Optimization of EDM Process Parameters through Teaching Learning Based Optimization Algorithm

A thesis submitted in partial fulfilment

of the requirements for the degree

of

Master of Technology in Production Engineering

by

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Department of Mechanical Engineering
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CERTIFICATE

This is to certify that the project report entitled "**Optimization of EDM process parameters using teaching-learning-based optimization**" submitted by Sri Ranjan Kumar Hasda has been carried out under my supervision in partial fulfilment of the requirements for the degree of Master of Technology in Production Engineering at National Institute of Technology, Rourkela and this work has not been submitted elsewhere before for any academic degree/diploma to the best of my knowledge.

Dr. Saroj Kumar Patel
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I am especially indebted to my parents for their love, sacrifice, and support. They are my first teachers after I came to this world and have set great examples for me about how to live, study and work.

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Contents

Abstract

Electrical Discharge Machining (EDM) is a non-traditional machining process where intricate and complex shapes can be machined. Only electrically conductive materials can be machined by this process and is one of the important machining processes for machining high strength, temperature-resistant (HSTR) alloys. For achieving the best performance of the EDM process, it is crucial to carry out parametric design responses such as Material Removal Rate, Tool Wear Rate, Gap Size etc. It is essential to consider most number of input parameters to get the better result. In the present work Teaching-Learning-Based optimization (TLBO) algorithm has been applied for multi-objective optimization of the responses of EDM process. The optimization performance of the TLBO algorithm is compared with that of other population-based algorithms, e.g., genetic algorithm (GA), ant colony optimization (ACO), and artificial bee colony (ABC) algorithm. It is observed that the TLBO algorithm performs better than the others with respect to the optimal process response values.

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CHAPTER 1

INTRODUCTION

1. Introduction

1.1 Electrical Discharge Machining

Electrical Discharge Machining (EDM) is a modern manufacturing process machining process, where electrically conductive material is removed by controlled erosion through a series of electric sparks of short duration and high current density between the electrode and the workpiece were both are submerged in a dielectric bath, containing kerosene or distilled water [1]. During this process thousands of sparks per second are generated, and each spark produces a tiny crater in the material along the cutting path by melting and vaporization. Generally the material is removed by erosion process. The top surface of the workpiece subsequently resolidifies and cools at a very high rate. The application of this process is mostly found in press tools and dies, plastic moulds, forging dies, die castings, aerospace, automotive, surgical components manufacturing industries etc. This process is not restricted by the physical and metallurgical properties of the work material as there is no physical contact due to high energy electrothermal erosion between the tool and the workpiece.

It uses electrothermal phenomenon, coupled with surface irregularities of the electrodes, interactions between two successive discharges and presence of debris particles makes the EDM process too abstruse, so that complete and accurate physical modelling of the process has been observed to be difficult to establish [1, 2]. The favourable EDM process parameters selection is required for obtaining the best machining performance by increasing the production rate at the same time reducing the machining time. The process parameters are generally determined based on experience or on handbook values. However, this does not confirm that the chosen machining parameters result in optimal or near optimal machining performance of the EDM process.

1.1.1 *Working Principle of Electrical Discharge Machining*

The machining process is carried out within the dielectric fluid which creates path for discharge. When potential difference is applied between the two surfaces of workpiece and tool, the dielectric gets ionized and electric sparks/discharge are generated across the two terminals. An external direct current power supply is connected across the two terminals to create the potential difference. The polarity between the tool and workpiece can be interchanged but that will affect the various performance parameters of EDM process. For extra material removal rate workpiece is connected to positive terminal as two third of the total heat generated is generated across the positive terminal. The inter electrode gap between the tool and workpiece has a significant role to the development of discharge. As the workpiece remain fixed to the base by the fixture arrangement, the tool helps in focusing the intensity of generated heat at the place of shape impartment. The application of focused heat of the tool raises the temperature of workpiece in that region, which consequently melts and evaporates the metal. In this way small volumes of workpiece material are removed by the mechanism of melting and vaporization during a discharge. In a single spark volume of material removed is very small in the range of 10^{-6}-10^{-4} mm^3, but this basic process is continuous around 10,000 times per second [3]. The layout of EDM is shown in Figure 1.1.

The material removal process caused due to a single electric spark generally passes through the following phases and as shown in Figures 1.2 and 1.3:

a) Pre-breakdown: During this phase the tool moves closer to the workpiece and voltage (V_0) is applied between the electrodes.

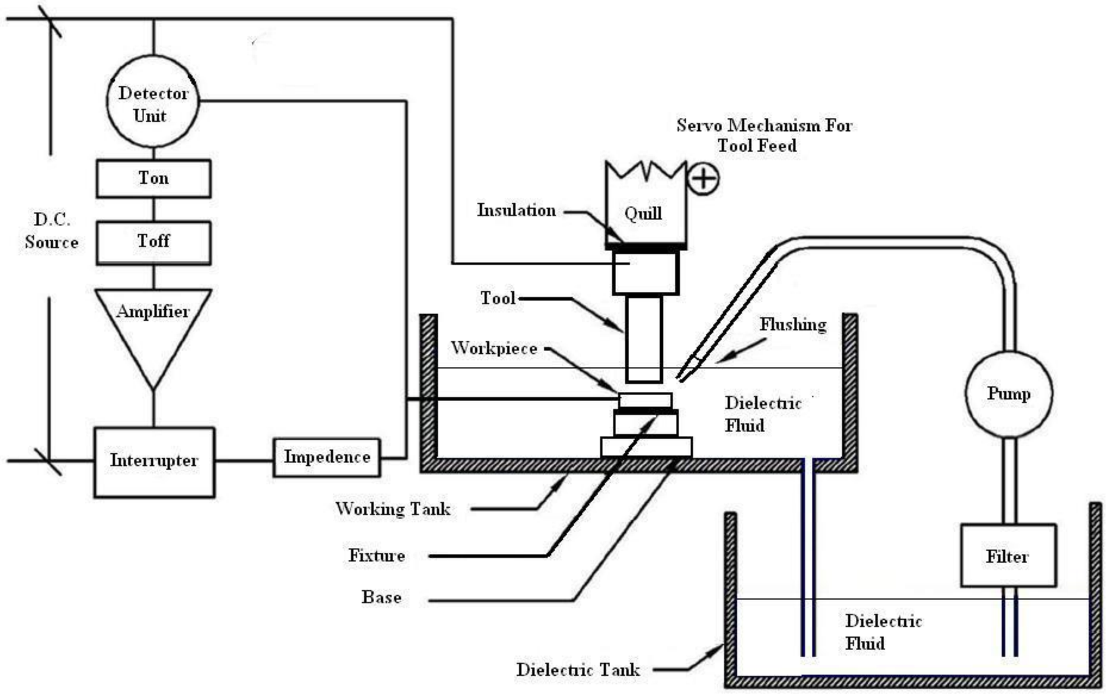

Figure 1.1: Layout of Electrical Discharge Machining

b) Breakdown: As the applied voltage cross the boundary limit of dielectric strength of dielectric fluid, this initiates the breakdown of the dielectric. Usually the dielectric breaks near the closest point between the tool and workpiece, but it also depend on conductive particles present between the gap if present any [3]. After the breakdown, the voltage falls and current rises suddenly. During this phase the dielectric between the electrodes gets ionized and a plasma channel is created.

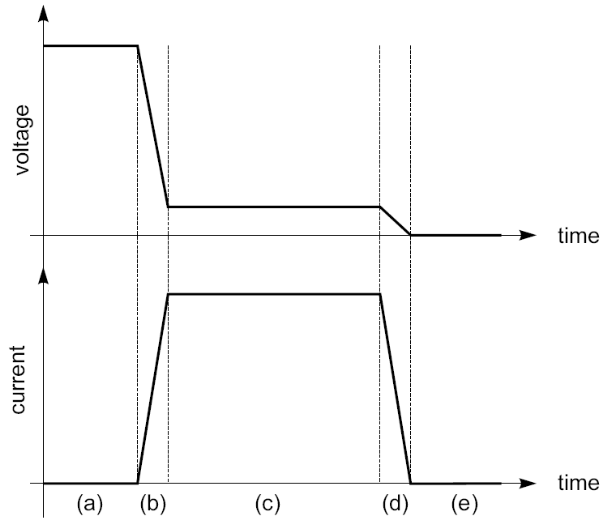

Figure 1.2: Variation of current and voltage in different phases of a spark [3]

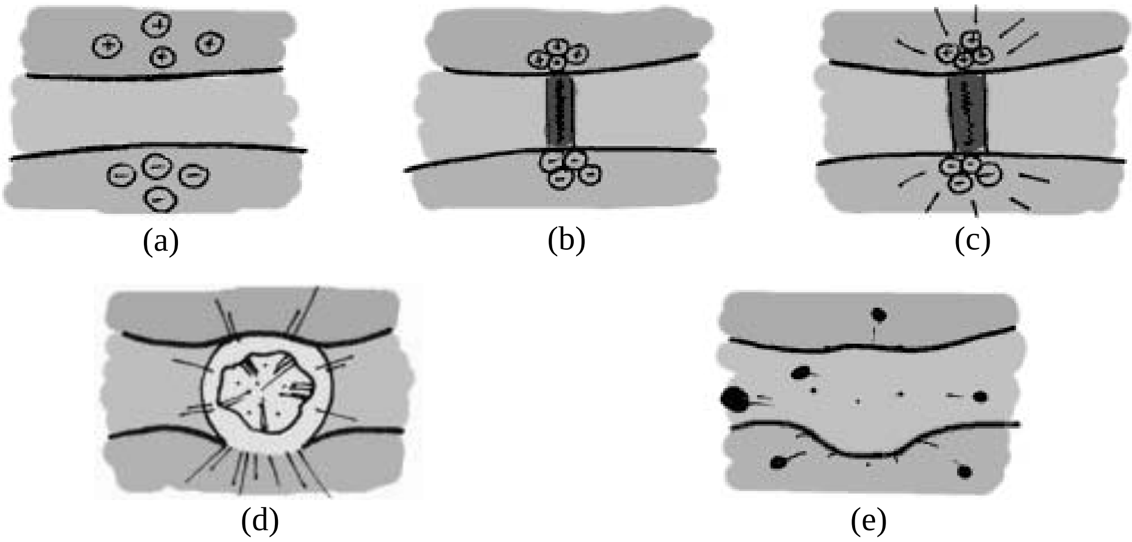

Figure 1.3: (a) Pre-breakdown phase (b) Breakdown phase (c) Discharge phase (d) End of the discharge and (e) Post-discharge phase [3]

c) Discharge: During this phase the discharge current is maintained at a constant level for a continuous bombardment of ions and electrons on the electrodes. Due to which there is strong heating of the workpiece (and also on the electrode), instantly creating a small molten metal pool at the surface of the workpiece and a small amount of metal gets vaporized due to the tremendous amount of heat. In this phase, the plasma channel expands and the radius of the molten metal pool also increases with time. Here some portion of the work-piece gets evaporated and some remains in the molten state. One of the important parameter in the discharge phase is the Inter Electrode Gap (IEG) which is estimated to be around 10 to 100 micrometers and is directly proportional to discharge current.

d) End of the discharge: At the end of the discharge phase the current and the voltage supply stops. The plasma collapses as there is no spark and also due to the pressure enforced by the surrounding dielectric.

e) Post-discharge: As during the end of discharge phase the plasma extinguishes. Here a small portion of metal will be removed and a thin layer of metal will recast on the surface of workpiece due to the cooling and collapsing of plasma. The thickness of the layer is around 20 to 100 microns and is known as white layer. Simultaneously, the molten metal pool is absorbed into the dielectric, leaving behind a small crater on the workpiece surface (around 1-500 micrometer in diameter, depending on the current).

1.1.2 Liquid Dielectric

Dielectric fluid act as an electric insulator until the voltage is high enough to overcome the dielectric potential of the dielectric fluid to change it into an electrical conductor. Some of the commonly used dielectric fluids are paraffin, de-ionized water, kerosene, transformer oil etc. The dielectric fluid helps in cooling the electrodes and also provides a high plasma pressure due to which there is a high removing force on the molten metal. When the plasma falls down, it solidifies the molten metal into small spherical shaped particles, and helps in flushing away these eroded particles [3]. If the particles within the electrodes are not properly flushed away, then there will be abnormal discharges in the subsequent discharges. This is caused mainly due to the particles present in the dielectric fluid which reduces the dielectric strength of the dielectric and also it may lead to arcing tendency which is not at all desirable for the machining process. To flushing of particles are enhanced by passing the dielectric fluid between the gaps of the electrodes.

1.1.3 Flushing

It is the process of supplying filtered dielectric fluid into the machining zone. When the dielectric is clean, it is free from eroded particles and carbon residue from dielectric cracking and its insulation strength is high, but with consecutive discharges the dielectric gets contaminated, dropping its insulation strength, and thus discharge can take place in an abrupt manner. If the concentration of the particles became high at certain points between the electrodes gap, bridges are formed, which lead to abnormal discharges and damage the tool along with the workpiece. Different types of flushing methods are: suction flushing, side flushing, injection flushing, motion flushing and impulse flushing.

1.1.4 *Machining parameters*

For the optimization of machining process or to perform efficient machining one should identify the process and performance measuring parameters. The EDM process parameters can be categorized into:

(i) Input or process parameters: The input parameters of EDM process which affects the performance of machining process are discharge current, spark-on time, voltage, duty factor, flushing pressure, work piece material, tool material, quill-up time, inter-electrode gap, working time, and polarity. So, process parameters are selected accordingly for optimal machining condition.

(ii) Response or performance parameters: These parameters are used for evaluation of machining process in both qualitative and quantitative terms. Some of the response parameters are Material Removal Rate, Surface Roughness, Over Cut, Tool Wear Rate, White Layer Thickness and Surface Crack Density.

1.2 Response Surface Methodology

The study of Response Surface Methodology is required for having an idea how the relations among the process parameters are generated for a particular response parameter. RSM is a regression technique used for prediction, determination and optimization of machine performances [4]. RSM is collection of statistical and mathematical technique required for developing, improving and optimizing a process. It is used in those circumstances where the output is dependent on many parameters. The multi parameter related output is called response. RSM involves planning of strategy for development of a relationship between different parameters and output. The relationship between different process parameters and response is approximately represented by the following equation.

$$Y = f\left(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_k\right) + \in \tag{1}$$

where Y is the response and ε_1, ε_2, ε_k are the various process parameters, and an additional term correspond to the background noise, error in measurement of response etc which all together represents the statistical error. The general form is written as

$$E(y) = E\left[f\left(\varepsilon_1, \varepsilon_2, \ldots., \varepsilon_k\right)\right] + E(\in) = f\left(\varepsilon_1, \varepsilon_2, \ldots., \varepsilon_k\right) \tag{2}$$

In terms of coded variables response surface equation can be approximated as follows

$$\eta = f\left(\mathrm{x}_1 \mathrm{x}_2 \ldots\ldots\ldots \mathrm{x}_\mathrm{k}\right) \tag{3}$$

where $x_1, x_2 \ldots x_k$ are coded values. For an approximate value generally a low order polynomial with a small region of independent variable space is used. The first order RSM model is used when the approximation of response surface is done on a very small region of the independent variable space and there is a little curvature in the response surface.

The first order model in coded form for two independent variables is given by equation.

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \tag{4}$$

If the interaction is considered between the terms then following equation is obtained:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \tag{5}$$

And if the addition of interaction terms is introduced then there is a curvature in the model which is not adequate to give exact approximation of the model. In such cases second order model is used which is represented by the following equation:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1 x_1 + \beta_{22} x_2 x_2 + \beta_{12} x_1 x_2 \tag{6}$$

This model is an exact representation to model the response surface in relatively small surface. The parameters are determined by least square method in second order response equation. The first order response model is represented by the following equation:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots + \beta_k x_k \qquad (7)$$

and the second order response model is represented by the following equation:

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j x_j + \sum_{j<}^{k} \beta_{ij} x_i x_j \qquad (8)$$

1.3 Teaching-Learning-Based Optimization

Teaching-learning-based optimization is based on teaching-learning process in which every learner tries to learn something from other individuals to improve themselves. This algorithm simulates the traditional teaching-learning phenomenon of a class room [5]. Here, two different teachers, T_1 and T_2 are assumed teaching same subject to the same merit level students in two different classes. The distribution of marks obtained by the learners of two different classes as shown in the Figure 1.4 is evaluated by the teachers.

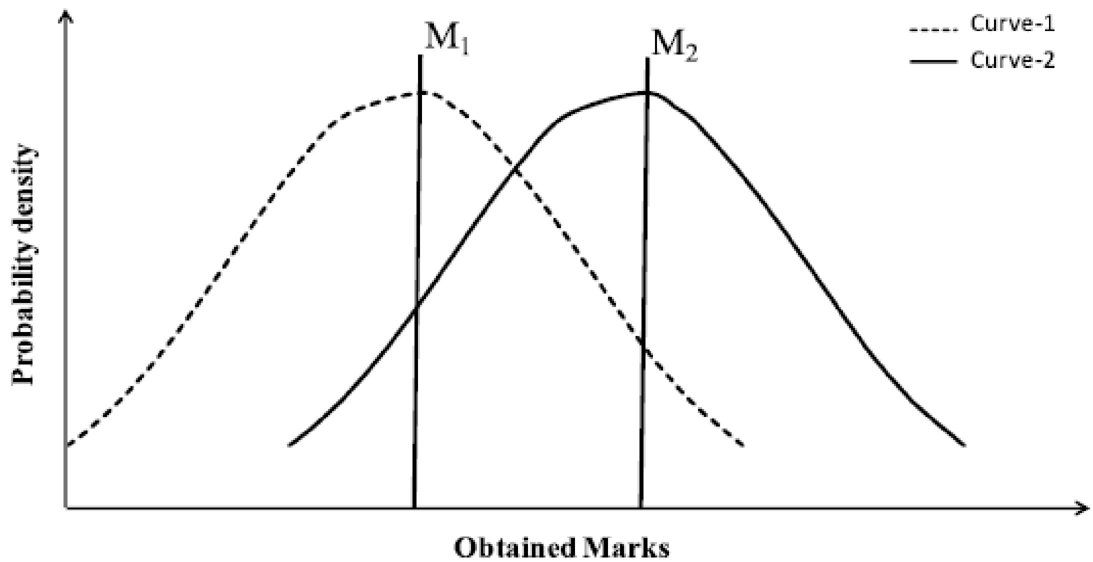

Figure 1.4: Distribution of marks obtained by learners taught by two different teachers [5]

Curves 1 and 2 shown in Figure 1.4 represent the marks obtained by the learners taught by teacher T_1 and T_2 respectively. Generally a normal distribution is assumed for the obtained marks. The normal distribution is defined as

$$f(X) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{9}$$

where, μ is the mean, σ^2 is the variance and x is any value for which the normal distribution function is required. As represented in the Figure 1.5, let us assume that the teacher T_2 is better than teacher T_1 in terms of teaching. The main difference between both the results is their mean (M_2 for Curve-2 and M_1 for Curve-1), i.e. a good teacher produces a better mean for the results of the learners. Learners also learn from the interaction among themselves, which helps in the in the improvement of their results. Considering this teaching learning process Rao et al. [5] developed a mathematical model and implemented it for the optimization of unconstrained non-linear continuous function, thereby developing a optimization technique called Teaching–Learning-Based Optimization (TLBO). Let the marks obtained by the learners in a class with curve-A be mean M_A as shown in the Figure 1.5. As the teacher is considered as the most knowledgeable person in the society, so the best learner imitate as a teacher, which is shown by T_A in Figure 1.5.

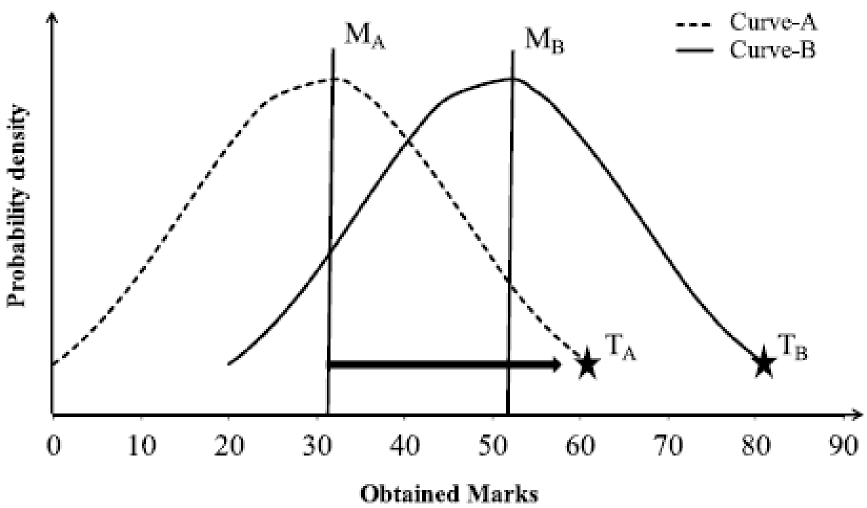

Figure 1.5: Model for the distribution of marks obtained for a group of learners [5]

The teacher tries to spread knowledge among learners, which will in turn enhance the knowledge level of the entire class and facilitate learners to get good marks or grades. Hence, the teacher increases the mean of the class according to his or her capability. The teacher T_A will try to move mean M_A towards their own level according to his or her capability, thereby increasing the learner's level to a new mean M_B. Teacher T_A will put maximum effort for teaching their students, but students will gain knowledge according to the quality of teaching delivered by a teacher and the quality of students present in the class. The quality of the students is judged from the mean value of the population. Teacher T_A puts effort in so as to increase the quality of the students from M_A to M_B, at which stage the students require a new teacher, of superior quality than themselves, i.e. in this case the new teacher is T_B. After which, there will be a new curve-B with new teacher T_B.

Like other nature-inspired algorithm, TLBO is also a population-based algorithm, where a group of students (i.e. learners) is considered the population of solutions to proceed to the global solution. The different design variables in the optimization problem are analogous to different subjects offered to the learners. The fitness value of the optimization problem is analogous to the results of the learners in the optimization problem. The best solution in the entire population is considered as the teacher. The next teacher is considered as the best teacher obtained.

This algorithm is divided into two levels of learning phase i.e. through the teacher (known as the teacher phase) and interacting with other learners (known as the learner phase). Figure 1.6 shows the two phase of learning process.

1.3.1 Teacher Phase

In this phase the learning is through the teacher. During the learning process the teacher spread knowledge among the learners and tries to increase the mean results of the class. At any iteration 'i', let, there are 'm' number of subjects (i.e design variables) offered

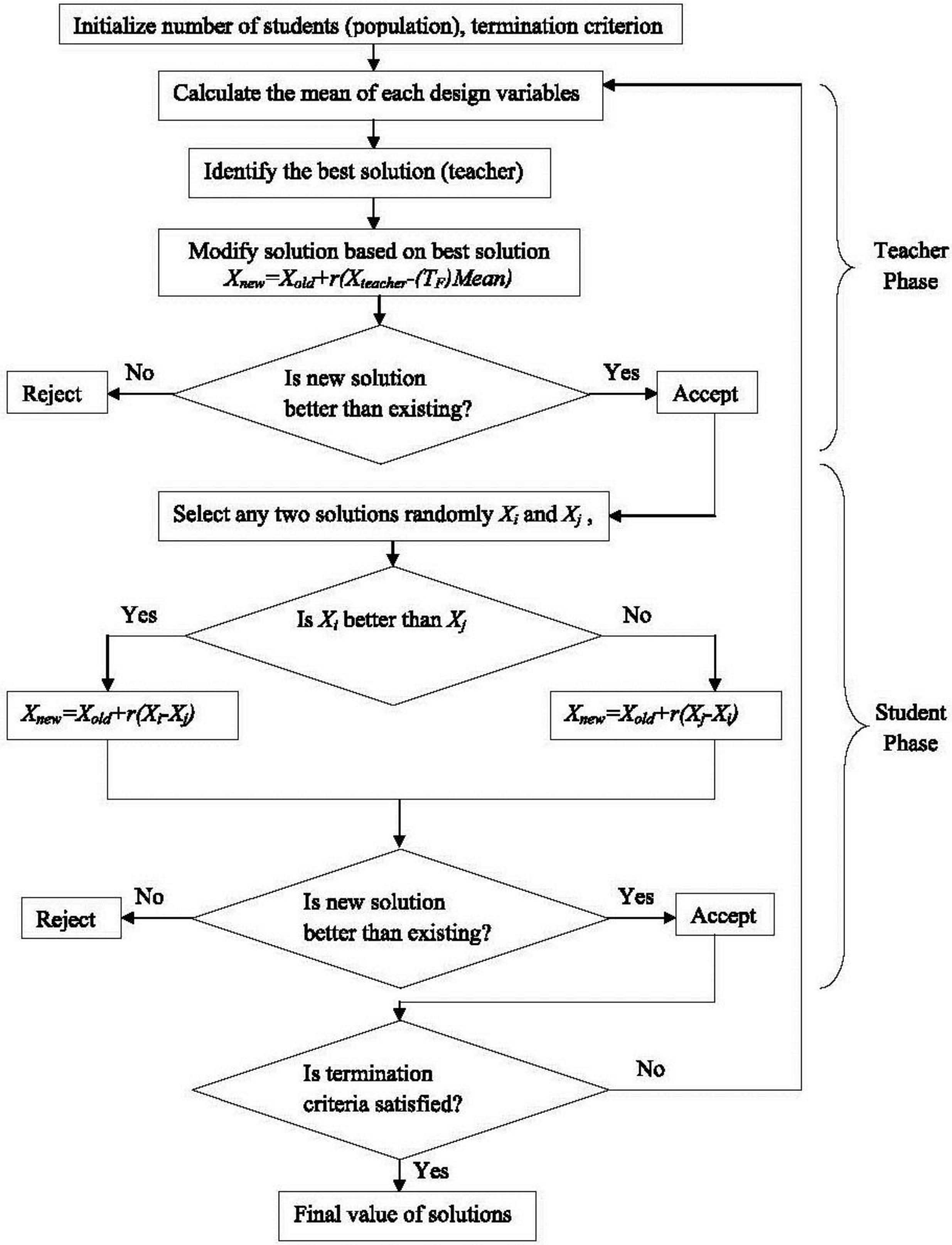

Figure 1.6: Flow chart for Teaching–Learning-Based Optimization (TLBO) [5]

to 'n' number of students (i.e. population of solutions i.e. k = 1, 2,…, n) and $M_{j,i}$ is the mean results of the students in a particular subject (j = 1, 2,…., m) As the teacher is considered as the most knowledgeable person in each subject, the best learner in the whole population is considered a teacher in the algorithm. The best overall result is $X_{total\text{-}kbest,i}$, obtained in the whole population of learners considering all the subjects together can be considered as a the result of best learner K_{best}. However, as the teacher is usually considered as a highly learned person who trains learners so that they can have better results, the best learner identified is considered as the teacher. The difference between the existing mean result of each subject and the corresponding result of the teacher for each subject is given by:

$$Difference\_Mean_{j,k,i} = r_i\ (K_{j,k\ best,i} - TF\ M_{j,i}) \qquad (10)$$

where $X_{j,kbest,i}$ is the result of the best learner (i.e., teacher) in subject j, TF is the teaching factor which decides the value of mean to be changed, and ri is the random number in the range [0,1]. The value of TF is decided randomly with equal probability as:

$$TF = round\ [1+rand\ (0, 1)\{2-1\}] \qquad (11)$$

TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Equation (11). Rao et al. [5] have conducted a number of experiments on many benchmark functions and it is concluded that the algorithm performs better if the value is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Equation (11). However, one can take any value of TF in between 1 and 2.

Based on the $Difference\_Mean_{j,k,i}$ the existing solution is updated in the teacher phase according to the following expression.

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,i} \qquad (12)$$

where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. $X'_{j,k,i}$ is accepted if it gives a better function value. At the end of teacher phase all the accepted values are maintained and these values become the input to the learner phase.

1.3.2 Learner Phase

Learners increase their knowledge by interacting themselves in this second section of this algorithm. A learner interacts randomly with other learners for enhancing their knowledge and experience. A learner learns new things or ideas if the other learner has more knowledge than him or her. Considering a population size of 'n', the learning phenomenon of this phase is expressed below.

Two learners P and Q are randomly selected such that

$X'_{total\text{-}P,i} \neq X'_{total\text{-}Q,i}$ (where, $X'_{total\text{-}P,i}$ and $X'_{total\text{-}Q,i}$ are the updated values of $X_{total\text{-}P,i}$ and $X_{total\text{-}Q,i}$ respectively at the end of teacher phase).

$$X''_{j,P,i}=X'_{j,P,i}+r_i(X'_{j,P,i}-X'_{j,Q,i}), \text{ if } X'_{total-P,i} < X'_{total-Q,i} \quad (13a)$$

$$X''_{j,P,i}=X'_{j,P,i}+r_i(X'_{j,Q,i}-X'_{j,P,i}), \text{ if } X'_{total-Q,i}<X'_{total-P,i} \quad (13b)$$

Accept $X''_{j,P,i}$, if it gives a better function value. All the accepted function values at the end of the learner phase are maintained and these values become the input to the teacher phase of the next iteration. The values of r_i used in above equations can be different. Repeat the procedure of teacher phase and learner phase till the termination criterion is met.

CHAPTER 2

LITERATURE SURVEY

2. Literature Survey

A literature survey was made on the various optimization techniques that have been used in the optimization of EDM process parameters. Some of the surveys have been listed below.

Bhattacharyya et al. [6] has developed mathematical models for surface roughness, white layer thickness and surface crack density based on response surface methodology (RSM) approach utilizing experimental data. It emphasizes the features of the development of comprehensive models for correlating the interactive and higher-order influences of major machining parameters i.e. peak current and pulse-on duration on different aspects of surface integrity of M2 Die Steel machined through EDM. From the obtained test results it is evident that peak current and pulse-on duration significantly influence various criteria of surface integrity such as surface roughness, white layer thickness and surface crack density. The optimal parametric combinations based on the developed models under present set of experimentations for achieving minimum surface roughness, white layer thickness and surface crack density are 2A/20μs, 2 A/20μs and 9 A/20μs, respectively. For achieving desired level of quality of the EDM_{ED} surface integrity utilizing present research findings lead to a significant step towards the goal of accomplishing high precision machining by EDM.

Tzeng et al. [7] had proposed an effective process parameter optimization approach that integrates Taguchi's parameter design method, response surface methodology (RSM), a back-propagation neural network (BPNN), and a genetic algorithm (GA) on engineering optimization concepts to determine optimal parameter settings of the WEDM process under consideration of multiple responses. Material removal rate and work-piece surface finish on process parameters during the manufacture of pure tungsten profiles by wire electrical discharge machining (WEDM).Specimens were prepared under different WEDM processing conditions based on a Taguchi orthogonal array of 18 experimental runs. The results were utilized to train the BPNN to predict the material removal rate and roughness average properties. Similarly, the RSM and GA approaches were individually applied to search for an optimal setting. In addition, analysis of variance (ANOVA) was implemented to identify significant factors for the process parameters, and results from the BPNN with integrated GA were compared with those from the RSM approach. The results show that the RSM and BPNN/GA methods are both effective tools for the optimization of WEDM process parameters.

Tzeng and Chen [8] analysed a hybrid method including a back-propagation neural network (BPNN), a genetic algorithm (GA) and response surface methodology (RSM) to determine optimal parameter settings of the EDM process. Material removal rate, electrode wear ratio and work-piece surface finish on process parameters during the manufacture of SKD61 by electrical discharge machining (EDM). Specimens were prepared under different EDM processing conditions according to a Taguchi's L18 orthogonal array. These experimental runs were utilized to train the BPNN to predict the material removal rate (MRR), relative electrode wear ratio (REWR) and roughness average (Ra) properties. Simultaneously, the RSM and GA approaches were individually applied to search for an optimal setting. Then, ANOVA was implemented to identify significant factors for the EDM process parameters. ANOVA indicated that the cutting parameter of discharge current and pulse-on time is the most significant factors for Ra. the higher discharge energy with the increase of discharge current and pulse on time leads to a more powerful spark energy, and thus increased MRR. REWR decreases with increase of pulse on-time under the same discharge current. The BPNN/GA could be utilized successfully to predict MRR, REWR and Ra resulting from the EDM process during the manufacture of SKD61, after being properly trained. Results from the BPNN with integrated GA were compared with those from the RSM approach. The results show that the proposed algorithm of GA approach has better prediction and gives confirmation results than the RSM method.

Lin et al. [9] has presented the use of grey relational analysis based on an orthogonal array and the fuzzy-based Taguchi method for the optimisation of the electrical discharge machining process with multiple process responses. Both the grey relational analysis method without using the S/N ratio and fuzzy logic analysis are used in an orthogonal array table in carrying out experiments. Experimental results have shown that both approaches can optimise the machining parameters (pulse on time, duty factor, and discharge current) with considerations of the multiple responses (electrode wear ratio, material removal rate, and surface roughness) effectively and can greatly improve process responses. It seems that the grey relational analysis is more straightforward than the fuzzy-based Taguchi method for optimising the EDM process with multiple process responses.

Panda and Bhoi [10] have applied ANN to model is checked with the experimental data. Selection of process parameters as the inputs of the neural network is based on factorial design of experiment, which enhances the capability of the neural network because only significant process parameters are considered as the input to the neural network model. The mathematical consideration of all these complex phenomena like growth of the plasma channel, energy sharing between electrodes, process of vaporization, and formation of recast layer, plasma-flushing efficiency and temperature sensitivity of thermal properties of the work material are a few physical phenomena that render the machining process highly difficult and stochastic. Therefore, mathematical prediction of material removal rate when compared with the experimental results shows wide variation. In such circumstances, the Levenberg-Marquardt back-propagation algorithm used in this paper, being a second-order error minimization algorithm, marginalizes the drawback of other back-propagation variants and to predict the material removal rate. Conclude that the artificial neural network model for EDM provides faster and more accurate results and the neural network model is less sensitive to noise.

Mandal et al. [11] made an attempt to model and optimize the complex electrical discharge machining (EDM) process using soft computing techniques. Artificial neural network (ANN) with back propagation algorithm is used to model the process. A large number of experiments have been conducted with a wide range of current, pulse on time and pulse off time. The MRR and tool wear have been measured for each setting of current, pulse on time and pulse off time. As the output parameters are conflicting in nature so there is no single combination of cutting parameters, which provides the best machining performance. An ANN model has been trained within the experimental data and various ANN architecture have been studied, and 3-10-10-2 is found to be the best architecture, with learning rate and momentum coefficient as 0.6, having mean prediction error is as low as 3.06%.A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Testing results demonstrate that the model is suitable for predicting the response parameters. A pareto-optimal set of 100 solutions has been predicted in this work.

Rao et al. [12] conducted the experiments by considering the simultaneous effect of various input parameters varying the peak current and voltage to optimizing the metal removal rate on the Die sinking electrical discharge machining (EDM). The experiments are carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Multi-perceptron neural network models were developed using Neuro solutions approach. Genetic algorithm concept is used to optimize the weighting factors of the network. It is observed that the developed model is within the limits of the agreeable error when experimental and network model results are compared for all performance measures considered. There is considerable reduction in mean square error when the network is optimized with GA. Sensitivity analysis is also done to find the relative influence of factors on the performance measures. From the sensitivity analysis it is concluded that type of material is having highest influence on all performance measures. It is observed that type of material is having more influence on the performance measures. Hybrid models are developed for MRR considering all the four material together which can predict the behaviour of these materials when machined on EDM.

Kansal et al. [13] aimed to optimize the process parameters using Response surface methodology to plan and analyze the experiments of powder mixed electrical discharge machining (PMEDM). Pulse on time, duty cycle, peak current and concentration of the silicon powder added into the dielectric fluid of EDM were chosen as variables to study the process performance in terms of material removal rate and surface roughness. The results identify the most important parameters to maximize material removal rate and minimize surface roughness. The silicon powder suspended in the dielectric fluid of EDM affects both MRR and SR. The MRR increases with the increase in the concentration of the silicon powder. There is discernible improvement in surface roughness of the work surfaces after suspending the silicon powder into the dielectric fluid of EDM. The analysis of variance revealed that the factor peak current and concentration are the most influential parameters on MRR and SR. The combination of high peak current and high concentration yields more MRR and smaller SR. The confirmation tests showed that the error between experimental and predicted values of MRR and SR are within±8% and −7.85% to 3.15%, respectively.

Sanchez et al. [14] have presented a study attempts to model based on the least squares theory, which involves establishing the values of the EDM input parameters namely peak current level, pulse-on time and pulse-off time to ensure the simultaneous fulfilment of material removal rate (MRR), electrode wear ratio (EWR) and surface roughness (SR). The inversion model was constructed from a set of experiments and the equations formulated in the forward model and In this forward model, the well-known ANOVA and regression models were used to predict the EDM output performance characteristics, such as MRR, EWR and SR in the EDM process for AISI 1045 steel with respect to a set of EDM input parameters. As a result, the predicted values of the parameters showed a good degree of agreement with those introduced experimentally. For instance, the response surface values of SR = 7.14 μm, EWR = 6.66% and MRR = 43.1 mm^3/min gave the predicted input parameters of I = 9.58 A, ton = 49.53 μs and t_{off} = 17.58 μs, which are close to those implemented in the experiments as input parameters (I = 9 A, t_{on} = 50 μs and t_{off} = 15 μs). Furthermore, since the differences between the predicted and experimental values of t_{on} and t_{off} are expressed in terms of microsecond, the results obtained by the inversion method show a good agreement to the input parameters introduced into the EDM machine during the experiments.

Kao et.al [15] have proposed an application of the Taguchi method and grey relational analysis to improve the multiple performance characteristics of the electrode wear ratio, material removal rate and surface roughness in the electrical discharge machining of Ti–6Al–4V alloy. The process parameters selected in this study are discharge current, open voltage, pulse duration and duty factor. Orthogonal array were used for conducting experiments. The normalized results of the performance characteristics are then introduced to calculate the coefficient and grades according to grey relational analysis. As a result, this method greatly simplifies the optimization of complicated multiple performance characteristics. The optimal process parameters based on grey relational analysis for the EDM of Ti–6Al–4V alloy include 5 amp discharge current, 200 V open voltage, 200 μs pulse duration and 70% duty factor. The optimized process parameters simultaneously leading to a lower electrode wear ratio, higher material removal rate and better surface roughness are then verified through a confirmation experiment. The validation experiments show an improved electrode wear ratio of 15%, material removal rate of 12% and surface roughness of 19% when the Taguchi method and grey relational analysis are used.

Rao et al. [12] has demonstrated to optimizing the surface roughness of EDM by considering the simultaneous effect of various input parameters namely peak current and voltage. The experiments are carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Multi-perception neural network models were developed using Neuro Solutions package and also genetic algorithm concept is used to optimize the weighting factors of the network. From the experiments it concluded that at 50 V and 12 A good surface finish is obtained for 15CDV6 and M250.When current increases at constant voltage surface finish reduces tremendously and for titanium alloy is that it has good surface finish at voltage 40V and at constant current of 16 A. It is observed that the developed model is within the limits of the agreeable error when experimental and network model results are compared. It is further observed that the error when the network is optimized by genetic algorithm has come down to less than 2% from more than 5%. Sensitivity analysis is also done to find the relative influence of factors on the performance measures. It is observed that type of material effectively influences the performance measures.

George et al. [17] have established an empirical models correlating process variables that are pulse current, pulse on time and gap voltage and their interactions with the said response functions named relative circularity of hole represented by the ratio of standard deviations, overcut, electrode wear rate (EWR) and material removal rate (MRR) while machining variables. The experimental investigations on the electrical discharge machining of carbon–carbon composite plate using copper electrodes of negative polarity. The Experiments are conducted on the basis of Response surface methodology (RSM) technique. The models developed reveal that pulse current is the most significant machining parameter on the response functions followed by gap voltage and pulse on time. These models can be used for selecting the values of process variables to get the desired values of the response parameters. These models can be effectively utilized by the process planners to select the level of parameters to meet any specific EDM machining requirement of carbon–carbon composite within the range of experimentation. The phenomenon of de-lamination of carbon–carbon composite, machined using electrical discharge machining, highly influences estimation of overcut and loss of circularity.

Caydas and Hascalik [18] studied the case of die sinking EDM process in which he has taken pulse on-time, pulse off-time and pulse current as input parameters with five levels. Central composite design (CCD) was used to design the experiments. Here, modelling of electrode wear (EW) and recast layer thickness (WLT) using response surface methodology (RSM). ANOVA have been used in study the adequacy of the modelled equation for the electrode wear and recast layer thickness. They concluded that the predicted value for EW and WLT are 0.99 and 0.97 respectively. For both EW and WLT pulse current as found to be most significant factor rather than pulse off-time.

Habib [19] presented an investigation on EDM process to form a mathematical modelled equation for material removal rate (MRR), electrode wear ratio (EWR), gap size (GS) and surface roughness (Ra). The adequacy of the modelled equation has been checked by using ANOVA (Analysis of variance). The input parameters were taken as pulse on-time, peak current, gap voltage and SiC particles percentage. He concluded that MRR increases with the increase of pulse on-time, peak current and with gap voltage and it decreases wit the decrease of SiC percentage. EWR increases with the increase of both pulse on-time and peak current and decreases with increase of both SiC percentage and gap voltage. Gap size (GS) reduces by increase of SiC percentage, pulse on-time, peak current and gap voltage. He modelled equations for the four responses by using RSM methodology. The modelled equations involves all the significant terms for the responses. Justification has been done through various experimental analysis and test results.

Assarzadeh and Ghorelshi [20] presented an approach on neural network for the prediction and optimal selection of process parameters in die sinking electrical discharge machining (EDM) with a flat electrode. For establishment of the process model a 3-6-4-2 size back propagation neural network was developed. The network input was taken as current (I), period of pulses (T) and source voltage (V) and material removal rate (MRR) and surface roughness (Ra) as output parameters. For training and testing the experimental data was used. Neural model declares the reasonable accuracy of the process performances under varying machining conditions. The variation sin the effects was analysed by the neural model. Augmented Lagrange Multiplier (ALM) algorithm evaluate the corresponding optimum machining conditions through maximizing MRR which subjects to appropriate operating and prescribed Ra constraints. Optimization has been done at each level of machining regimes. Machining regimes such as finishing, semi finishing and roughing from which optimal settings of machining parameters were obtained. There was no single combination of input parameters which were optimal for both MRR and Ra. This approach noticed to be superior because of only experimental data without any mathematical model it is giving relation input and output variables. They concluded that BP neural network model was effective for the prediction of MRR and Ra in EDM process. Appropriate trained neural network model with the ALM neural network positively synthesize the optimal input conditions for the EDM process. And the optimal setting of input maximizes the MRR. At the absence of the analytical model process optimization can be done by observing the experimental data.

Sohani et al. [21] investigated the effect of process parameters like pulse on time, discharge current, pulse off time and tool area through the RSM methodology for effect of tool shape such as triangle, square, rectangle and circular. The mathematical model was developed for MRR (material removal rate) and TWR (tool wear rate) using CCD in RSM. The ANOVA has been used for testing the adequacy of model for the responses. It also resulted that circular tool shape was best followed by triangular, rectangular and square cross sections. Interaction between discharge current and pulse on time was highly effective term for both TWR and MRR. Pulse off time and tool area was individually significant for both MRR and TWR. MRR increases directly proportional whereas TWR in a non linear manner.

Chiang [22] proposed the mathematical modelling and analysis of machining parameters on the performance in EDM process of Al_2O_3+ TiC mixed ceramic through RSM to explore the influence of four input parameters. The input parameters were taken as discharge current, pulse on time, open discharge voltage and duty factor and the output parameters as MRR (material removal rate), EWR (electrode wear ratio), and SR (surface roughness). ANOVA has been used for investigating the influence of interaction between the factors. Resulted as discharge current and duty factor were the most statistical significant factors.

Chiang et al. [23] presented the systematic methodology for the purpose of modeling and analyzing the rapidly resolidified the layers of SG (spheroidal graphite) cast iron in the EDM process by using RSM (response surface methodology). The performance of rapidly resolidified layer was investigated in terms of layer thickness and ridge density. CCD in RSM was used to design experiments. ANOVA describes the adequacy of the modelled equation obtained for responses. It was concluded that quantity of graphite particles and area fraction of graphite particles are the most significant factors on the layer thickness and ridge density of graphite particles. Quantity and area fraction of graphite particles were most significant factors for re-solidified layer thickness and ridge density.

Ponappa et al. [24] studied effects of EDM on drilled-hole quality as taper and surface finish. The input parameters were taken as pulse-on time, pulse-off time, voltage gap, and servo speed. ANOVA was used to identify the significant factors and accuracy for hole. Surface roughness and taper both depends on the speed and pulse on time. After optimization damaged to the surface roughness was minimized.

Joshi and Pande [25] reported an intelligent approach for modelling and optimization of electrical discharge machining (EDM) using finite element method (FEM) has been integrated with the soft computing techniques like artificial neural networks (ANN) and genetic algorithm (GA) to improve prediction accuracy of the model with less dependency on the experimental data. Comprehensive thermo-physical analysis of EDM process was carried out using two-dimensional axi-symmetric non-linear transient FEM model etc. to predict the shape of crater, material removal rate (MRR) and tool wear rate (TWR). A comprehensive ANN based process model is proposed to establish relation between input process conditions (current, discharge voltage, duty cycle and discharge duration) and the process responses (crater size, MRR and TWR) and it was trained, tested and tuned by using the data generated from the numerical (FEM) model. The developed ANN process model was used in conjunction with the evolutionary non-dominated sorting genetic algorithm II (NSGA-II) to select optimal process parameters for roughing and finishing operations of EDM. Two basic ANN configurations viz. RBFN and BPNN were developed and extensively tested for their prediction performance and generalization capability. Optimal BPNN based network architecture 4-5-28-4 was found to give good prediction accuracy (with mean prediction error of about 7%). The proposed integrated (FEM–ANN–GA) approach was found efficient and robust as the suggested optimum process parameters were found to give the expected optimum performance of the EDM process.

2.1. Objective of the Present Work

From the literature review, it was observed that lot of optimization techniques have been used for the optimization of Electrical Discharge Machining process parameters. The Teaching-Learning-Based Optimization is the recent evolutionary algorithm which claims to be the best among other evolutionary algorithms. However, this optimization technique has not been used in the optimization of the Electrical Discharge Machining process parameters where the optimal setting is required for a better performance. Hence, the optimization of EDM process parameters has been carried out using TLBO algorithm and the performance has been compared with other evolutionary algorithms.

CHAPTER 3

OPTIMIZATION OF EDM PROCESS PARAMETERS USING TLBO

3. Optimization of EDM Process Parameters Using TLBO

Optimization performance of TLBO was determined by the experimental data and mathematical modelling as considered here. Single objective optimizations of responses were performed here. A computer code was developed using MATLAB R2010b for the parametric optimization in EDM process considering the following parameters: population size = 20 and numbers of generations = 500.

Influences of various EDM process parameters like pulse-on time, peak current, average gap voltage, and percent volume fraction of SiC present in the aluminum matrix on four machining responses were studied by Habib [19] i.e., MRR (mm^3/min), TWR (mm3/min), gap size (GS, mm), and surface finish (Ra, µm). Experiments were conducted by him on a numerically controlled EDM machine by using a copper electrode of 15 mm diameter and 50 mm height. For commercial purpose kerosene was used as a dielectric fluid in EDM. Each EDM process parameters was set at five different levels, as shown in Table 3.1.

CCD (Central Composite Design) of second order was used for rotatable design plan; the corresponding RSM-based equations were developed for each of the four responses, as given in Equations (14 – 17):

$$\begin{aligned} Yu(MRR) = {} & 618.5593 - 7.50416 \times 10^{-3} x_1 - 6.56817 x_2 - 30.0990 x_3 - 2.59182 x_4 \\ & - 1.74368 \times 10^{-5} x_1^2 + 0.12973 x_2^2 + 0.39257 x_3^2 + 6.68543 \times 10^{-2} x_4^2 \\ & + 2.4234 \times 10^{-4} x_1 x_2 + 2.49988 \times 10^{-4} x_1 x_3 + 7.51773 \times 10^{-5} x_1 x_4 \\ & + 0.10008 x_2 x_3 - 2.99715 \times 10^{-2} x_2 x_4 + 0.02686 x_3 x_4 \end{aligned} \quad (14)$$

$$\begin{aligned} Yu(TWR) = {} & 61.76541 - 7.90436 \times 10^{-2} x_1 + 0.10946 x_2 - 3.07572 x_3 - 0.24833 x_4 \\ & + 6.3985 \times 10^{-5} x_1^2 + 8.79244 \times 10^{-3} x_2^2 + 4.05242 \times 10^{-2} x_3^2 \\ & + 6.26469 \times 10^{-3} x_4^2 - 1.11638 \times 10^{-3} x_1 x_2 - 1.5125 \times 10^{-3} x_1 x_3 \\ & + 5.75982 \times 10^{-4} x_1 x_4 - 1.19799 \times 10^{-3} x_2 x_3 - 3.16275 \times 10^{-3} x_2 x_4 \\ & + 8.311 \times 10^{-4} x_3 x_4 \end{aligned} \quad (15)$$

$$\begin{aligned}Yu(GS) = &- 0.22445 + 1.47807 \times 10^{-4} x_1 + 1.57186 \times 10^{-3} x_2 + 1.85221 \times 10^{-2} x_3 \\ &- 6.4621 \times 10^{-4} x_4 - 1.94435 \times 10^{-7} x_1^2 - 5.5177 \times 10^{-3} x_2^2 \\ &- 3.18672 \times 10^{-4} x_3^2 - 4.40999 \times 10^{-6} x_4^2 - 1.14697 \times 10^{-6} x_1 x_2 \\ &+ 6.90315 \times 10^{-11} x_1 x_3 + 6.07739 \times 10^{-7} x_1 x_4 + 2.67992 \times 10^{-5} x_2 x_3 \\ &- 1.24999 \times 10^{-5} x_2 x_4 + 1.46688 \times 10^{-5} x_3 x_4 \end{aligned} \quad (16)$$

$$\begin{aligned}Yu(R_a) = &\ 28.17869 + 3.96302 \times 10^{-2} x_1 - 2.44761 \times 10^{-6} x_2 - 1.47874 x_3 \\ &+ 0.2412 x_4 - 3.66634 \times 10^{-5} x_1^2 - 4.24572 \times 10^{-3} x_2^2 + 1.9191 \times 10^{-2} x_3^2 \\ &- 1.272 \times 10^{-3} x_4^2 + 2.71171 \times 10^{-4} x_1 x_2 - 5.62393 \times 10^{-4} x_1 x_3 \\ &+ 2.05371 \times 10^{-4} x_1 x_4 + 5.22354 \times 10^{-3} x_2 x_3 + 1.64502 \times 10^{-3} x_2 x_4 \\ &- 3.74646 \times 10^{-3} x_3 x_4 \end{aligned} \quad (17)$$

These RSM based Equations (14 – 17) contains independent, quadratic, and interactive terms which shows the effect of the terms on the considered responses. Coefficients of these equations show the comparative importance of different terms.

3.1. Single-objective Optimization

Habib [19] determined the optimal combination of various process parameters for maximizing MRR and minimizing EWR, GS, and Ra values for controlled EDM operation. Those optimal values are listed in Table 3.1. This table also shows the results when the GA, ACO, ABC, BBO and TLBO algorithms are used to optimize the above mentioned RSM-based equations for the four responses. The optimal setting for the five optimization algorithm has been listed in Table 3.2.

Table 3.1: Different EDM process parameters with their levels [9]

Parameters	Level				
	–2	–1	0	1	2
Pulse-on time (μs) (x_1)	50	100	150	200	500
Peak current (amp) (x_2)	10	14	20	24	30
Average gap voltage (V) (x_3)	30	32	34	36	38
Percent volume fraction of SiC (%) (x_4)	0	5	10	20	25

Table 3.2: Single objective optimization results

Optimization method	Response	Value	Pulse-on time	Peak current	Average gap voltage	Percent volume fraction of SiC
Habib [19]	MRR	79.4128	250	30	30	0
	TWR	2.2519	500	28	36	0
	GS	0.057	50	10	28	25
	R_a	2.2156	50	10	38	0
GA algorithm [26]	MRR	60.76	225	28	32	2
	TWR	1.0596	212	12.48	30.71	24.23
	GS	0.0636	436.66	10.59	37.03	24.09
	R_a	4.2355	75	14	30	0
ACO algorithm [26]	MRR	70.69	400	28	30	0
	TWR	0.7768	350	10.6	35.7	22.42
	GS	0.0592	190.88	10.59	36.71	24.19
	R_a	3.1331	50	12	32	0.5
ABC algorithm [26]	MRR	76.81	175	30	30	1
	TWR	0.3892	422	11.2	37.57	9.9265
	GS	0.0503	66.05	10.55	36.41	20.38
	R_a	2.5629	60	10	35	0
BBO algorithm [26]	MRR	75.0753	250	30	31.5	0
	TWR	0.2254	169.405	10.44	32.96	16.85
	GS	0.0444	74.24	10.37	37.43	24.97
	R_a	2.0026	58	12.5	34	0
TLBO Algorithm	MRR	79.4422	208.34	30	30	0
	TWR	0.0012	500	28.372	38	1.4758
	GS	0.03222	5	10	38	25
	R_a	1.3515	5	10	37.23	0

It is clearly observed that the TLBO algorithm outperforms the other four population-based optimization algorithms with respect to the optimal values of the process responses. Figure 3.1 shows the convergence of all the considered optimization algorithms for MRR. These results are compared with the results of Habib and it is found that MRR is marginally increased from79.4128 mm^3/min to 79.4422 mm^3/min, TWR is drastically reduced from 2.2519 mm^3/min to 0.0012 mm^3/min, GS is decreased from 0.0570 mm to 0.0322 mm, and R_a is also reduced from 2.2156 µm to 1.3515 µm. Figure 3.2 shows the convergence of TLBO algorithm for MRR.

Variation in response of MRR with respect to pulse-on time, peak current, average gap voltage, and percent volume fraction of SiC is shown in Figure 3.2. Habib [19] observed that an increase in pulse-on time causes an increase in MRR slightly until it reaches to a point of 200 μs then the MRR begins to decrease. Figure 3.2 shows almost similar observation where MRR initially increases up to pulse-on time = 250 μs and then it starts reducing. At pulse-on time (400 μs) the value of MRR steadies a bit and afterwards it reduces again. An increase in pulse-on time will cause an increase in heat that is conducted into the workpiece causes to expand the plasma channel, which will result in increased value of MRR. As the discharge duration increases, the pressure inside the plasma channel will be lower. After that.

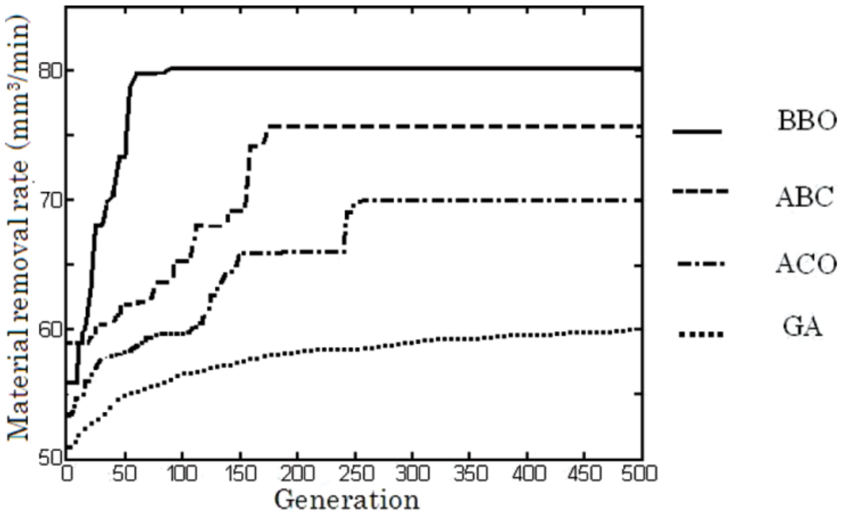

Figure 3.1: Convergence of BBO, GA, ACO and ABC algorithm for MRR [26]

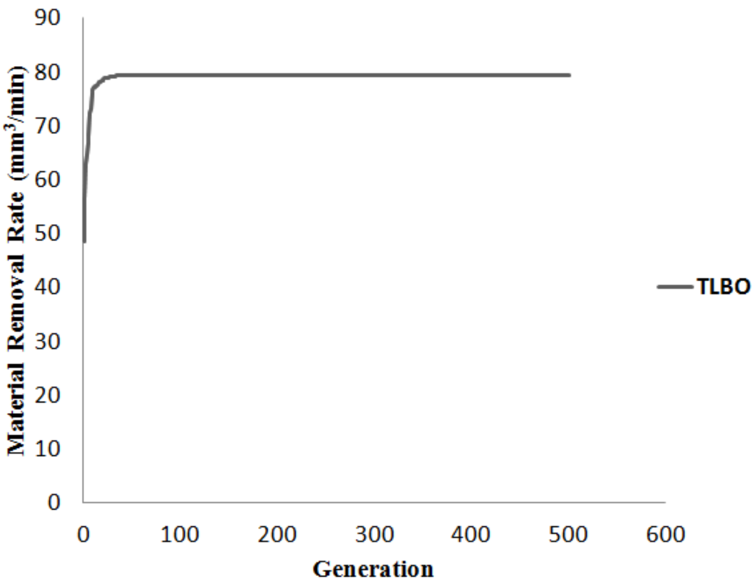

Figure 3.2: Convergence of TLBO algorithm for MRR

there will be no more increment in MRR, since the molten metal volume does not change and further increase may cause decrease in MRR. MRR also decreases with the increase in SiC percent of amount. During the machining process SiC ceramic particles are not melted. In this case, the removal of the particles causes reinforced aluminum alloy matrix composite through the melting and vaporizing process of the aluminum matrix material around the SiC ceramic particles. The value of MRR is the highest when SiC percent is zero, and with the increase in SiC percent, MRR reduces. It has also been noticed that MRR increases with the increase in values of peak current for all values of gap voltages. The increase in peak current will increase in pulse discharge energy channel diameter and hence will cause an increase in the crater diameter and depth, which in turn, will improve the MRR. The same observation is observed in the Figure 3.3 where MRR increases steadily with increase in peak current. Habib also found that MRR decreases nonlinearly with the increase in gap voltage and higher values of gap voltages resulted in relatively lower metal removal rates. Here also as the plot shows, higher value of MRR is possible at the lower values of gap voltage. The highest possible MRR occurs at about gap voltage = 30 V and after that MRR starts reducing with the

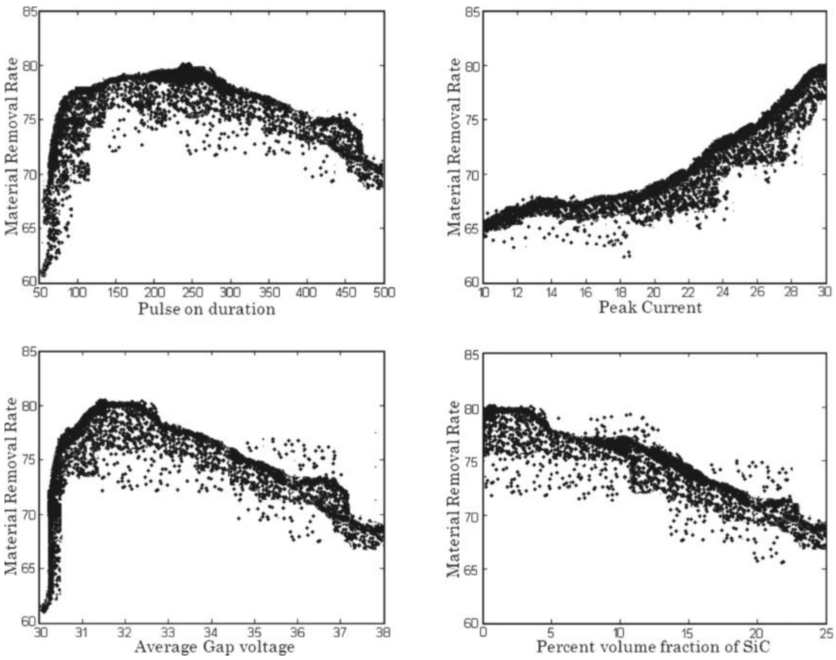

Figure 3.3: Variations of MRR with respect to four EDM process Parameters [26]

increase in gap voltage. For the other three responses (i.e., EWR, GS, and R_a) the findings derived by employing the TLBO algorithm also almost corroborate with those obtained by Habib.

3.2. Multi-Objective Optimization

Multi-objective optimization has been defined as finding a vector of decision variables while optimizing (i.e. minimizing or maximizing) several objectives simultaneously, with a given set of constraints. In the present work, four such objectives namely maximizing the MRR and minimizing TWR, GS and R_a are considered simultaneously for multi-objective optimization. Weight method is implemented in the present work for multi-objective optimization.

The single objective functions from the previous section are put together for multi-objective optimization. The normalized multi-objective function (Z_2) is formulated considering equal weight factors to all the objectives and is given by the following equation:

$$\text{Min}(Z_2) = 0.25 \times TWR / TWR_{min} + 0.25 \times GS / GS_{min} + 0.25 \times R_a / R_{a\ min} - 0.25 \times MRR / MRR_{max} \quad (18)$$

where Yu(TWR), Yu(GS), Yu(Ra), and Yu(MRR) are the second order response surface equations for TWR, GS, Ra, and MRR, respectively; TWR_{min}, GS_{min}, and Ra_{min} are the minimum values of TWR, GS, and Ra, respectively; and MRR_{max} is the maximum value of MRR. Here, equal weight is given to all the responses and the minimum value of Z_2 is calculated as 0.4437. Table 3.3 shows these multi-objective optimization results obtained using the TLBO algorithm. It is observed that a parametric combination of pulse-on time = 5 ms, peak current =30 amp, average gap voltage = 38V, and 0% of SiC will simultaneously optimize all the responses. Comparing with the results of Mukherjee and Chakorborty [26], the MRR is increased from 74.04 mm^3/min to 75.52 mm^3/min, TWR decreased from

Table 3.3: Multi-objective Optimization results

Optimization Method	Response	Value	Pulse-on time	Peak current	Average gap voltage	Percent volume fraction of SiC
TLBO algorithm	MRR	75.5161	5	30	380	0
	TWR	1.2387				
	GS	0.0482				
	R_a	1.9630				
BBO algorithm	MRR	74.04	90.2325	29.72	37.97	0.27
	TWR	3.5132				
	GS	0.0623				
	R_a	3.96				

3.5132 mm^3/min to 1.2387 mm^3/min, the gap size decreased from 0.0623 mm to 0.0482 mm, surface roughness decreased from 3.96 µm to 1.9630 µm. The multi- objective function using TLBO gave a better result by fulfilling all the objectives. In the present case the optimized parameters setting, also obtained by using the TLBO algorithm and has given the compromising solution for the combined objective functions.

CHAPTER 4

CONCLUSION

4. Conclusion

In this present study, the TLBO algorithm is applied to determine the optimal parametric combinations for four EDM processes for achieving better machining performance. Both single- and multi-objective optimization problems were solved using this algorithm. When comparison is done with other population-based optimization algorithms, like GA, ACO, ABC and BBO it is observed that the TLBO algorithm gives better results. This algorithm can be applied as a global optimization tool for the purpose to select process parameter values. It can also be successfully applied for optimizing other nontraditional machining processes. Not relying on the manufacturer's data or handbook data, the process engineers can now select the optimal process parameter settings for different processes to achieve the desired machining performance.

4.1. Scope of further research work

Future research may focus on the multi-objective optimization of other manufacturing processes using TLBO as less work has been done on this recent optimization technique.

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