Data-Driven Analysis In Magnetic Field-Assisted Electrical Discharge Machining of High Volume SiCp/Al

Tao Xue

Huazhong University of Science and Technology

Long Chen

Huazhong University of Science and Technology

Zhen Zhang (✉ jameszhang198808@gmail.com)

Huazhong University of Science and Technology <https://orcid.org/0000-0001-8867-9174>

Jiaquan Zhao

Huazhong University of Science and Technology

Yi Zhang

Huazhong University of Science and Technology

Dongxu Wen

Huazhong University of Science and Technology

Huachang Wang

Huazhong University of Science and Technology

Research Article

Keywords: Magnetic Field-assisted EDM, Predication modelling, Machine learning, Multi-objective moth search optimization

Posted Date: January 3rd, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1212102/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Data-driven Analysis in Magnetic Field-assisted Electrical Discharge Machining of High Volume SiCp/Al

Tao Xue¹, Long Chen¹, Zhen Zhang^{1*}, Jiaquan Zhao^{1*}, Yi Zhang¹, Dongxu Wen²
and Huachang Wang¹

¹School of Aerospace Engineering, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan, 430074, Hubei, China.

² School of Materials Science and Engineering, Huazhong University of Science and Technology, 1037 Luoyu Road, Wuhan, 430074, Hubei, China.

*Corresponding author(s). E-mail(s): jameszhang198808@gmail.com;
jianquan_zhao@hust.edu.cn;

Abstract

This paper presents a framework of data-driven intelligence system which can be applied on magnetic field-assisted electrical discharge machining (MF-EDM) machining process for SiC particulate reinforced Al-based metal matrix composites (SiCp/Al) with different high-volume fractions. The implemented system consists of data modelling, predicating, optimization and monitoring modules. A multi-objective moth search (MOMS) optimization algorithm with back-propagation neural network (BPNN) model and multi-hierarchy non-dominated strategy is proposed for tuning optimal processing performance. Data are collected from machining different fraction volumes of SiCp/Al composites by MF-EDM, with peak current, magnetic, pulse width and pulse interval time as input, and material removal rate, electrode wear rate, surface roughness as output. The BPNN model shows the best accuracy compared to K-nearest neighbours, least square support vector machine and Kriging model. To demonstrate the effectiveness of the MOMS optimization algorithm, a set of results is selected as paradigm, which dominates 95.83% original experiments. A verification experiment is also done for an optimized parameter with 65% fraction and 0.2T magnetic. Both result data and three-dimensional surface topography comparison show that the verification experiment result dominates the original experiment of similar input designs.

Keywords: Magnetic Field-assisted EDM, Predication modelling, Machine learning, Multi-objective moth search optimization

1 Introduction

With the development of modern processing technology and computer science, artificial intelligent has been extensively introduced into manufacture fields. Especially in machining, data information are collected and analysed to promote

the performance of different kinds of processing, like cutting [1], milling [2], drilling [3] and Wire-EDM [4].

Due to the characteristics of light weight, high strength and high toughness, the SiCp/Al composite materials are broadly applied in many

modern industries such as electronics, automotive field and aerospace area [5, 6]. Especially, high volume fraction SiCp/Al composites have brighter application prospects in the field of military aviation [7]. With the wide application of composite materials with high SiC volume fraction, the requirements of geometric precision and surface precision of parts have also improved.

Although SiCp/Al composites are heat-resistant, wear-resistant and have good fatigue resistance, they are difficult to be machined by traditional contact machining methods because the material contains SiC ceramic particles with high hardness which are completely opposite to the characteristics of Al body. It is not only easy to damage the tool and reduce the tool life, but also can cause large cracks on the material surface due to stress concentration by traditional contact machining methods. The surface quality has a more significant destructive effect when the volume fraction of SiC is high. Therefore, it is urgent to adopt non-contact machining methods without macro-cutting force to fabricate SiCp/Al composite structure [8–10]. Among non-conventional machining, such as electro-chemical, laser-beam, abrasive water jet machining and electro-discharge, electrical discharge machining (EDM) is a high-precision special machining technology which can be used for complex structure shaping [11]. Since EDM has no macro cutting force in the process, EDM is suitable for machining SiCp/Al composites with high brittleness and hardness, to achieve high dimensional accuracy and good surface quality [12, 13]. But there are also shortcomings in EDM: low machining efficiency, inevitable electrode wear, significant recast layer and cracks on the machined surface. Moreover, ceramic reinforced phase SiC particles of SiCp/Al damage to the formation of discharge channels, resulting in unstable EDM process and seriously affecting the processing efficiency and surface quality [14, 15].

According to the latest research, the magnetic field assisted method has a significant positive influence on the formation of EDM discharge channel, the process of discharge erosion and the formation of molten pool, so it can improve the efficiency of debris removal, the surface quality, and the rate of material removal [16, 17]. Since there are lots of input parameters in the process of EDM like peak current value, pulse width

time and pulse interval time. These parameters have a great influence on the machining results, like surface roughness (RA), material removal rate (MRR) and electrode wear rate (EWR). Appropriate combinations of parameters are needed to obtain the desired machining performance, but this is not easy because of the lots of input parameters and the complexity and randomness of machining process. Thus a well developed data-driven intelligent system for machining should contain suitable modelling and optimization modules to generate the relationship between input values and output results [18, 19].

This paper proposes a data-driven system for transverse magnetic field-assisted EDM process for SiCp/Al composites with different high volume fractions. The system contains 3 functions: (1) apply modelling method on the experiment data, generate a model for data predication; (2) use optimization algorithm to optimize the parameters and outcomes; (3) record the pulses states to monitor the machining process.

Machining Data

Generally, the machining experiments takes several different input parameters and provide output results. Full cases design considering all possible cases for all the parameters can surely provide the most comprehensive results. However, due to the highly cost of time and material for the experiments, Taguchi orthogonal experiment is the most applied method for machining experiments [20]. It makes a robust design of experiment while decreasing the variation, and provides necessary minimum data collection required to determine the product performance.

Predication Modelling

Various modelling techniques have been used to build the process model of EDM machining. Neural networks (NN) methods are popular in the recent years, which also have been successful used for EDM process modelling in many studies. Maity and Mishra applied an artificial neural network (ANN) for wire-EDM data predication and got agreeable results when compared with experimental data [19]. A radial basis function neural network (RBFNN) model were used by Ong et.al. [21] for modelling electrical discharge machining of polycrystalline diamond, which gave

Fig. 1 Modules of Intelligent System for MF-EDM Processing

a considerable small mean-squared error. A back propagation neural network (BPNN) model was used by Zhang et.al. [16] for magnetic-assisted EDM modelling. However, due to the experiment cost, the machining process result set is usually in a comparative small size. This drawback limits the use of NN methods, other algorithms may present better modelling capability than ANN in some studies. Jurkovic et.al. [22] applied support vector machine (SVM) for data regression over 3 output values, tool lifetime, roughness and cutting force. In their research, although ANN had the better performance than SVM in tool lifetime modelling, SVM is better in surface roughness and cutting force prediction. It releases a signal that, to generate a more accurate model for data prediction, different methods should be applied and compared to find an appropriate model.

Optimization

Intelligent optimization algorithms are widely adopted to optimize and select the process parameter in EDM. Researchers are seeking for efficient algorithm with multi-dimensional input for EDM cases. For example, genetic algorithm (GA) [23, 24], artificial bee colony (ABC) [25] and particle swarm optimization (PSO) [16, 26] have all been apply for EDM process optimization. Moth search algorithm (MS) proposed by Wang is a heuristic algorithm based on the phototaxis behavior of the moths with Lévy fly strategy [27]. The

algorithm is flexible with simple operators. After testing by a set of IEEE CEC benchmarks and real word problems, it has shown superior performance comparing to ABC, stud GA, PSO, biogeography-based optimization (BBO) and differential evolution (DE) under multi-dimensional cases [27]. Ong et.al. employed moth search algorithm as parameter optimizer for EDM process [21], where peak current value, pulse width and pulse interval are input parameters, MRR and EWR are output objectives. The MRR was maximized and EWR was minimized after applying the algorithm. The performance has encouraged us to apply MS algorithm on the optimization cases with more input and output dimensions. On the other hand, in Multi-objective optimization, Pareto surface is optimized output. Data are usually disposed directly when they are dominated by others, though they still contain useful information. Making using of these data with a suitable method should improve the performance of optimization algorithm.

Monitoring

To guarantee the processing is in the right state, pulse state is a important value in electrical discharge machining. Sparks are the desired pulse state, and transition arcs are also acceptable. However, since open and short circuits are unavoidably taken place, monitor and record these states could help system to decide whether

the processing is in good manner.

In this work, 35%, 45% and 65% SiCp/Al composites are used in EDM processing. Peak current, magnetic, pulse width and pulse interval time are also considered as inputs and MRR, EWR and RA values are output criteria. Four different algorithms, k-nearest neighbors, least square support vector machine, Kriging model and back propagation neural network are used to construct models for the EDM experiment. Comparing the accuracy of modelling results, a back propagation neural network model with 6 neuron hidden layer is chosen for optimization. Then a multi-objective moth search algorithm is introduced for parameter optimization. A multi-hierarchy non-dominated strategy is used in the algorithm trying to make full use of all the data in the optimization process.

The remain texts are constructed as follows: Section 2 presents the experimental procedure and data; Section 3 describes four different methods for data modelling which are used in the work and multi-objective moth search algorithm for parameter optimization; in Section 4, the experiment data sets are applied in the algorithms, BPNN is selected as the most accurate model after comparison and used as fitness function for optimization, verification experiment is conducted for optimization performance assessment; Section 5 describes the implementation of intelligent system for MF-EDM processing; Section 6 concludes the work and proposes the future work.

2 Experimental procedure

2.1 Experimental device

To carry out the experimental research on the magnetic field EDM process, a magnetic field assisted EDM experimental device, as shown in Figure 2, is built, which mainly includes the main structure, electromagnetic equipment, control system, circulating filtering and cooling system, air compressor, machining monitoring system and exhaust system. Meanwhile, SiCp/Al composite plates with SiC volume fraction of 35 %, 45 % and 65 % are selected as experimental materials, and the thickness of the plates are 4mm (see Table 1). The melting point and boiling point of aluminum substrate are 660 °C and 2327 °C respectively,

and the sublimation temperature of SiC particles is 2700 °C. The electrode is made of cylindrical brass with a diameter of 10 mm and a length of 80 mm.

The main structure includes regulated power supply, working machine tool (GF FORM E350), vertical feed mechanism, electrode fixture, etc. The electromagnetic equipment includes a pair of cylindrical electromagnetic poles (diameter is 30mm), DC excitation power supply and Tesla meter. The processing sample is installed between the two magnetic poles with a clamp, and the magnetic field intensity in the processing area is changed by adjusting the current and the gap between the magnetic poles. The magnetic field intensity is accurately measured with a Tesla meter, and the maximum magnetic field intensity can reach 0.4t. The control system is used to set the parameters (current, pulse width, pulse interval) of EDM, and automatically control the electrode vertical feed according to the program. The circulating filtration and cooling system include liquid storage tank, high-pressure pump, filter element, water cooler, hydraulic valve and relevant pipelines to ensure the circulating supply of working fluid at a constant temperature (20 °C).

2.2 Experimental method

This work mainly focuses on process parameters current, pulse width, pulse interval and magnetic field strength in magnetic field-assisted EDM. In order to accurately analyze the influence of process parameters on material removal rate (MRR), electrode wear rate (EWR) and surface roughness (RA), four horizontal values are set for each process parameter. DOE module of Minitab software is used for parameter design of Taguchi orthogonal experiment, and 16 groups of experiments parameters are generate for each volume fraction of SiCp/Al Composites. The processing time t of each experiment group is recorded during the experiment. Due to the material etching shape is a cylinder with diameter of 10mm and height of 1mm, the electrode feed depth is setting as 1mm and the diameter is 10mm for each group of experiment. The calculation formula of material removal rate is $MRR = 10^2 \pi / t$.

Unprocessed brass electrodes are used for each group of experiment. After each processing, the electrode is cleaned by ultrasonic cleaner for 15

Fig. 2 Experimental Device and Workpiece Samples

Table 1 Machining Conditions of Magnetic Field Assisted EDM

Conditions	Values
SiC volume fraction	35 %, 45 % and 65 %
Workpiece Size (mm ³)	Cuboid, 40 × 150 × 4
Melting point of aluminum substrate(°C)	660
Boiling point of aluminum substrate(°C)	2327
Sublimation temperature of SiC particles (°C)	2700
Processing angle	Straight down
Dielectric liquid temperature (°C)	20
Electrode materials	Brass
Electrode size(mm ³)	Cylinder, Diameter 10mm, Length 80mm

minutes. The brass electrode is measured by electronic balance both before and after processing. The mass are recorded respectively. The calculation formula of electrode loss rate is $EWL = (m_1 - m_2)/t$.

The surface roughness of machined micro-holes is measured by TR-200 roughness meter. In order to compare the material surface morphology under the conditions of magnetic field and non-magnetic field in further detail, the machined surface defects and the thickness of recast layer are detected by scanning electron microscope (model JSM-7600F) and the 3D surface morphology of processed

SiCp/Al composites is analyzed by ultra-depth three-dimensional microscope.

3 Prediction and Optimization Methodology

3.1 Prediction Methodology

To find a suitable model for the experiment data, four different methods, k-nearest neighbors, least square support vector machine, Kriging model and neural network with back propagation strategy are tried to generate the models in this work.

Table 2 Main Factors and their level for machining experiments (4 inputs and 4 levels)

Volume	Current (A)	Pulse width (μ s)	Pulse interval (μ s)	Magnetic (T)
35%	10	120	100	0
	15	150	120	0.1
	20	180	140	0.2
	25	210	160	0.3
45%	10	150	120	0
	15	180	140	0.1
	20	210	160	0.2
	25	240	180	0.3
65%	15	120	80	0
	20	150	100	0.1
	25	180	120	0.2
	30	210	140	0.3

K-Nearest Neighbours

K-nearest neighbors (KNN) [28] is a simple but powerful supervised machine learning algorithm that can be used for regression. It is based only on the basic assumption: observations with similar characteristics tend to produce similar results. It examines a set of data points, which are called neighbours around the target point, then makes a prediction about the target value.

Least Square Support Vector Machine

Support Vector Machine (SVM) [29] is a supervised learning method. It usually applied for data classification and regression within a given decision boundary. Least Square Support Vector Machine (LSSVM) [30] is a reformulation of the principles of SVM. Instead of the inequality constraints and e-insensitive loss function, LSSVM uses the equality constraints and least squares loss function for data processing.

Kriging method

Kriging is a meta-modelling method with Bayesian interpolative strategy. It was originally introduced for the geostatistic study, and extended to deterministic computer research later [31]. Kriging model can not only give the estimate value of the unknown function, but also give the error estimate of the estimate value [32]. With a distinct error estimation function, it has exceptional capability for nonlinear function approximation. The interpolation result of Kriging model is defined as the summation of the sample function response value with weights.

3.2 Neural Networks

Artificial neural networks is a popular and fast developing tool in the recent years, which simulates the learning process of human brain. A neural network model usually contains an input layer, an output layer and several internal layers. The backpropagation neural network (BPNN) [33] is a neural network method that uses backpropagation strategy to modify the weights of internal network layers after each training cycle to reduce errors [34]. BPNN is widely used in function estimation in the mechanical engineering because of its simple structure and good ability for nonlinear function approximation.

3.3 Optimization with Multi-objective Moth Search Algorithm

3.4 Moth Search Algorithm

Moth search algorithm (MS) originally given by [27] is a heuristic algorithm based on the phototaxis behaviors of the moths. In MS, the best moth is considered as the source of light. The moths close to the best individual make Lévy flights near their own positions, other moths far from the best individual are prone to fly towards to it directly due to the phototaxis. During the process, Lévy flights guarantee the exploitative and phototaxis guarantees the explorative, so the algorithm can make balance between the both.

When the moths fly around the best individual in the form of Lévy flights, for moth i , the position can be updated as:

$$x_i^{t+1} = x_i^t + \alpha L(s) \quad (1)$$

t is the current generation, x^{t+1} and x^t are respectively the updated and original position at generation t . $L(s)$ is the step length of Lévy flights and α is a scale factor defined as:

$$\alpha = \frac{S_{max}}{t^2} \quad (2)$$

$$L(s) = \frac{(\beta - 1)\Gamma(\beta - 1) \sin \frac{\pi(\beta - 1)}{2}}{\pi s^\beta} \quad (3)$$

S_{max} is max walk step and s is a constant larger than 0, the values are set according to the

given problem. $\Gamma(p)$ is the gamma function defined as

$$\Gamma(p) = \int_0^{+\infty} e^{-x} x^{p-1} dx$$

and β is a tuning factor usually set to be 1.5.

For the moths far from the best individual, they tend to fly directly the best in a straight line. For moth i , the position is randomly updated by equation (4) or equation (5) with the same possibility:

$$x_i^{t+1} = \lambda \times (x_i^t + \frac{1}{\varphi} \times (x_{best}^t - x_i^t)) \quad (4)$$

$$x_i^{t+1} = \lambda \times (x_i^t + \varphi \times (x_{best}^t - x_i^t)) \quad (5)$$

where x_{best}^t is the best moth at generation t , φ is an acceleration factor, and λ is a scale factor. The detailed process can reference literature [27].

3.5 Multi-hierarchy Non-dominated Set

Consider a problem with m minimized objectives. Let f_k^i be the scaled value of the k^{th} objective for the i^{th} data in a particular generation. The j^{th} data dominates the i^{th} design if:

$$f_k^i \geq f_k^j \quad \forall k \in \{1 \dots m\}$$

$$f_k^i > f_k^j \quad \exists k \in \{1 \dots m\}$$

For two data X and Y , it is called X dominates Y , if:

$$\forall y \in Y, \exists x \in X, \text{ where } x \text{ dominates } y$$

To make full use of each data, a multi-hierarchy strategy for non-dominated set is used. All the data points are separated to several hierarchies, each hierarchy is a non-dominated set. The hierarchies are marked with level numbers 1,2,... The top level, hierarchy 1, is the utmost non-dominated set, which dominates the set of all the rest designs. Then the rest designs are considered without hierarchy 1, finding a new utmost no-dominated set, marking with number 2. Such procedure is repeated until all the points are marked in the corresponding set. Suppose m hierarchies are generated at the end, generally, the set of hierarchy i dominates all the union of all the sets in hierarchies $i+1, i+2, \dots, m$. Finally, instead of a single Pareto front obtained by non-dominated

set, several Pareto fronts are generated (see Figure 3).

Fig. 3 Multi-hierarchy Pareto fronts

To get more uniformed solutions, crowded degree is considered to avoid closed designs. It is calculated by space between the nearest two elements after sorted. In multi-hierarchy strategy, the crowded degree is calculated for each non-dominated level and used to sort the samples in the same dominance hierarchy level (see Figure 3).

With such multi-hierarchy non-dominated strategy and crowded degrees for each level, every design X has two aspects, X_{level} and X_{crowd} , X_{level} stands for the level of hierarchy and X_{crowd} is the value of crowded degree. The whole design set then is a total order set where all the designs can be ordered. Suppose the design set is D , the order relation $\sqsubseteq$ for the set is defined as $\forall X, Y \in D$,

$$X \sqsubseteq Y \iff (X_{level} < Y_{level}) \vee (X_{level} = Y_{level} \wedge X_{crowd} > Y_{crowd})$$

3.6 Multi-objective moth search algorithm(MOMS)

In the multi-objective moth search algorithm (MOMS), suppose the population of moths is pop . A new set of moths is generated in every iteration based on the moth algorithm. For each generation, half of the individuals with higher priority from the previous generation are selected as the parent population. The previous and current two generations will be merged together and sorted by the order relation $\sqsubseteq$. The moths at the end of the order

will be removed to keep the population size being *pop*. Such process keeps going until the max iteration is reached. Finally, the non-dominated set with level 1 is chosen as the output of the algorithm. The detailed steps for MOMS are described in algorithm 1.

4 Results and discussion

The experiment data is shown in Table 3. Four methods KNN, LSSVM, Kriging and BPNN are used to generate model to simulate the experiment. Five statistics measures are applied to compare the residual errors of different models in order to select the best model, which is used as fitness function for multi-objective optimization with MS algorithm.

4.1 Comparative analysis of prediction models

The experimental data sets (Table 3) are split into two parts. 42 sets of data are used to build regression model and the rest 6 are used to test the accuracy the models. In order to make a comprehensive validation set, the selected data should cover all different value of volume fraction percentage, current, pulse width time, pulse interval time and magnetic. Following such guideline, data of No.7, No.16, No.20, No.27, No.38 and No.45 from the experimental data are picked for model validation, the sets are renumbered as T1 to T6 (see Table 4).

KNN, LSSVM, KRIGING, and BPNN are used to train 4 different regression models with 42 training data. All the models has five input values (volume fraction percentage, current, pulse width time, pulse interval time and magnetic) and three output values (RA, MMR and EWR). Some key settings for each model are as follows: the KNN model takes K as 5 and uses Euclidean metric for distance measuring; the LSSVM model chooses an Gaussian RBF kernel; the KRIGING model uses Gaussian correlation; the BPNN model has one hidden layer with 6 neurons. All the four models are tested with the values from Table 4 and the validation results are listed in Table 5.

For RA, BPNN model provides 4 best results: T2 (8.4551), T3 (4.9602), T4 (4.7812) and T5 (3.8641), the values are 9.1%, 2.7%, 8.1% and 16.4% different from experiment data respectively.

Algorithm 1 Multi-objective moth search algorithm

BEGIN

STEP 1: Initialization.

Set the generation number $t = 1$; Initialize the population P of N moths randomly using uniform distribution, the maximum generation $MaxGen$, max walk step S_{max} , the index β , acceleration factor φ , the max capacity of solutions $nrep$, scale factor λ , and factor s .

STEP 2: Fitness evaluation.

Evaluate each moth individual according to its position.

STEP 3: Sort for the moths.

Non-dominated sort for all the moth individuals by their fitness. Calculate the crowded degree of moths to sort the individuals in the same dominance hierarchy. Roulette method is used to select the leader from non-dominated front.

STEP 4:

while $t < MaxGen$ **do**

for $i = 1$ to $\frac{P}{2}$ **do**

 Generate x_i^{t+1} by performing Lévy flights as Eq. (1).

end for

end

for $i = \frac{N}{2} + 1$ to N **do**

if $rand > 0.5$ **then**

 Generate x_i^{t+1} by Eq. (4);

else

 Generate x_i^{t+1} by Eq. (5).

end if

end for

end for

end

Evaluate the fitness for off-spring individuals. Non-dominated sort for all the moth individuals by their fitness.

Collect the optimal solution

Put the non-dominated front into *rep*, do non-dominated sort for *rep* and remove the individuals, which are dominated by others.

while the number of samples in *rep* $> nrep$ **do**

 Remove the samples with crowded degree, keep *nrep* individuals in *rep*;

end while

end

Select half of the individuals with higher priority as the parent population, and use Roulette method choose the leader from non-dominated front.

$t = t + 1$.

end while

end

STEP 5: Output the best solution.

 Output *rep*.

END

Table 3 Experimental Data of 35% 45% and 65% Volume Fraction SiC_p/Al

Exp No.	Volume (%)	Current (A)	Pulse width (μ s)	Pulse interval (μ s)	Magnetic (T)	RA (μ m)	MRR (mm^3/min)	EWR (mg/min)
1	35	10	120	100	0	8.4	0.36	3.33
2	35	10	150	120	0.1	8.2	0.22	3.51
3	35	10	180	140	0.2	5.6	0.11	3.01
4	35	10	210	160	0.3	9.1	0.12	3.29
5	35	15	120	120	0.2	8.3	1.98	7.81
6	35	15	150	100	0.3	8.7	1.41	6.95
7	35	15	180	160	0	6.8	1.03	6.61
8	35	15	210	140	0.1	8.5	0.62	5.24
9	35	20	120	140	0.3	8.6	6.00	13.33
10	35	20	150	160	0.2	9.4	4.39	13.08
11	35	20	180	100	0.1	8.5	5.11	15.03
12	35	20	210	120	0	6	3.12	12.89
13	35	25	120	160	0.1	8	13.34	20.54
14	35	25	150	140	0	7.3	10.99	20.13
15	35	25	180	120	0.3	9	10.21	21.54
16	35	25	210	100	0.2	9.3	8.13	21.03
17	45	10	150	120	0	4.7	0.22	2.15
18	45	10	180	140	0.1	4.8	0.08	1.95
19	45	10	210	160	0.2	4.1	0.08	2.09
20	45	10	240	180	0.3	5.1	0.06	2.03
21	45	15	150	140	0.2	4.8	1.13	5.28
22	45	15	180	120	0.3	4.6	0.99	5.11
23	45	15	210	180	0	4.7	0.63	4.09
24	45	15	240	160	0.1	6.6	0.50	4.03
25	45	20	150	160	0.3	4.2	4.69	11.38
26	45	20	180	180	0.2	6.2	3.66	9.06
27	45	20	210	120	0.1	5.2	3.05	11.56
28	45	20	240	140	0	4.3	2.49	9.38
29	45	25	150	180	0.1	3.9	11.31	15.95
30	45	25	180	160	0	4.1	9.48	15.56
31	45	25	210	140	0.3	3.8	9.42	15.49
32	45	25	240	120	0.2	4.2	8.14	15.84
33	65	15	120	80	0	5.63	1.35	2.86
34	65	15	150	100	0.1	5.6	0.81	2.77
35	65	15	180	120	0.2	5.8	0.69	2.21
36	65	15	210	140	0.3	5.83	0.54	2.17
37	65	20	120	100	0.2	5.49	5.51	6.83
38	65	20	150	80	0.3	4.62	5.77	7.61
39	65	20	180	140	0	5.47	3.79	5.87
40	65	20	210	120	0.1	6.22	2.60	4.76
41	65	25	120	120	0.3	5.63	11.70	9.16
42	65	25	150	140	0.2	6.09	10.29	9.60
43	65	25	180	80	0.1	6.16	8.80	10.39
44	65	25	210	100	0	6.35	7.76	9.48
45	65	30	120	140	0.1	5.89	16.60	10.77
46	65	30	150	120	0	5.67	14.94	11.62
47	65	30	180	100	0.3	5.87	14.02	11.72
48	65	30	210	80	0.2	5.88	12.68	11.87

Table 4 Selected Experimental data for Model Validation

Test No.	Volume (%)	Current (A)	Pulse width (μ s)	Pulse interval (μ s)	Magnetic (T)	RA (μ m)	MRR (mm^3/min)	EWR (mg/min)
T1(7)	35	15	180	160	0	6.8	1.03	6.61
T2(16)	35	25	210	100	0.2	9.3	8.13	21.03
T3(20)	45	10	240	180	0.3	5.1	0.06	2.03
T4(27)	45	20	210	120	0.1	5.2	3.05	11.56
T5(38)	60	20	150	80	0.3	4.62	5.77	7.61
T6(45)	60	30	120	140	0.1	5.89	16.60	10.77

Table 5 Validation Accuracy Comparison of Different Models

	Cases	KNN	LSSVM	KRIGING	BPNN	EXP
RA	T1	5.1750	7.8793	6.7460	7.2531	6.8
	T2	7.4625	7.0620	7.7512	8.4551	9.3
	T3	6.1250	7.1008	6.3007	4.9602	5.1
	T4	6.1300	4.1804	6.0404	4.7812	5.2
	T5	5.7200	6.7534	5.7623	3.8641	4.62
	T6	6.4975	4.7937	5.8684	6.315	5.89
MRR	T1	3.3325	0.7403	2.2147	0.9613	1.03
	T2	6.5500	6.8633	9.0444	9.417	8.13
	T3	0.3325	2.3384	2.0422	0.0605	0.06
	T4	3.9400	3.6022	3.6000	3.2025	3.05
	T5	4.1175	3.4066	5.6594	4.7459	5.77
	T6	10.7325	22.7274	11.5080	14.494	16.60
EWR	T1	7.3950	6.8630	6.1994	4.4505	6.61
	T2	14.7350	19.9895	18.2449	20.2555	21.03
	T3	3.3750	0.0455	4.9297	2.6447	2.03
	T4	9.5950	9.3034	10.2401	11.6615	11.56
	T5	5.7125	4.8659	7.999	7.404	7.61
	T6	10.9275	13.6159	10.7557	11.9841	10.77

KRIGING model is the best in other 2: T1 (6.7460) and T6 (5.8684), the values are 0.79% and 0.37% different from experiment data respectively.

For MRR, BPNN has 4 best simulation results: T1 (0.9613), T3(0.0605), T4(3.2025) and T6(14.4940), the values are 6.7%, 0.83%, 5.0% and 12.7% different from experiment data respectively. KRIGING model is the best in other two: T2 (9.0444) and T5 (5.6594), the values are 11.2% and 2% different from experiment data respectively.

For EWR, BPNN also has 4 most outstanding simulation results T2 (20.2555), T3(2.6447), T4 (11.6615) and T5 (7.404), the values are 3.7%, 30.2%, 0.88% and 2.7% different from the experiment data respectively. LSSVM has one best result: T1 (6.863), the values is 3.8% different from the experiment data respectively. KRIGING model is the best in rest one result: T6 (10.7557) which is 0.13% different from the experiment data.

The above analyse of data in Table 5 shows that BPNN performs slightly better in all RA, MRR and EWR modelling . It provides the best predication in 2/3 cases. Figure 4(a)-(c) presents that the BPNN line is closer to the experiment data line than other methods. However, to make a more comprehensive model comparison, some statistics measures are still required. The following 5 statistics measures are applied to evaluate the residuals for all the models: (1)Root Mean Square Error (RMSE); (2) Normalized Root Mean Square Error (NRMSE) (3) Mean Absolute Error (MAE); (4) Mean Absolute Percentage Error (MAPE); (5) Symmetric Mean Absolute Percentage Error (SMAPE). Suppose $v = \{v_1, v_2, \dots, v_n\}$ is the real

experimental value and $\hat{v} = \{\hat{v}_1, \hat{v}_2, \dots, \hat{v}_n\}$ is the value predicated by the model, the measures are defined as follows.

- Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{v}_i - v_i)^2}$$

- Normalized Root Mean Square Error (NRMSE)

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{v}_i - v_i)^2}}{\max v - \min v}$$

- Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{v}_i - v_i|$$

- Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{\hat{v}_i - v_i}{v_i} \right|$$

- Symmetric Mean Absolute Percentage Error (SMAPE)

$$\text{SMAPE} = \frac{100\%}{n} \sum_{i=1}^n \frac{|\hat{v}_i - v_i|}{(|\hat{v}_i| + |v_i|)/2}$$

Table 6 and Figure 5 present the values for RMSE, NRMSE, MAE, MAPE and SMAPE between regression data and experiment data for

(a) Data validation comparison for RA

(b) Data validation comparison for MRR

(c) Data validation comparison for EWR

Fig. 4 Data validation of four models(KNN, KSSVM, KRIGING and BPNN) for RA, MRR and EWR:(a)Comparison for RA;(b)Comparison for MRR;(c)Comparison for EWR

Table 6 Residuals Evaluation for Different Models

	Measure	KNN	LSSVM	KRIGING	BPNN
RA	RMSE	1.2591	1.6817	0.9878	0.5577
	NRMSE	0.2690	0.3593	0.2111	0.1192
	MAE	1.1875	1.5946	0.8013	0.5063
	MAPE	0.1929	0.2726	0.1371	0.0835
	SMAPE	0.1914	0.2577	0.1289	0.0865
MRR	RMSE	2.7635	2.8958	2.3242	1.0930
	NRMSE	0.1671	0.1751	0.1405	0.0661
	MAE	2.0942	2.1463	1.6390	0.7731
	MAPE	1.3172	6.5617	5.8009	0.0981
	SMAPE	0.6129	0.5648	0.5449	0.1006
EWR	RMSE	2.8734	2.0739	1.7429	1.0930
	NRMSE	0.1512	0.1092	0.0917	0.0575
	MAE	2.0742	1.8541	1.3031	0.8450
	MAPE	0.2524	0.3142	0.2983	0.1358
	SMAPE	0.2412	0.4817	0.2019	0.1390

(a) Measure Comparison for RA

(b) Measure Comparison for MRR

(c) Measure Comparison for EWR

Fig. 5 Five Measures for Modelling Errors of Models (KNN, KSSVM, KRIGING and BPNN):(a)Comparison for RA;(b)Comparison for MRR;(c)Comparison for EWR

all three criterion RA, MRR and EWR. It clearly presents that BPNN provides the most accurate predication in all the aspects from the results. Since NRMSE, MAPE and SMAPE calculate the normalized or percentage values, they are more convinible measures which should be looked into in more details. For RA with BPNN algorithm, NRMSE is 11.92%, MAPE is 8.35% and SMAPE is 8.65%; for MRR with BPNN, NRMSE is 6.61%, MAPE is 9.81% and SMAPE is 10.06%; for EWR with BPNN, NRMSE is 5.75%, MAPE is 13.58% and SMAPE is 13.9%.

Comparing the results of Table 5 and Table 6, BPNN is the best model for RA, MRR and EWR

in both point-to-point and mean error comparison. Especially for the overall comparison with mean error criteria, the results from BPNN are less than 70% of all the others, some aspects are even less than 10%. The results show that such BPNN model has quite acceptable performance for this EDM study. Hence, such BPNN model is selected as fitness function for data optimization in the next part.

4.2 Optimization result

In the optimization process, the population size N is set to be 500, BPNN model generated in the previous part is used as multi-objective fitness function with 5 inputs and 3 outputs. The algorithm runs for 1000 iterations, λ is set to a random number drawn by the standard uniform distribution $([0,2])$ and other constants are setting as: $S_{max} = 1$, $\beta = 1.5$, $nrep = 500$, $\varphi = 0.618$, $s = 0.5$. For the 3 objectives RA, MRR and EWR, the values of RA and EWR are the less the better, the values of MRR are the more the better.

The optimization results are plotted in Figure 6, a Pareto surface is constructed by the optimized results. The free points out of the surface are experiment results. It is clearly shown that almost all the experiment results on the same side of the surface. Since we demand small RA/EWR values and large MRR value. This Figure shows the optimized results dominates almost all the experiment results, which means the optimization progress has successfully made better optimal results.

Fig. 6 Pareto surface of all optimized results VS. experiment results

(a) Selected optimized results VS. Experiment results (RA and MRR)

(b) Selected optimized results VS. Experiment results (EWR and MRR)

Fig. 7 Selected optimized results VS. Experiment results: (a) results for RA and MRR; (b) results for EWR and MRR

To guide the future EDM process, 12 results are selected from all the optimized results, and shown in Table 7. The selected results cover all ranges of RA, MRR and EWR, and suggest better machining performance than the experiment data. From Figure 7(a), the optimized results tend to have smaller RA values when the MRR are at the same level with experiment data; from Figure 7(b), the optimized results tend to have larger MRR values when the EWR are at the same level with experiment data. The experiment points are more on the left and upper side on both figures, which means they have comparative smaller RA/MRR values and larger EWR values than the experiment points. Most experiment data are dominated by some optimized data from Table 7. For example, No.1-8 experiment results in Table 3 are dominated by No.3 optimized result in

Table 7 Selected optimized results

Opt No.	Volume (%)	Current (A)	Pulse width (μ s)	Pulse interval (μ s)	Magnetic (T)	RA (μ m)	MRR (mm^3/min)	EWR (mg/min)
1	52	14	120	180	0.05	3.92	1.01	0.71
2	52	16	160	169	0.05	3.74	1.41	3.08
3	57	19	120	180	0.05	5.53	4.07	2.26
4	57	22	205	179	0.15	4.19	5.10	5.52
5	57	20	120	180	0.05	5.13	5.57	3.78
6	55	21	129	152	0.14	4.50	6.55	7.61
7	61	25	240	127	0.31	3.27	7.31	9.69
8	65	25	145	180	0.20	5.59	10.40	7.79
9	65	26	120	180	0.05	4.77	11.94	9.07
10	58	30	240	159	0.35	2.86	13.03	13.62
11	62	30	120	172	0.35	5.50	14.77	11.60
12	48	30	120	164	0.28	2.26	15.21	17.16

Table 7; No.9-12 experiment results are dominated by No.7 optimized result; No.13-16 experiment results are dominated by No.9 optimized result. In fact, from all the data, only experiment data No. 45 and 46 are not dominated by any optimized data in Table 7, they have a non-dominated relation with the selected optimized data set. It means that the selected results are strictly better than 95.83% experiment data.

4.3 Experimental verification and analysis

To verify the performance of the parameter optimization process, verification experiment is carried out. The parameters of No.8 result in Table 7 is taken as input, where the volume fraction is 65%, current is 14A, magnetic field is 0.2T, pulse width and interval are 145 and 180 μ s respectively. An experiment under is made under these optimized parameters, providing results: RA=5.17 μ m, MRR=11.3mm³/min and EWR=8.25mg/min. Compare to the the corresponding values of No.8 result in Table 7, the relative errors are 8.12%, 8.00% and 5.58% for RA, MRR and EWR respectively (see Table 8), which is within an acceptable state. The No.42 result in Table 3 where magnetic field is also 0.2T is dominated by the optimized experiment result. If looking at experiments without magnetic field, the original experiment No.44 in Table 3 is dominated by the optimized experiment result as well (see Table 8). It verifies the effectiveness of the optimization process.

Figure 8(a) demonstrates SEM surface micro structure for the verification experiment in the condition of $\times 1000$ for EDM with magnetic field 0.2T, the recast layer is 32 μ m, Figure 8(b)

and 8(c) demonstrate two test areas of three-dimensional topology, the highest peaks of EDM process are 4.380 μ m and 4.220 μ m. For the original experiment No.44, Figure 9(a) demonstrates SEM surface micro structure in the condition of $\times 1000$ for EDM without magnetic field, the recast layer is 56 μ m, Figure 9(b) and 9(c) demonstrate two test areas of three-dimensional topology ,the highest peaks of EDM process are 8.150 μ m and 5.850 μ m.

The results show that the application of an external magnetic field in the EDM process can help to reduce the thickness of the recast layer and surface roughness, and significantly improve the surface integrity. This is mainly because the magnetic field makes the particles inside the plasma move more orderly under the action of Lorentz force, and the energy distribution of the plasma channel is more uniform. At the same time, because the charged particles of the material are discharged from the processing area in time under the action of Lorentz force, it improves The discharge stability of EDM is improved, thereby effectively improving the surface quality.

5 MF-EDM Processing Intelligent System

Based on the modelling and optimization algorithms, to realize data-driven MF-EDM processing. An intelligent system for FEDM processing is developed. The system mainly realizes the following three functions:

- Predication function. When the user provides the processing conditions (volume fraction percentage, current pulse, magnetic value, pulse width and pulse interval), the system predicates

Table 8 Selected optimized result, verification experiment and original experiment comparison

	Volume (%)	Current (A)	Pulse width (μs)	Pulse interval (μs)	Magnetic (T)	RA (μm)	MRR (mm^3/min)	EWR (mg/min)
No.8 in Table 7	65	25	145	180	0.20	5.59	10.40	7.79
Verification experiment	65	25	145	180	0.20	5.17	11.3	8.25
Relative errors	-	-	-	-	-	8.12%	8.00%	5.58%
No.42 in Table 3	65	25	150	140	0.20	6.09	10.29	9.60
No.44 in Table 3	65	25	210	100	0	6.35	7.76	9.48

(a) SEM surface topography of EDM

(a) SEM surface topography of EDM

(b) Test area 1

(b) Test area 1

(c) Test area 2

(c) Test area 2

Fig. 8 Three-dimensional surface topography of EDM (optimized experiment): (a)SEM surface topography of EDM; (b) Test area 1;(c) Test area 2**Fig. 9** Three-dimensional surface topography of EDM (No.44 in Table 3): (a)SEM surface topography;(b) Test area 1;(c) Test area 2

the value of the three output process parameters EWR, MRR and Ra;

- Optimization function: providing desired output values EWR, MRR and Ra, the system can give some sets of input parameters, which can produce such outputs (volume fraction percentage, current pulse, magnetic value, pulse width and pulse interval).
- On-line gap discharge waveform monitoring function. The state of the collected discharge waveform can be judged and recognized. According to the state of the gap discharge waveform, the processing parameters can be modified accordingly.

To implement all these 3 functions, the system consists of 4 basic modules: modelling, predication, optimization and monitoring (see Figure 10).

Modelling Module

For the modelling part, the experiment data should be loaded first. The system can load a set of experiment data from the file, also can add and edit single data. A set of multiple choice boxes are used to select different modelling algorithms with parameters. Once the data are loaded and algorithms are selected, modelling button can be pressed for data modelling.

Predication Module

When data models are generated, the predication part can be used to predication machining process. In the system, volume fraction percentage, current, pulse width, pulse interval and magnetic are required input values. With the values, and pick an modelling algorithm from the drop-list, RA, EWR and MRR values are calculated as output.

Optimization Module

The optimization module is used to suggest machining parameters under given RA, EWR and MRR values. Modelling algorithm combining with optimization algorithm should be chosen first in this module. Under the selected algorithm, some data sets are presented. These data have RA, EWR and MRR values close to the input, and give suggested volume fraction percentage, current, pulse width, pulse interval and magnetic values for machining.

Monitoring Module

The On-line gap discharge waveform monitoring module reflects the pulse states of the machining process. The most recent spark, transition arc, open circuit and short circuit figures are shown in the corresponding box. The accumulation of each stats are also recorded in the module to show whether the machining process is in a healthy behavior.

6 Conclusion

This paper proposes A data-driven intelligent system for a transverse magnetic field-assisted EDM machining process for SiCp/Al composites with different high volume fractions. Carefully designed modelling and optimization techniques are used to generate the most efficiency machining parameters. The major work are as follows:

1. 35%, 45% and 65% SiCp/Al composites are used in EDM processing. 16 groups of Taguchi orthogonal experiments for each volume fraction of SiCp/Al Composites have been completed. Peak current, magnetic, pulse width and pulse interval time are taken as machining parameters, MRR, EWR and RA values are output criteria.
2. KNN, LSSVM, Kriging model and BPNN are used to build models for the EDM experiment. After comparing the accuracy of modelling results, a BPNN model with 6 neuron hidden layer is chosen for parameter optimization using multi-objective moth search (MOMS) algorithm. A multi-hierarchy non-dominated strategy is used in the algorithm for population generating in each generation, to keep both explorative and exploitative. A set of 12 optimized results is selected as paradigm, which dominates 95.83% experiment data.
3. A verification experiment is done for 65% SiCp/Al composites with 0.2T magnetic from the optimized data (No.8 in Table 7). The relative errors between verification experiment and the optimized result for RA, MRR and EWR are 8.12%, 8.00% and 5.58% respectively. Through both result data and 3D surface topography comparison, the verification experiment result dominate a similar original experiment without magnetic field.

Fig. 10 The interfaces of MF-EDM intelligent system

4. A data-driven intelligent system MF-EDM processing is developed to provide help for the FEDM processing in the aspects of modelling, predication, optimization and monitoring.

The work has shown that in the proposed data-driven intelligent system, multi-objective moth search algorithm with BPNN modelling can be nicely used to tune EDM processing parameters. It is also verified that the application of an external magnetic field in the EDM process can help to reduce the thickness of the recast layer and surface roughness.

Authors' contributions. Tao Xue: conceptualization, methodology and writing; Long Chen: software and validation; Jiaquan Zhao: design and writing; Zhen Zhang: experiment and analysis; Yi Zhang: experiments; Dongxu Wen: funding and resources.

Funding. This research is supported by National Key R&D Program of China (No. 2020YFB2008203), Project named "Mold design,

manufacturing and high-efficiency precision molding of small module gear".

Acknowledgments. The authors would like to thank Mr. Haishen Yu and Mr. Liquan Lin for preparing the experiments.

Declarations

- **Conflict of interest** The authors declare no competing interests.
- **Ethics approval** There is no ethical approval needed in the present study.
- **Consent to participate** Not applicable.
- **Consent for publication** All authors agree to publish

References

- [1] Chen Wang, Yi Wang, KeSheng Wang, Yao Dong, Xueliang Zhou, and Shenghuai Wang. Cutting parameters optimization based on itlbo algorithm with big data driven. In *2017 IEEE International Congress on Big Data (BigData Congress)*, pages 577–581, 2017.

- [2] Hao Luo, Kuan Li, Okay Kaynak, Shen Yin, Mingyi Huo, and Hao Zhao. A robust data-driven fault detection approach for rolling mills with unknown roll eccentricity. *IEEE Transactions on Control Systems Technology*, 28(6):2641–2648, 2020.
- [3] Mattia Bellotti, Ming Wu, Jun Qian, and Dominiek Reynaerts. Tool wear and material removal predictions in micro-edm drilling: Advantages of data-driven approaches. *Applied Sciences*, 10(18), 2020.
- [4] Subhankar Saha, Kritesh Kumar Gupta, Saikat Ranjan Maity, and Sudip Dey. Data-driven probabilistic performance of wire edm: A machine learning based approach. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, December 2021.
- [5] Xianjun Kong, Jin Wang, Minghai Wang, Ben Wang, Yaohui Zheng, and Lijun Yang. Mechanisms involved in the tool life improvement of laser assisted machining 45% sicp/al composites. *Optics & Laser Technology*, 139:106919, 2021.
- [6] Bowen Xiong, Zhifeng Xu, Qingsong Yan, Baiping Lu, and Changchun Cai. Effects of sic volume fraction and aluminum particulate size on interfacial reactions in sic nanoparticle reinforced aluminum matrix composites. *Journal of Alloys and Compounds*, 509:1187–1191, January 2011.
- [7] Benji Maruyama. Discontinuously reinforced aluminum: Current status and future direction. *Journal of the Minerals, Metals & Materials Society*, 51:59–61, 1999.
- [8] Suhasini Gururaja, Mamidala Ramulu, and William Pedersen. Machining of mmcs: A review. *Machining Science and Technology*, 17(1):41–73, 2013.
- [9] Jinguang Du, Wuyi Ming, Yang Cao, Wenbin He, and Xiaoke Li. Particle removal mechanism of high volume fraction sicp/al composites by single diamond grit tool. *Journal of Wuhan University of Technology-Mater. Sci. Ed.*, 34:324–331, 04 2019.
- [10] A. Pramanik. Developments in the non-traditional machining of particle reinforced metal matrix composites. *International Journal of Machine Tools and Manufacture*, 86:44 – 61, 2014.
- [11] Wuyi Ming, Haojie Jia, Hongmei Zhang, Zhen Zhang, Kun Liu, Jinguang Du, Fan Shen, and Guojun Zhang. A comprehensive review of electric discharge machining of advanced ceramics. *Ceramics International*, 46(14):21813–21838, 2020.
- [12] K.H Ho and S.T Newman. State of the art electrical discharge machining (edm). *International Journal of Machine Tools and Manufacture*, 43(13):1287–1300, 2003.
- [13] Rajiv Garg, Kalyan Singh, Sachdeva Anish, Vishal Sharma, Kuldeep Ojha, and Sharanjit Singh. Review of research work in sinking edm and wedm on metal matrix composite materials. *International Journal of Advanced Manufacturing Technology*, 50:611–624, 09 2010.
- [14] Y. W. Seo, D. Kim, and M. Ramulu. Electrical discharge machining of functionally graded 15-35 vol% sicp/al composites. *Materials and Manufacturing Processes*, 21(5):479–487, 2007.
- [15] Wen-Shu Yang, Guo-Qin Chen, Ping Wu, Murid Hussain, Jia-Bing Song, Rong-Hua Dong, and Gao-Hui Wu. Electrical discharge machining of al2024-65 vol% sic composites. *Acta Metallurgica Sinica (English Letters)*, 30:447–455, 05 2017.
- [16] Zhen Zhang, Yi Zhang, Liquan Lin, Jinhong Wu, Haishen Yu, Xin Pan, Guangliang Li, Jie Wu, and Tao Xue. Study on productivity and aerosol emissions of magnetic field-assisted edm process of sicp/al composite with high volume fractions. *Journal of Cleaner Production*, 292:126018, 2021.
- [17] Zhen Zhang, Yi Zhang, Wuyi Ming, Yanming Zhang, Chen Cao, and Guojun Zhang. A review on magnetic field assisted electrical discharge machining. *Journal of Manufacturing Processes*, 64:694–722, 2021.

- [18] Jian-guang Li and Rashid Laghari. A review on machining and optimization of particle-reinforced metal matrix composites. *The International Journal of Advanced Manufacturing Technology*, 100, 02 2019.
- [19] Kalipada Maity and Himanshu Mishra. Ann modelling and elitist teaching learning approach for multi-objective optimization of μ -edm. *Journal of Intelligent Manufacturing*, 29:1599–1616, 2018.
- [20] G. Taguchi, E. A Elsayed, and T. C. Hsiang. *Quality Engineering in Production Systems*. McGraw-Hill College, 1988.
- [21] Pauline Ong, Chon Haow Chong, Mohammad Zulafif bin Rahim, Woon Kiow Lee, Chee Kiong Sia, and Muhammad Ariff Haikal bin Ahmad. Ann modelling and elitist teaching learning approach for multi-objective optimization of μ -edm. *Journal of Intelligent Manufacturing*, 31:227–247, 2020.
- [22] Zoran Jurkovic, Goran Cukor, Miran Brezocnik, and Tomislav Brajkovic. A comparison of machine learning methods for cutting parameters prediction in high speed turning process. *Journal of Intelligent Manufacturing*, 29:1683C1693, 12 2018.
- [23] Kuntal Maji and Dilip Pratihari. Modeling of electrical discharge machining process using conventional regression analysis and genetic algorithms. *Journal of Materials Engineering and Performance*, 20:1121–1127, 10 2011.
- [24] Wuyi Ming, Jun Ma, Zhen Zhang, Hao Huang, Dili Shen, Guojun Zhang, and Yu Huang. Soft computing models and intelligent optimization system in electro-discharge machining of sic/al composites. *International Journal of Advanced Manufacturing Technology* Soft computing models and intelligent optimization system in electro-discharge machining of SiC/Al composites, 87:201–217, 2016.
- [25] Saikat Chakraborty, Rishiraj Chakraborty, Kona Nagendrababu, Gangadhar Talla, and Soumya Gangopadhyay. Multi-response optimisation of surface texturing using artificial bee colony algorithm. *International Journal of Mechatronics and Manufacturing Systems*, 9:272–295, 01 2016.
- [26] Chinmaya Mohanty, Siba Mahapatra, and Dr. Manas Singh. A particle swarm approach for multi-objective optimization of electrical discharge machining process. *Journal of Intelligent Manufacturing*, 27:1–20, 07 2014.
- [27] Gaige Wang. Moth search algorithm: a bio-inspired metaheuristic algorithm for global optimization problems. *Memetic Computing*, 10:151–164, 2018.
- [28] Jerome H. Friedman. Flexible metric nearest neighbor classification. Technical report, 1994.
- [29] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine Learning*, 20:273–297, 1995.
- [30] Johan A K Suykens, Tony Van Gestel, Jos De Brabanter, Bart De Moor, and Joos Vandewalle. *Least Squares Support Vector Machines*. World Scientific, 2002.
- [31] D.G. Krige. A statistical approach to some basic mine valuation problems on the witwatersrand. *Journal of the Southern African Institute of Mining and Metallurgy*, 52(6):119–139, 1951.
- [32] Ji Cheng, Ping Jiang, Qi Zhou, Hu Jiexiang, Tao Yu, Leshi Shu, and Xinyu Shao. A lower confidence bounding approach based on the coefficient of variation for expensive global design optimization. *Engineering Computations*, 36:830–849, 04 2019.
- [33] David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. Learning representations by back-propagating errors. *Nature*, 323:533–536, 1986.
- [34] Hecht-Nielsen. Theory of the backpropagation neural network. In *International 1989 Joint Conference on Neural Networks*, pages 593–605 vol.1, 1989.