared with other optimization algorithms.
	2022, Mondal et al. [54], EDM	Pulse-on time (Ton), discharge current (Ip), gap voltage (Vg)	MRR and SR	The ACO algorithm had converged after 50 iterations.	The performance of finding the optimal parameters needs to be improved.
PSO	2014, Aich and Banerjee [55], EDM	Ton, pulse-off time (Toff), and Ip	MRR and Ra	The PSO algorithm had converged after 20 iterations.	The search time of the algorithm is longer than 1 h.
	2020, Saffaran et al. [56], EDM	Ton, Toff, Ip, Vg and duty factor (Df)	MRR, SR, and TWR	Optimization error was less than 7%; the performance of PSO was better than SA.	The sample data is too small, which affects the robustness of the model.
	2020, Singh et al. [68], GA-EDM	Ton, Toff, Df, Rs, and gas discharge pressure (Gp)	MRR and SR	Could be an efficient and productive approach.	The performance of the proposed PSO should be mensurated.

Table 1. *Cont.*

Techniques	Year, Authors, Process	Parameters	Performance	Findings	Shortcomings or Limitation
GA	2013, Tzeng and Chen [57], EDM	Ton, Ip, and Vg	MRR, Ra, and TWR	The GA approach had better prediction than the RSM method.	The number of samples needs to be increased to improve robustness.
	2018, Mahanta et al. [58], EDM	Ip, Df, Toff, and Vg	Power consumed and SR	To be an effective tool with minimum effort.	Other important performance is not involved, such as MRR.
	2020, Rouniyar and Shandilya [69], EDM	Ip, Ton, Toff, concentration of powder (Cp), and magnetic field intensity	MRR, and TWR	The GA approach could be applied to solve this process parameters optimization problem.	Performance needs to be improved.
ABC	2011, Mukherjee and Chakraborty [59], EDM	Ip and Ton	MRR, and SR	The number of iterations (<250) of ABC was less than ACO algorithm or GA.	Few process parameters to be optimized.
GSO	2017, Zainal et al. [60], EDM	Ton and Toff, Ip, and servo voltage (Sv)	Ra	The minimal Ra of 2.03 μm could be searched by the proposed method.	Few machining performances to be considered.
CSA	2011, Shen et al. [61], EDM	Ton, Toff, Ip, and Sv	MRR, and Ra	The number of iterations of the IBCS algorithm was eight iterations.	Multi-objective optimization needs to perform for MRR and Ra.
DEA	2020, Kumar et al. [62], EDM	Vg, Ip, Rs, and cycle time	MRR, SR, TWR, overcut and circularity error	The optimization performance could be acceptable.	The accuracy and consistency of the derived optimal solutions needs to be improved.
GP	2020, Ghadai et al. [63], EDM	Ip, Ton and Toff	MRR, and TWR	Both single-objective optimization and multi-objective optimization were investigated.	The experimental data is too small to affect the accuracy of the model.
EP	2020, Jafarian et al. [64], EDM	Vg, Ton, Ip, and Toff	MRR and Ra	The optimal process combination was successfully achieved using the GP algorithm.	The processing performance involved is relatively small.
GWO	2022, Danish et al. [70], HPM-EDM	Ip, Ton, Vg, and hydroxyapatite amount	MRR, Ra, and RLT	With less than 10% inaccuracy.	Three-objective optimization should be performed for MRR, Ra, and RLT.

3.3. Multi-Objective Optimization

Dang et al. [71] employed the PSO method to conduct the restricted multi-objective (MRR, SR, and tool wear rate (TWR)) optimization of process parameters, which was regarded as the intelligent optimization of the EDM machining process. The results demonstrated that effective process parameter selection could assist the EDM operator in reducing cutting time, as well as expenses. Moghaddam and Kolahan [72] utilized the PSO algorithm to optimize several response characteristics (MRR, SR, and TWR). The proposed approach accurately simulated the actual EDM process with less than 1% inaccuracy, according to the results. Zhang et al. [73] adopted the proposed PSO algorithm, combining quantum behavior and Gaussian local attractor, to provide the best processing parameters for the green MF-EDM while machining SiCp/Al, as depicted in Figure 2. The points in Figure 2 are 15 selected optimized results, which contains minimal and maximum MRR, EWR, and aerosol emissions values, as well as some compromised points. Compared with the average experimental data, the average optimal solution for SiCp/Al, TWR (EWR), and aerosol emissions decreased by around 7.8% and 12.5% respectively, while the MRR increased by around 6.05%. Garg and Lam [74] used the GP technique to model the multiple-response features. The multi-response features, namely one manufacturing aspect (TWR) and two environmental aspects (dielectric consumption and heat energy consumption), were considered in their investigation, and the efficacy of the suggested GP models was validated using experimental data.

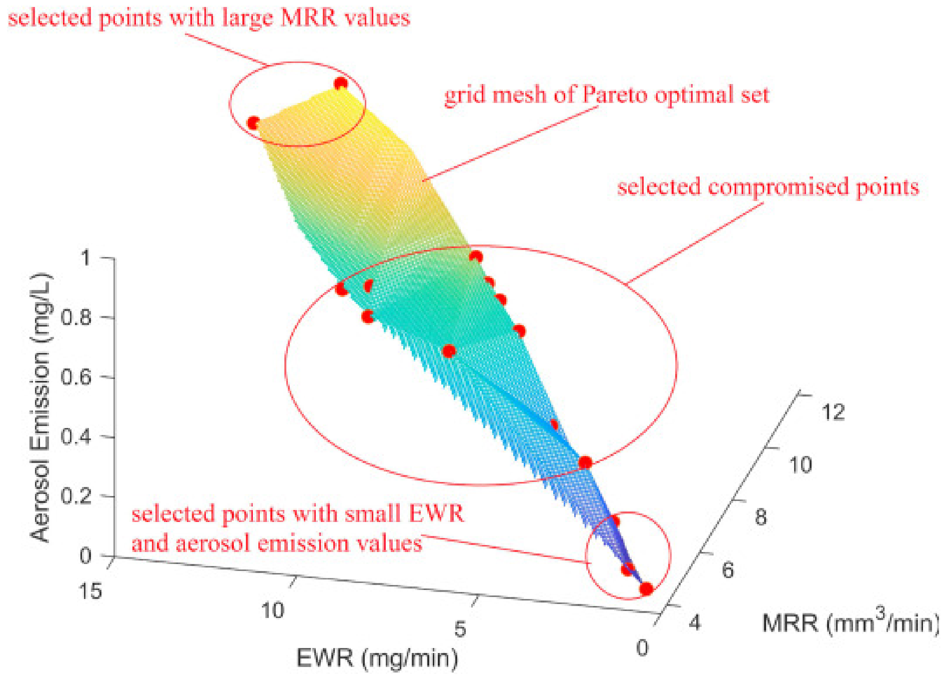


Figure 2. Optimal Pareto for MF-EDM while green machining SiCp/Al, reproduced from [73], permission with Elsevier, 2020.

During the green machining of Al 6061 and SKD 11, Ming et al. [75] recommended utilizing the GSO algorithm to optimize parameters to reduce exhaust emissions and energy consumption. The Pareto frontiers of the multi-objective optimization for Al 6061 and SKD 11 are illustrated in Figure 3, which demonstrate the Pareto frontier of MRR and exhaust emissions characteristics (EEC). The intended EEC in Figure 3a,b was less than 180 μg/m^3 for integrating cutting productivity with environmental friendliness while milling Al 6061. Similarly, the intended EEC for SKD 11 did not exceed 160 μg/m^3. As a result, as shown in Figure 3, the left sides below these criteria are colored green. This suggests that the optimized outcomes in the green zone were less harmful to the environment. The targeted energy efficiency per volume (EEV) in Figure 3c,d was less than 0.51 KJ/mm^3 for integrating machining output with environmental friendliness while cutting Al 6061. Moreover, for SKD 11, the targeted EEV does not exceed 5.5 KJ/mm^3. Similarly, the desired outcomes in the green region were energy efficient. Hence, the optimized combination of cutting process parameters for multi-objective optimization could meet the prediction accuracy.

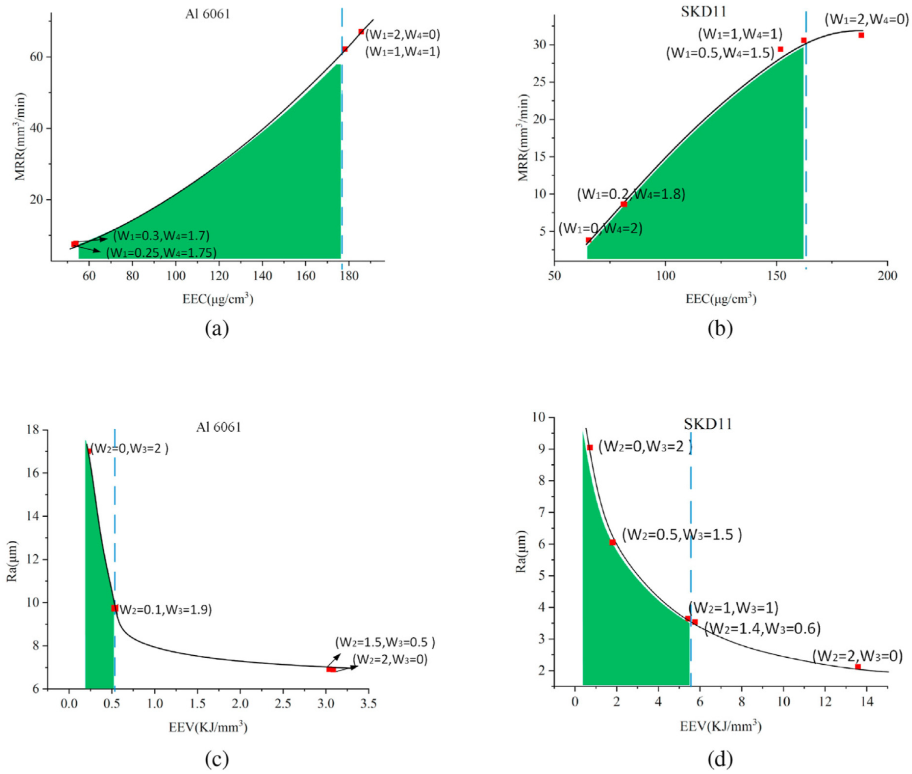


Figure 3. Optimal Pareto for EDM while green machining Al6061 and SKD 11: (**a**) Pareto frontier of MRR and EEC for Al 6061, (**b**) Pareto frontier of MRR and EEC for SKD 11, (**c**) Pareto frontier of Ra and EEV for Al 6061, (**d**) Pareto frontier of Ra and EEV for SKD 11 reproduced from [75], permission with Elsevier, 2021.

3.4. Summary

From the existing optimization of EDM process parameters, most of the research is still focused on single-objective optimization, and the number of research papers on multi-objective optimization is relatively small. This may be related to the characteristics of the swarm intelligence algorithm, which is not suitable for multi-objective optimization. Moreover, in actual production, the demand for single targets may be more urgent under specific circumstances. In addition, since most of the studies are traditional sinker-EDMs, the amount of hybrid sinker-EDMs is also relatively small. Therefore, there have not been many swarm intelligence algorithms involved. Furthermore, it is found that the PSO and GA are the most widely used in the optimization, and the number of studies is also significantly more than other swarm intelligence algorithms. One of the most important reasons for this may be that the PSO and GA algorithms are easy to implement, and their robustness is relatively good, which can meet the needs of engineering applications. Optimization algorithms provide the results of EDM improvements, and the optimized processing parameters can significantly guide the EDM process in an economical and environmentally friendly manner and meet sustainable manufacturing needs.

4. Wire-EDM

4.1. Brief Introduction for Wire-EDM

According to wire speed, wire-EDM (WEDM) can be divided into two categories: high speed wire-EDM (HS-WEDM) and low speed wire-WEDM (LS-WEDM) [76–78]. The wire feed speed of the HS-WEDM ranges from 6 to 12 m/s, and it is commonly employed in low/medium quality mold manufacture and special component processing, and the equipment of the process is depicted in Figure 4a [77]. The HS-WEDM tool electrode is a molybdenum wire, which is fed in a cyclic manner and can be reused. Unfortunately, the electrode wire jitter is high due to the difficulty in applying consistent tension control to the electrode wire, and the wire is easily broken during processing. Furthermore, because the electric wire is reciprocally employed, it will result in electrode wire loss, decreased processing accuracy, and surface quality deterioration. The LS-WEDM electrode wire employs copper wire as the tool electrode and normally travels in a single direction at less than 0.2 m/s, the equipment of the process is depicted in Figure 4b. A pulse voltage of 60–300 V is delivered between the copper wire and the treated material, such as copper, steel, or a superhard alloy, while maintaining a spacing of 550 µm. The gap is filled by deionized water (like distilled water) and other insulating media, resulting in a spark discharge between the electrode and the treated material, which consume and corrode each other [78]. The discharge phenomena are uniform due to digital program control, monitoring and control, and servo mechanism execution, allowing the treated item to be processed, and producing a product with the requisite size and shape precision [79,80]. The HS-WEDM affects the machining accuracy as the electrode wire is recycled, and as the electrode wire continuously wears out. Generally, the accuracy of products machined by the HS-WEDM is ±0.015~0.02 mm. The LS-WEDM electrode wire is not recycled, which greatly improves the machining accuracy, and the machining accuracy of the machine can reach ±0.002 mm.

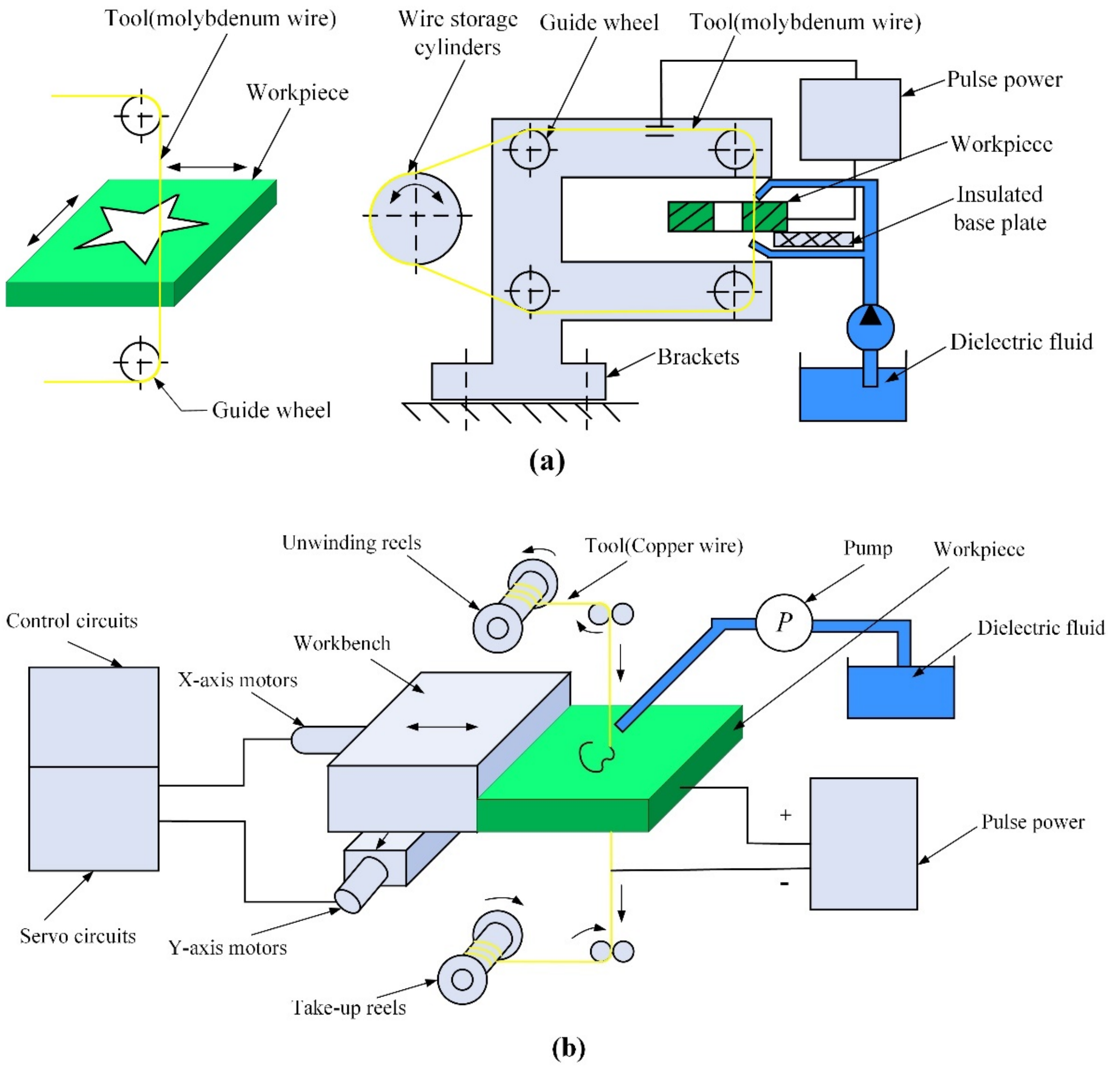


Figure 4. Equipment of the process of WEDM; (**a**) HS-WEDM, (**b**) LS-WEDM.

4.2. Single-Objective Optimization

In single-objective optimization, the optimization of one desired response at a time is carried out. Sharma et al. [81] adopted the PSO method, integrating evaluation based on distance from the average solution (EDAS), to optimize the wire-EDM parameters when cutting biomedical materials. Figure 5 depicts the process flow of the PSO method for optimizing the wire-EDM parameters. The best configuration for reducing the surface imperfections when milling titanium alloy on LS-WEDM was suggested as Ton: 8 µs; Toff: 13 µs; Vs: 45 V; and wire tense: 8 N. Moreover, the forthcoming solution at the optimal parametric values had the following values: an Ra of 3.163 µm, an Rz of 22.99 µm, a wire loss of 0.0182 g, and a dimensional accuracy of 95% [81]. To find the best parameter settings for the LS-WEDM process, Tzeng et al. [82] suggested a hybrid approach combining the GA, a back-propagation neural network (BPNN), and the RSM. The outcomes showed that the GA approach's suggested algorithm provided superior prediction and confirmation results compared to the RSM technique. This means that the GA optimization techniques have a lot of promise for challenging applications in industry. Furthermore, the similar integrating method was also used in the process of the HS-WEDM by our team [83]. For fabricating microchannels in industrial applications, Singh et al. [84] used the GA approach to accomplish the multi-response optimization of the LS-WEDM process parameters for the fabrication of a brass microchannel. They found that the single-response optimization through the GA approach for a maximum MRR = 7.10 mm^3/min and a minimum Ra = 3.36 µm could be obtained. The validation outcomes demonstrated the effectiveness of the proposed optimization models. Kuruvilla and Ravindra [85] applied the Taguchi and GA methods to determine the influence of process parameters on the oil-hardened non-shrinkage steel (OHNS) material with a thickness of 40 mm by LS-WEDM. The variation of the performance parameters with machining parameters was mathematically modeled using the Regression analysis method. The results showed that, in the processing parameters, it was better to use a smaller pulse closing time to achieve a good performance overall.

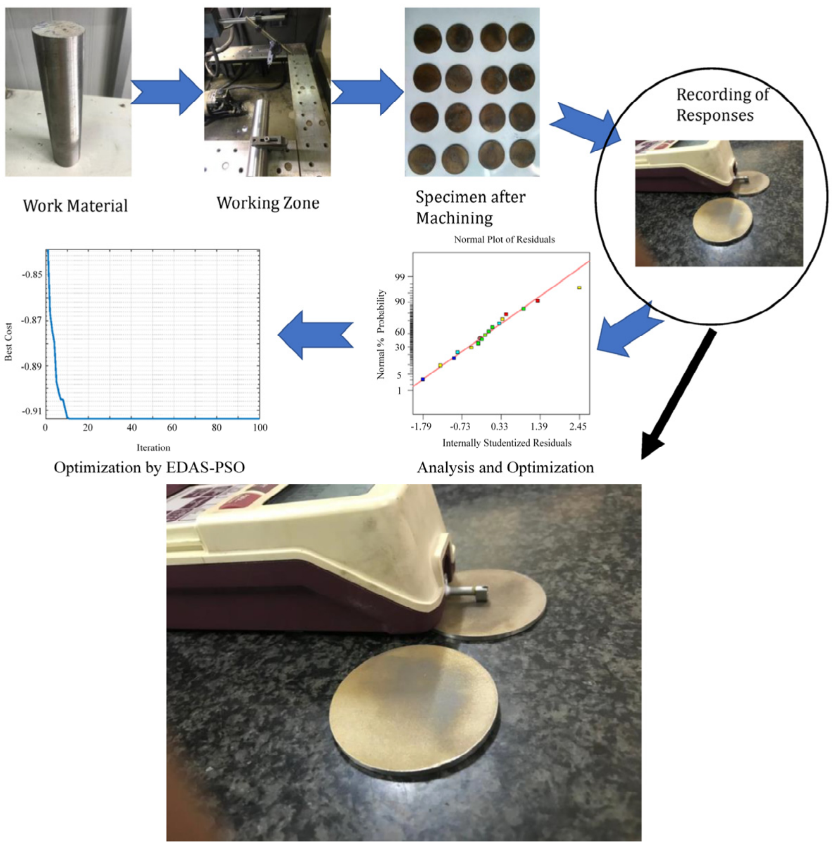
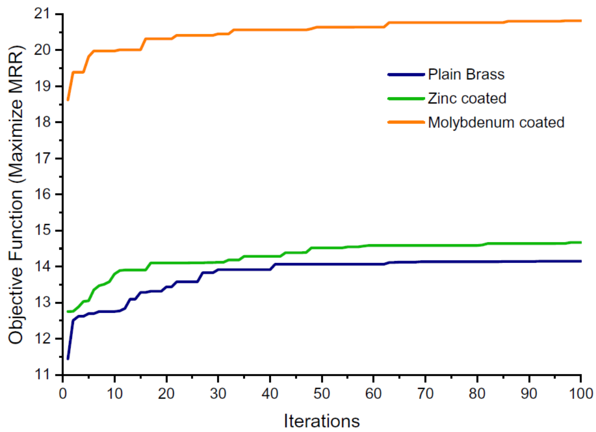


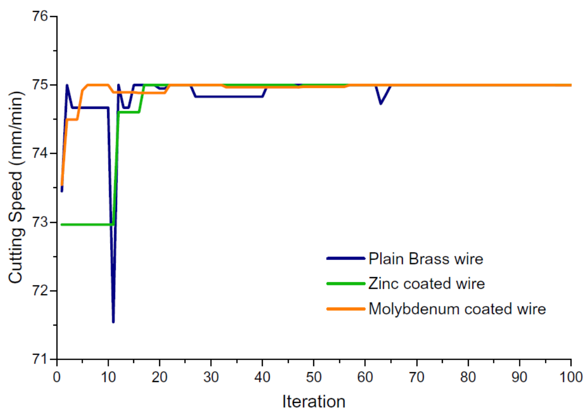
Figure 5. Process flow of the PSO method for optimizing the wire-EDM parameters, reproduced from [81].

Rao and Pawar [86] modeled and optimized the process parameters of LS-WEDM using the RSM and ABC methods. Through the proposed methods, a maximum MRR of 7.10 mm^3/min and a minimum Ra of 3.36 µm were obtained. This demonstrated that the

ABC method, an advanced algorithm of swarm intelligence, could solve the engineering problems. In order to optimize the multiple performance of the dry LS-WEDM process of Al-SiC metal matrix composite, Fard et al. [87] proposed an intelligent model that integrated the ABC algorithm. In this model, the impact of the discharge current, pulse-on time, pulse-off time, wire tension, gap voltage, and wire feed on cutting velocity and Ra was examined. The results showed that brass wire and oxygen gas ensured superior cutting velocity. Additionally, it was discovered that the ABC algorithm could predict the ideal set of process parameters with accuracy. Rao and Venkaiah [88] proposed a modified CSA to optimize the LS-WEDM process when machining Inconel-690 to significantly enhance the performance of the cuckoo search. In comparison to the GA, PSO, and the standard cuckoo search, the proposed method was determined to be accurate and quick. The industry will also benefit from the machining data produced by this endeavor. Similar results could also be confirmed in our previous study in another engineering field [38]. Saravanan et al. [89] investigated the parameters (pulse-on time, pulse-off time, cutting speed, discharge current, wire tension, wire feed, servo voltage, and servo feed) optimization of LS-WEDM through CSA. The optimum machining performance for different conditions could be obtained in no more than 100 iterations, as depicted in Figure 6. Figure 6a represents the variation of the obtained objective function values, where it is observed that the molybdenum wire outperforms the other two wires, namely plain brass and galvanized, during the iterative process. Figure 6b shows that the optimum value of the input parameter cutting speed is 75%, and the speed of molybdenum wire is relatively higher than that of galvanized and ordinary brass wire.



(**a**)



(**b**)

Figure 6. Optimum machining performance for different conditions, reproduced from [89], with permission from Elsevier, 2020; (**a**) MRR, (**b**) cutting speed.

Kulkarni et al. [90] analyzed the machinability and optimized the LS-WEDM of NiTiNOL memory alloy using the modified DEA method. The results confirmed that the convergence curve of the modified DEA was much better than that of the conventional DEA, and the convergence speed was twice as fast as before, thus saving calculation time. Nayak et al. [91] established a genetic programming (GP) model to study six process parameters to optimize angle error and minimize surface roughness. The results demonstrated that GP was a cost-effective and time-saving method compared with typical prediction methods. Xu et al. [92] optimized the process parameters, as depicted in Figure 7, of wire cutting nickel-titanium shape memory alloy (NiTi-SMA) with the help of the BA algorithm and multiple regression (MLR)/BPNN to obtain the maximum processing speed and ideal kerf width. The experimental results showed that the prediction error of the proposed optimization method could be within ±2%, which was valuable for engineering application. As listed below, the comparison of various swarm intelligence techniques for parameters optimization in the wire-EDM process is depicted in Table 2.

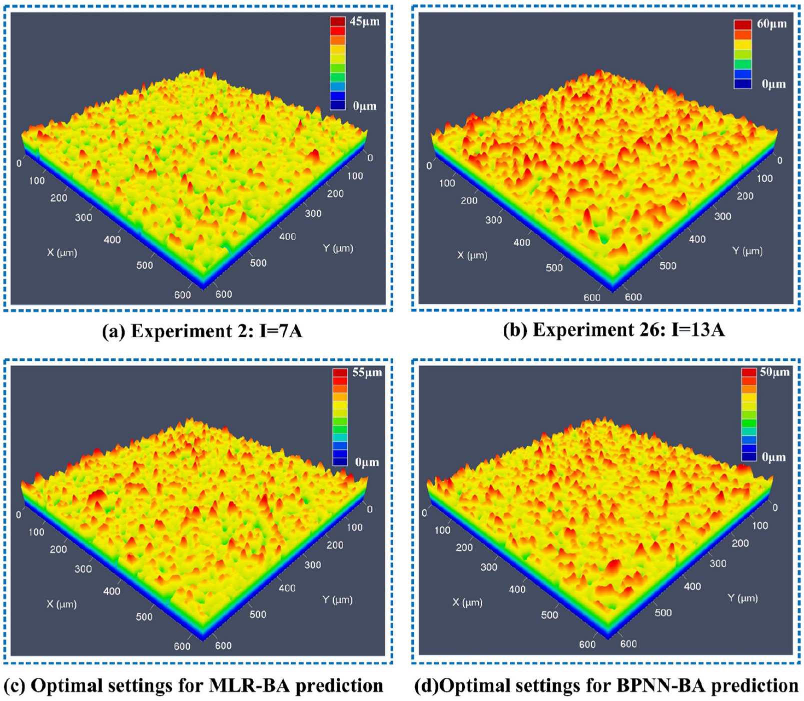


Figure 7. Optimal settings results of 3D CLSM images of the sample surface: (**a**) low discharge energy, (**b**) high discharge energy, (**c**) optimal settings for MLR-BA prediction, (**d**) optimal settings for BPNN-BA prediction, reproduced from [92], with permission from Elsevier, 2022.

Table 2. Comparison of various swarm intelligence techniques for parameters optimization in the wire-EDM process.

Techniques	Year, Authors, Process	Parameters	Performance	Findings	Shortcomings or Limitation
PSO	2023, Sharma et al. [81], LS-WEDM	Ton, Toff, vs. and wire tension (Wt)	Surface roughness (Ra and Rz), wire loss, and dimensional accuracy	The PSO's efficiency in accurately forecasting the outcomes of WEDM-processed machining of pure titanium (Grade 2) was validated.	Multi-objective optimization does not perform.

Table 2. *Cont.*

Techniques	Year, Authors, Process	Parameters	Performance	Findings	Shortcomings or Limitation
GA	2011, Tzeng et al. [82], LS-WEDM	Ton, Toff, arc-off time (Tarc), Vs, wire feed rate (Wf), Wt and Wp	MRR and Ra	The GA optimization techniques have a lot of promise for challenging applications.	The number of samples needs to be increased to improve robustness.
	2013, Zhang et al. [83], HS-WEDM	Ton, Toff, Ip, Wf, and tracking coefficient	MRR and Ra	The prediction error of the model was no more than 10%.	Multi-objective optimization is not considered.
	2020, Singh et al. [84], LS-WEDM	Ip, Ton, and Toff	MRR, and Ra	The maximum MRR = 7.10 mm^3/min and minimum Ra = 3.36 µm could be obtained.	The engineering application is worthy of further study.
ABC	2009, Rao and Pawar [86], LS-WEDM	Ton, Toff, Ip, and servo feed setting	Cutting velocity (CV), and SR	The desired value of Ra = 2.1 µm and CV = 1.106 mm/min could be achieved.	There are few process parameters to be optimized.
	2012, Fard et al. [87], dry LS-WEDM	Ip, Ton, Toff, Wt, Vg, and Wf	CV and SR	The ideal set of process parameters could be predicted.	It is not compared with other optimization algorithms.
CSA	2017, Rao and Venkaiah et al. [88], LS-WEDM	Ton and Toff, Ip, and Vs	MRR, SR, and kerf width	Both single-objective and multi-objective optimization were investigated.	The engineering application should be investigated.
MDE	2020, Kulkarni et al. [90], LS-WEDM	Ton, Toff, vs. and Wf	MRR, SR, and TWR	The convergence speed of modified DEA was twice as fast as conventional DEA.	Multi-objective optimization of MRR, SR, and TWR should be involved.
GP	2022, Nayak et al. [91], LS-WEDM	Ip, Tom, Wt, wire speed, workpiece thickness, and taper angle	Angular error, and SR	GP model was an effective tool for solving this problem.	Other processing properties are not involved.
BA	2022, Xu et al. [92], LS-WEDM	Ip, Wp, Wt, Wf, and discharge frequency	CV and kerf width	The prediction error was within ±2%.	Multi-objective optimization of CV and kerf width should be performed.

4.3. Multi-Objective Optimization

Multi-objective optimization is the process of optimizing two or more conflicting objectives. In machining operations, there are often situations where the desired responses are inherently conflicting. An improvement in one response can worsen another. Ranjan et al. [93] performed the multi-objective optimization of an abrasive powder, including SiC and Al_2O_3, mixed WEDM (APM-EDM) of Inconel 718 using the PSO method. Using a hybrid artificial neural network (ANN) linked GA technique, Vaidyaa et al. [94] sought to maximize the multi-objective optimization of LS-WEDM on AlSi10Mg. In their investigation, the following optimal process parameters were established: vs. of 42 V, Ip of 12 A, and Ton of 12 µs result in a maximum micro-hardness of 478 VHN and a minimum SR of 4.3 µm. Zhang et al. [95] used BPNN combined with the GA (BPNN-GA) and the non-dominated sorting genetic algorithm-II (NSGA-II) to optimize the process parameters on surface integrity, such as white layer thickness (WLT), surface crack density (SCD), and SR, in the LS-WEDM process of the tungsten tool YG15. The best optimum solutions for WEDM machining, which balanced the performance of SR, SCD, and WL, as well as the

Pareto-optimal front of three-objective optimization, were discovered by their proposed methods. Similarly, the gray relational analysis technique (GRA) and the backpropagation neural network-genetic algorithm (BPNN-GA) were used by Soepangkat et al. [96] to accomplish multi-objective optimization in the LS-WEDM process of SKD 61 tool steel. Setting Ton, Toff, and vs. to 3 ms, 10 ms, and 38 V, respectively, would yield the lowest RLT, SR, and SCD.

When performing multi-objective optimization for LS-WEDM on Ti6Al4V alloy, Jain and Parashar [97] compared a priori and a posteriori approaches. A multi-objective ABC with GRA was selected as an a priori approach, and a multi-objective grasshopper optimization algorithm (MO-GOA) was selected as an a posteriori approach. According to the amount of calculating time, it was discovered that the a priori approach to multi-objective optimization was superior to the a posteriori approach. Similarly, the Pareto front was found by extending the modified CSA to simultaneously optimize the MRR, SR, and kerf [88]. Majumder et al. [98] studied the multi-objective optimization of the LS-WEDM process when cutting RAFM steel manufactured in India. They compared the performance of giving optimal results of the FA, the PSO, and the DEA, and found that the FA was better than the others (DEA and PSO). Kondayya et al. [99] described an approach of an evolutionary strategy for the optimization of a LS-WEDM process. The result of Pareto optimal solutions, as depicted in Figure 8, confirmed that the all-encompassing evolutionary strategy was a solution for the process optimization. In the beginning, it was possible to machine components with the best surface quality, but with the lowest MRR. Finally, the highest material removal rate could be achieved, but with the worst surface quality.

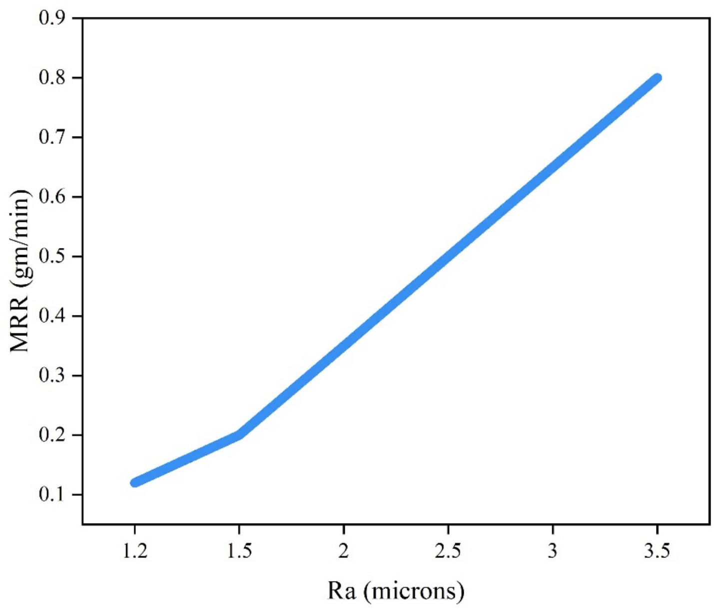


Figure 8. Pareto front of LS-WEDM for the selection of optimum values.

4.4. Summary

One of the most researched areas in machining is process modeling and optimization, as this can reduce production costs and improve product quality. However, experimental optimization of any machining process is expensive and time consuming due to the complexity, coupling, and nonlinear nature of the input and output variables of the process. There are various optimization methods for process parameter optimization. Based on the existing research literature, most of the process parameter optimizations of wire-EDM have been aimed at LS-WEDM, with very few involving HS-WEDM. This is because the machining performance of HS-WEDM equipment is poor, and its processing dimensional accuracy and surface quality are not as good as LS-WEDM. As a result, its application scope is also limited, and the number of relevant research results is very scarce. Most of the machining performances studied in the literature have mainly involved the MRR and the SR, while others such as kerf width, TWR, and angular error are relatively few. Similarly, it has been found that PSO and GA are the most widely applied in the optimization of wire-EDM process parameters, and the number of research articles is also significantly higher than that of other swarm intelligence algorithms, such as the ABC, GP, or BA methods. Furthermore, it is concluded that the attention of researchers has focused on single-objective optimization, and the involved methods of wire-EDM are traditional wire-EDM.

5. Micro-EDM

5.1. Brief Introduction for Micro-EDM

With the increasing miniaturization and precision of products worldwide, micro-fabrication and small-hole EDM, one of the non-contact microfabrication methods, has become an important part of micromechanics and is widely used in the manufacturing industry because of its superfine and high-precision machining characteristics. Although micro-EDM and sinker-EDM are based on the same physical principle of spark erosion, there are still obvious differences. This is because, during its processing, the discharge energy is reduced to the order of 10^{-6}~10^{-7} J to minimize the amount of material removal per unit time and realize the micro-level EDM process. This means that, compared with sinker-EDM, micro-EDM has more difficulties in terms of power control, manufacturing methods of micro-tools, real-time processing monitoring, and other aspects [100–103]. Micro-EDM technology can be categorized into five different types: micro sinker-EDM, micro wire-EDM, micro drilling-EDM, micro milling-EDM, and micro wire electro-discharge grinding [102,104]. Figure 9 demonstrates the principle of the process of micro drilling-EDM and micro milling-EDM.

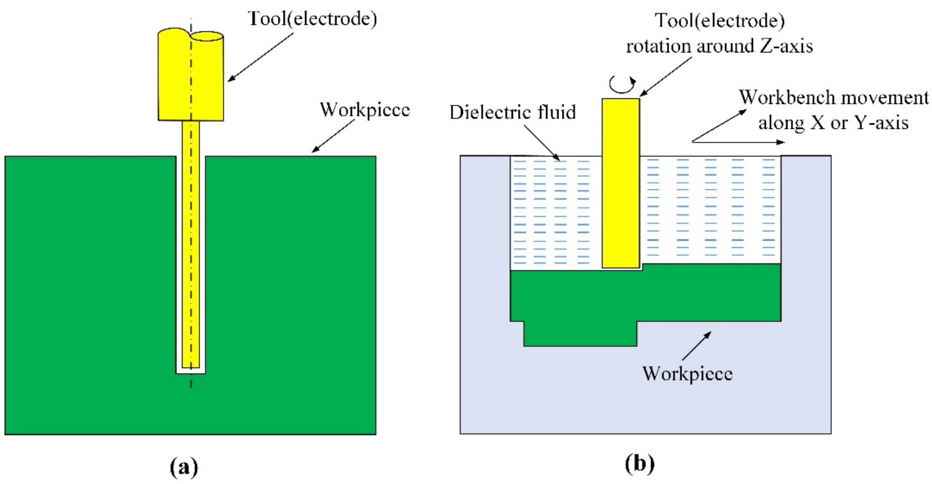


Figure 9. Principle of the process of micro-EDM; (**a**) micro drilling-EDM, (**b**) micro milling-EDM.

5.2. Parameters Optimization

With the use of the PSO optimization technique, Chen et al. [105] suggested a hybrid optimization strategy that increased MRR by a maximum of 49.1% and decreased Ra by a maximum of 37.8% in the micro-WEDM process while machining 65 vol.% SiCp/Al composite. Moreover, the Pareto optimum solution sets, as depicted in Figure 10, had great accuracy and dependability. Similarly, Quarto et al. [106] completed a micro-EDM optimization with the PSO approach. The results showed that the suggested optimization approach may adapt to the automated environment in both scenarios of externally imposed material or processing performance. For optimizing the multi-objective performance of the circularity at the entrance, the hole overcut, and the circularity at the exit of drilled micro holes, a hybrid approach of the PSO integrating gray relational analysis was used in the process of micro hole drilling in Mg alloy [107]. Regarding the prediction of micro-hole quality (radial over-cutting, recast layer thickness, and MRR) on Inconel 718 superalloy treated by micro-EDM, Rao [108] suggested a prediction model based on the bionic intelligent hybrid algorithm. The prediction approach was based on the combination of the adaptive neuro-fuzzy inference system (ANFIS) and the PSO/GA algorithms (ANFIS-PSO/ANFIS-GA). Comparing the ANFIS-PSO against the ANFIS-GA, ANFIS, and ANN models, it was discovered that ANFIS-PSO was superior.

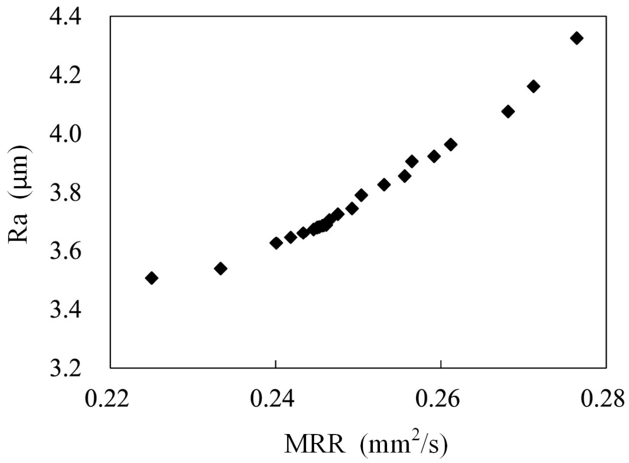
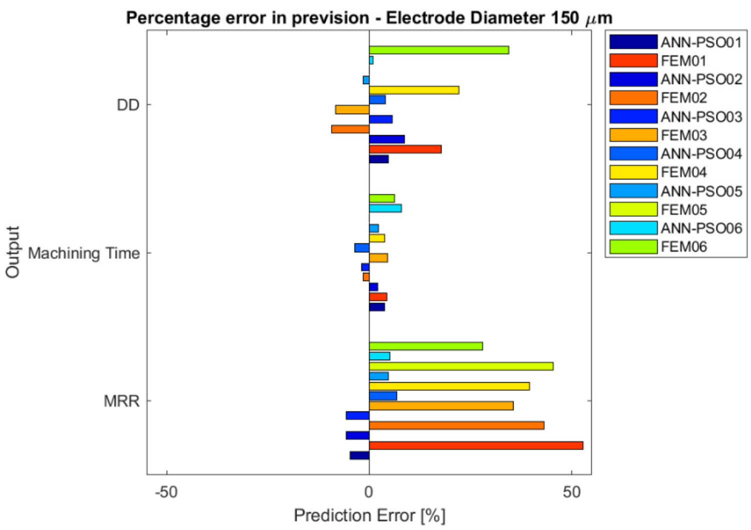


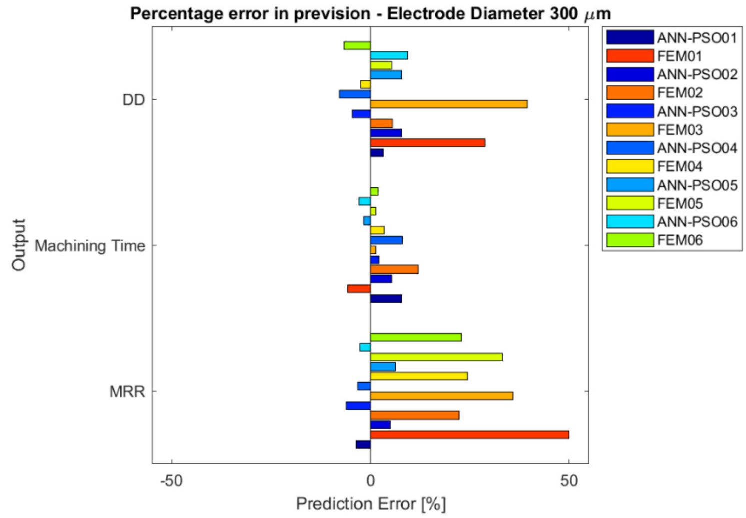
Figure 10. The Pareto optimal solution of MRR and Ra in the micro-WEDM process while machining 65 vol.% SiCp/Al composite, reproduced from [105], with permission from Elsevier, 2021.

To predict the performance (machining time, MRR, and dimensional deviation) of micro drilling-EDM, Quarto et al. [109] compared a finite element model (FEM) simulation and an integrated ANN and PSO technique. In order to meet various industrial objectives, the combined ANN-PSO approach included a twofold direction functionality. It provided a way to anticipate process performance while simultaneously optimizing the process parameters (discharge current, voltage, frequency, tool diameter, workpiece, and tool materials) in relation to the needed performance levels. Figure 11 depicts the bar chart of the prediction error between the experimental results and models simulation, while drilling micro-EDM. The findings demonstrated that the combined ANN-PSO technique provided performance predictions that were more accurate. The ANN-PSO approach was also quicker and simpler to use, but it needed a lot of historical data to train the ANN. In contrast, setting up the FEM was more difficult because it required several physical and thermal properties of the materials, and single simulation took a long time.



(**a**)

Figure 11. *Cont.*



(**b**)

Figure 11. Bar chart of prediction error between experimental results and models simulation while drilling micro-EDM with a tool diameter of (**a**) 150 μm, and (**b**) 300 μm, reproduced from [109].

In micro-EDM, processing parameters greatly affect processing efficiency and stability. Based on Taguchi experiments with support vector machines, Zhang et al. [110] developed a process model for micro-EDM and suggested a novel multi-objective optimization GA to optimize process parameters and decrease machining time and TWR. The GA is an evolutionary algorithm that uses genetic operators to obtain optimal solutions without any assumptions about the search space. GA works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to simultaneously capture several solutions. The suggested multi-objective GA was accurate and efficient in producing Pareto optimum solutions for parameter settings, according to the experimental data. The optimal parameter combination could significantly decrease machining time while maintaining a manageable TWR. Hence, the suggested technology could increase the stability and efficiency of machining while also being appropriate for the parameter adjustment of micro-EDM. Dilip et al. [111] carried out the multi-objective optimization of process parameters on Inconel 718 using weighted objective summation and GA techniques to enhance the processing quality of drilling cooling holes for turbine blades. According to the experimental data, the inner wall's surface roughness could be reduced to 13,587 μm under the ideal cutting circumstances. Furthermore, the confirmed experiments confirm that the maximum relative error obtained was less than 10%.

5.3. Summary

Compared to sinker-EDM and wire-EDM, the number of publications on process parameter optimization for micro-EDM is significantly lower. The reason is that compared to sinker-EDM and wire-EDM, micro-EDM is not widely used, especially in industrial applications. Most of the existing literature on micro-EDM remains at the laboratory stage, mainly focusing on the research of processing mechanisms. Indeed, micro-ED is a branch of EDM, and the machining mechanism of electrical discharge machining, like other special machining, is very complex [112–114]. The existing research has not fully understood its working mechanism [3,115–117]. In addition, the swarm intelligence algorithms for the process parameter optimization of micro-EDM have mainly focused on PSO and GA methods. This is primarily because PSO and GA methods are relatively simple and robust compared to other methods. In micro-EDM, the machining parameters have a great influence on the machining efficiency and stability. In order to correctly set the process parameters of micro-EDM, the process is generally modeled and several new multi-objective optimization GA algorithms are proposed. At the same time, properly selected process parameters can obtain a good clearance state, ensure the stability of the process, and result in low electrode wear, thus greatly improving the machining efficiency.

6. Discussion

This review focuses on the progress in the application of the SI technique in the optimization of EDM process parameters. In this study, the parameter optimizations of sinker-EDM (SEDM), wire-EDM (WEDM), and micro-EDM (MEDM) with various hybrid techniques using SI technique are comprehensively reviewed. This section discusses the three aspects of similarity, individuality, and complementarity of these different SI techniques and machining methods.

6.1. Similarity

The PSO method, which is frequently employed in the optimization of these three categories of EDM process parameters, is the primary representative algorithm of swarm intelligence. The fundamental idea, which looks for the best solution through individual cooperation, comes from research on the behavior of bird flocks moving in groups. First designed to graphically represent the ethereal and erratic movements of flocks of birds in two dimensions, it was later extended to the multidimensional space and used to the solution of optimization problems. The ACO method, which uses the collective optimization capability of biological ant colonies that can find the shortest path from the ant nest to food by straightforward information flow between individuals, is another example of a representative algorithm of swarm intelligence.

The similar characteristics of swarm intelligence can be summarized as follows: At first, because control is decentralized and not centralized, the system is better equipped to adapt to the network and is less likely to be adversely affected by the failure of one or more individual. Second, through indirect communication, each member of a group has the power to influence the environment, spread knowledge, and work together. Third, because each member of a group has very basic skills or behavioral norms, group intelligence is simpler and easier to use. Lastly, because of their ability to self-organize, groups exhibit complex actions that are the result of intelligence that develops via the interaction of individuals [118].

6.2. Individuality

Of course, different swarm intelligence algorithms also have certain differences. The swarm intelligence optimization algorithm mainly simulates the swarm behavior of insects, herds of animals, flocks of birds, and schools of fish. Due to the differences between species, there are certain differences in the implementation methods of different algorithms. For example, the GA has a strong global search ability but a weak local search ability, often only obtaining suboptimal solutions rather than optimal solutions. It can achieve over 90% of the optimal solution with extremely fast speed, but it takes a long time to achieve the true optimal solution, which means that the local search ability is insufficient [88]. The ACO parameter settings are complex, and if the parameters are not properly set, it is easy to deviate from the high-quality solution. Therefore, for different EDM methods, one or more swarm intelligence algorithms can be selected according to the actual situation to optimize their process parameters. In addition, it is worth noting that although sinker-EDM, wire-EDM, and micro-EDM are all branches of electrical discharge machining, their machining mechanisms are basically similar. However, due to significant differences in processing objects, control methods, and processing performance, there are still certain differences in the optimization of process parameters.

Single-objective optimization evaluates only one objective and requires only the optimal value to be found according to the specific satisfaction function conditions. Multi-objective optimization has multiple evaluation functions in place and the solutions, using different evaluation functions, are different. Single-objective optimization problems are simple to implement and have well-established algorithms for solving them, with the disadvantage that they can only be solved for a single objective. Multi-objective optimization is more comprehensive and detailed for objective solving. The disadvantages of multi-objective optimization are that the units are not consistent among objectives of different nature, which are not easy to compare, and the assignment of weighted values for each objective is more subjective. The main algorithms for single objective optimization are the ACO, the PSO, the GA, ABC, the GSO, etc. The main types of multi-objective optimization are weighted methods, constrained methods, and hybrid methods combining weighted and constrained methods and multi-objective genetic algorithms. From the existing research on the optimization of EDM process parameters, most of the research is still focused on single-objective optimization, with relatively few research papers on multi-objective optimization. This may be related to the characteristics of group intelligence algorithms, which are not suitable for multi-objective optimization.

6.3. Complementarity

At present, the mathematical and theoretical foundation of swarm intelligence algorithms is relatively weak. For example, there is no exact theoretical basis for the parameter settings of related algorithms, which significantly depends on specific issues and application environments. In order to better solve practical engineering problems, such as the optimization of EDM process parameters, various types of swarm intelligence algorithms can be used for optimization, thereby increasing the probability of obtaining a global optimal solution. In addition, the existing comparative research on the optimization of EDM process parameters is insufficient, and there is a lack of standard test sets for performance evaluation. This means that there is no absolute credibility or application risk. Therefore, it is necessary to establish a diverse and unified evaluation platform to facilitate the complementary application of swarm intelligence algorithms and improve the engineering application's ability to solve practical problems.

7. Outlooks

Based on the literature review in this study, the future development directions of parameters optimization of EDM using swarm intelligence are as follows.

(1) As one of the five major intelligent forms focused on the development of the new generation of artificial intelligence, swarm intelligence has important application prospects in both civil and military fields. At present, swarm intelligence is still in its infancy in basic theory and mechanism innovation and key technology applications, and various algorithms still need to be continuously studied, improved, and expanded in scope of application. Especially in the field of electrical discharge process parameter optimization, swarm intelligence still has broad application and development space [3,26]. Integrating different swarm intelligence algorithms for optimizing electrical discharge process parameters and better searching for global optimal solutions may be a future development direction.

(2) The existing optimization of EDM process parameters is mainly oriented towards machining performance, such as MRR, SR, TWR, machining accuracy, etc. With the increasing attention paid to sustainable manufacturing, green EDM will become a key feature in the future. The response of processing output not only involves processing performance, but also involves environmental impacts, such as toxic gas emissions, processing noise, green dielectric, and so on [75,116,119,120]. Therefore, there will be more goals to optimize and the difficulty will further increase.

(3) Swarm Intelligent is a heuristic search algorithm based on the behavior of a population to find optimization for a given goal, and is centered on the ability of a population of simple individuals to achieve a more complex function through simple cooperation between them. There are many existing swarm intelligence algorithms, such as ACO, ABC, GSO, etc. These algorithms will be improved as they are applied, and it is believed that future artificial intelligence will also produce more new algorithms that

the optimization algorithm will apply to the EDM, such as selfish herds optimization, bald eagle search, etc.

(4) With the fast advancement of technology, machine learning (ML) has found widespread use in a variety of industries, including industrial testing [121–123], medical diagnostics [124,125], life sciences [126,127], and renewable energy [128–130]. AlphaFold2, for instance, created a protein structure prediction model using ML, which can predict the properties of proteins based on gene sequences and achieve 98.5% of the structure of human proteins [126]. With preliminary artificial intelligence, combining ML techniques with swarm intelligence algorithms to achieve autonomous parameter setting, the dynamic adjustment of search directions, etc., may become a research focus in the future.

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