Parameters optimization of advanced machining processes using TLBO algorithm

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Abstract

Nowadays advanced machining processes are widely used by manufacturing industries in order to produce high quality precise and very complex products. These advanced machining processes involve large number of input parameters which may affect the cost and quality of the products. Selection of optimum machining parameters in such advanced machining processes is very important to satisfy all the conflicting objectives of the process. In this research work a newly developed advanced algorithm is applied for the process parameter optimization of selected advanced machining processes. This algorithm is inspired by the teaching-learning process and it works on the effect of influence of a teacher on the output of learners in a class. The detailed algorithm is explained in this paper. The important advanced machining processes identified for the process parameter optimization in this work are electrochemical machining (ECM) process and electrochemical discharge machining (ECDM) process. Two different multiobjective problems of these processes are considered in this work which was attempted previously by various researchers using recent optimization technique such as artificial bee colony algorithm (ABC). However, comparison between the results gives the superiority of the new algorithm in terms of population size, number of generations and computational time.

Keywords: Advanced machining processes, Electrochemical machining process, Electrochemical discharge machining process, Multiple objective decision making, Teaching-learning-based optimization algorithm.

Introduction

With the industrial and technological growth, development of harder and difficult to machine materials, which find wide application in aerospace, nuclear engineering and other industries, has been witnessed in the past few decades. These materials possess high strength to weight ratio, hardness and heat resistance qualities. Advanced machining has grown out of the need to machine such materials. The advanced machining processes are also referred as non-traditional in the sense that they do not employ traditional tools for metal removal and instead they directly use other forms of energy. The problems of high complexity in shape, size and higher demand for product accuracy and surface finish can be solved through advanced machining processes.

Advanced machining consists of various precision activities to be performed on very small work pieces having complex surfaces, especially in the electronic and computer industries. When those things are performed with conventional machining techniques, the problems one usually encounters are high tool wear rate and heat generation at the tool and work piece interface and subsequent alteration of work piece material characteristics, etc. A rigidity requirement for the tool is another problem in the conventional machining of small and deep holes, complex surface and shapes.

Stringent design requirements and difficult-to-machine materials such as tough super alloys, ceramics, and composites, have made conventional machining processes costly and obsolete. As a result, manufacturers and machine design engineers are turning to

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advanced machining processes. These machining processes utilize electrical, chemical and optimal sources of energy to form and cut the materials. Large numbers of advanced machining processes are in existence today and few important among them are listed below:

- Ultrasonic machining
- Electro chemical machining
- Electrical discharge machining
- Laser beam machining
- Electron-beam machining
- Water-jet machining
- Abrasive-jet machining

Presently, advanced machining processes possess virtually large capabilities except for volumetric material removal rates, for which great advances have been made in the past few years to increase the material removal rates. As removal rate increases, the cost effectiveness of operations also increase, thereby providing economical use of advanced machining processes in the industries.

In the present work electrochemical machining process (ECM) and electrochemical discharge machining process (ECDM) is considered for its process parameters optimization using the new algorithm. The next section presents the detailed literature review on both the processes.

Literature Review

a) Electrochemical machining process

Electrochemical machining (ECM) is an advanced machining process belonging to electrochemical category. In electrochemical machining, the removal of metal is controlled by the anodic dissolution in an electrolytic cell in which the work piece is the anode and the tool is cathode. The electrolyte is pumped through the gap between the tool and the work piece, while direct current is passed through the cell, to dissolve metal from the work piece. ECM is widely used in machining of jobs involving intricate shapes and to machine very hard or tough materials those are difficult or impossible to machine by conventional machining. It is now routinely used for the machining of aerospace components, critical deburring, fuel injection system components, etc. ECM is also most suitable for manufacturing various types of dies and moulds.

The important input parameters of ECM process are feed rate, electrolyte flow rate, current, voltage, interelectrode gap, etc. which affects the process responses like metal removal rate, tool life, surface finish and production cost. In the past various researchers had attempted the process parameter optimization of ECM process.

Bhattacharyya *et al*. (1973) proposed a two-dimensional interelectrode gap model in which maximization of the metal removal rate was considered as the objective function with the tool feed rate and electrolyte flow velocity as the design variables. The three constraints considered were temperature, passivity, and choking. However, the authors had considered only a single-objective optimization problem and solved the same using a graphical solution technique, which, in itself, was less accurate. This model was also based on many simplified assumptions, such as the constant void fraction, electrolyte conductivity as a function of the void fraction only, and constant electrolyte pressure along its flow path.

Dardery (1982) proposed a cost model of the ECM process considering various costs involved in the process. The cost equation was arranged in terms of decision variables, namely feed rate, electrolyte flow rate, and voltage. The optimum values of the decision variables were obtained by partial differentiation of the cost equation with respect to the decision variables. However, as no constraints were considered in this model, the values of decision variables obtained were not practical.

Acharya *et al*. (1986) considered the multi-objective optimization model for the ECM process with maximization of the material removal rate, minimization of dimensional inaccuracy, and maximization of tool life as three conflicting objectives. The decision variables were the tool feed rate, electrolyte flow velocity, and applied voltage. The constraints used in this model were temperature constraint, passivity constraint, and choking constraint. The optimization problem was solved by goal programming. This model overcomes the limitations of the model proposed by Bhattacharyya et al. (1973). However, it did not include the variable bounds for feed rate and differences in the interelectrode gap.

Hewidy *et al*. (2007) analysed the components of ECM cost (such as costs of power consumption, machining, electrolyte, and labour) with the objective to set out the basic principles for selecting a suitable electrochemical machine to meet the local production requirements of a company. The authors mentioned the impossibility of having a generalized model for this purpose. In another work, Hewidy *et al*. modelled the performance of ECM assisted by low-frequency vibrations using an analytical approach.

Jain *et al*. (2007) formulated the optimization model based on the analysis given in Acharya *et al*. (1986) with certain modifications, i.e. expanding the variable bound ranges for the tool feed rate and electrolyte flow velocity. The optimization problem was then solved using a genetic algorithm. However, the authors had considered only a single objective optimization problem, i.e. to minimize the dimensional inaccuracy. Also the passivity constraint was violated in their approach. Furthermore, the genetic algorithm has its own limitations, such as the risk of replacement of a good parent string with the deteriorated child, less convergence speed, and difficulty in selecting the controlling parameters such as population size, crossover rate, and mutation rate.

Asokan *et al*. (2008) used artificial neural network approach to determine the optimal machining parameters in ECM. Current, voltage, flow rate and interelectrode gap are considered as machining parameters and metal removal rate and surface roughness are considered as the objective functions.

Rao *et al*. (2008) had applied particle swarm optimization technique to the optimization model of Acharya *et al*. (1986) and obtained very improved results. Multiobjective optimization problem was also effectively solved by using particle swarm optimization technique. Datta and Das (2010) used experimental dataset for modeling the ECM process parameters through regression analysis. Genetic algorithm was then applied to those developed linear model and an exponential model for maximizing material removal rate and minimizing surface roughness. Samanta and Chakraborty (2011) had used artificial bee colony (ABC) algorithm for the maximization of metal removal rate and minimization of overcut in the ECM process.

It is observed from the review of past work that various traditional optimization techniques such as graphical method and mathematical programming techniques like goal programming, partial differentiation, etc., had been used to solve the problems of optimization of ECM process parameters. Subsequently it is proved that the results obtained by these traditional techniques are not the optimum and also these techniques are very complex in nature and cannot handle multiobjective problems effectively. To overcome the drawbacks of traditional optimization techniques, few researchers attempted the advanced optimization techniques like genetic algorithm, particle swarm optimization and artificial bee colony algorithm. However, to check for any improvement in the results, the teaching-learning-based optimization algorithm is considered here for the parameter optimization of ECM process. A multiobjective problem is considered here and its details along with the result are given in example 1.

b) Electrochemical discharge machining process

Electrochemical discharge machining (ECDM) is a hybrid advanced machining process which combines the features of electrochemical machining (ECM) and electro discharge machining (EDM). One of the major advantages of ECDM, over ECM or EDM, is that the combined metal removal mechanisms in ECDM, yields a much higher machining rate (Mediliyegedara *et al*. 2005). If a voltage is applied to an electrochemical cell beyond critical voltage, discharge initiates between one tool of the electrodes and the surrounding electrolyte, which is termed here as electrochemical discharge. When the applied voltage is increased beyond a threshold value, hydrogen gas bubbles evolve in large number at the tip of cathode and grow in size. Their nucleation site density increases, current path gets restricted between cathode and electrolyte interface causing discharge to occur at this interface instantly. Thus, discharge in ECDM always occurs when the voltage in an electrolytic cell is increased beyond a threshold value (Kulkarni *et al*. 2002). ECDM is a very recent technique in the field of advanced machining to machine electrically non conductive materials using electrochemical discharge phenomenon (Basak and Ghosh 1997). Various input parameters involved in the ECDM process are electrolyte, temperature, applied voltage, inductance, current, pulse density, discharge frequency, etc. In the literature, few works were reported on the electrochemical discharge machining.

Basak and Ghosh (1997) had developed theoretical model for material removal rate and then estimated the nature of MRR characteristics under different input conditions. The experimental result indicates that, the MRR can be substantially increased by introducing an additional inductance in the circuit. Kulkarni *et al*. (2002) proposed the basic mechanism of temperature rise and material removal through experimental observations of time-varying current in the circuit.

Wuthrich and Fascio (2005) had reviewed the machining of non-conducting materials like glass or ceramics using electrochemical discharge machining with more focus on experimental difficulties. Mediliyegedara *et al*. (2005) presented the new developments in process control for the hybrid ECDM process and carried out a system identification experiment to obtain the dynamics of the system and a process control algorithm was implemented in the software form.

Sarkar *et al.* (2006) described the development of a second order, non-linear mathematical model for establishing the relationship among machining parameters during an ECDM operation. Various parameters considered were applied voltage, electrolyte concentration and inter-electrode gap, etc. and the responses includes material removal rate, radial overcut and thickness of heat affected zone. The model was developed based on response surface methodology and finally the output of the work recommended that applied voltage has more significant effects on all the responses as compared to other machining parameters. Samanta and Chakraborty (2011) used the advanced optimization technique for the parameter optimization for ECDM process. Artificial bee colony algorithm was used to maximize material removal rate and minimization of heat affected zone and operating cost.

It is clearly observed from the literature that very little work was carried out on the parameter optimization of ECDM process. Even though in few cases, the ECDM process was involved, but the work was restricted up to the experimental remarks in many cases. Hence in the present work, efforts are carried out for the parameter optimization of ECDM process.

Teaching-learning-based optimization algorithm

Teaching-learning-based optimization algorithm (TLBO) is a teaching-learning process inspired algorithm proposed by Rao *et al.* (2011a, 2011b), which is based on the effect of influence of a teacher on the output of learners in a class. The algorithm mimics the teaching-learning ability of teacher and learners in a class room. Teacher and learners are the two vital components of the algorithm and describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). The output in TLBO algorithm is considered in terms of results or grades of the learners which depend on the quality of teacher. So, teacher is usually considered as a highly learned person who trains learners so that they can have better results in terms of their marks or grades. Moreover, learners also learn from the interaction among themselves which also helps in improving their results.

TLBO is population based method. In this optimization algorithm a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and learners' result is analogous to the 'fitness' value of the optimization problem. In the entire population the best solution is considered as the teacher. The working of TLBO is divided into two parts, 'Teacher phase' and 'Learner phase'. Working of both the phase is explained below.

i) Teacher phase

It is first part of the algorithm where learners learn through the teacher. During this phase a teacher tries to increase the mean result of the class room from any value M_1 to his or her level (i.e. T_A). But practically it is not possible and a teacher can move the mean of the class room M_1 to any other value M_2 which is better than M_1 depending on his or her capability. Considered M_j be the mean and Ti be the teacher at any iteration i. Now T_i will try to improve existing mean M_j towards it so the new mean will be T_i designated as M_{new} and the difference between the existing mean and new mean is given by (Rao *et al.*, 2011).

$$Difference\_Mean_i = r_i \left(M_{new} - T_F M_j \right) \quad (1)$$

Where 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]. Value of TF can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as:

$$T_F = round\left[1 + rand(0,1)\{2-1\}\right] \quad (2)$$

The teaching factor is generated randomly during the algorithm in the range of 1-2, in which 1 corresponds to no increase in the knowledge level and 2 corresponds to complete transfer of knowledge. The in between values indicates amount of transfer level of knowledge. The transfer level of knowledge can be any depending on the learners capabilities. In the present work, attempt was carried out by considering the values in between 1-2, but any improvement in the results was not observed. Hence to simplify the algorithm the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria. However, one can take any value of TF in between 1-2.

Based on this Difference_Mean, the existing solution is updated according to the following expression

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \quad (3)$$

b) Learner phase

It is second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. A learner learns new things if the other learner has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed below.

At any iteration i, considering two different learners X_i and X_j where $i \neq j$

$X_{new,i} = X_{old,i} + r_i \left(X_i - X_j \right)$ If f (Xi) < f (Xj) (4)

$X_{new,i} = X_{old,i} + r_i \left(X_j - X_i \right)$ If f (Xj) < f (Xi) (5)

Accept X_{new} if it gives better function value. The implementation steps of the TLBO are summarized below:

Step 1: Initialize the population (i.e. learners') and design variables of the optimization problem (i.e number of subjects offered to the learner) with random generation and evaluate them.

Step 2: Select the best learner of each subject as a teacher for that subject and calculate mean result of learners in each subject.

Step 3: Evaluate the difference between current mean result and best mean result according to equation (1) by utilizing the teaching factor (TF).

Step 4: Update the learners' knowledge with the help of teacher's knowledge according to equation (3).

Step 5: Update the learners' knowledge by utilizing the knowledge of some other learner according to Eqs. (4) and (5).

Step 6: Repeat the procedure from step 2 to 5 till the termination criterion is met.

The next section presents the applications of the proposed algorithm for the parameter optimization of ECM and ECDM process.

Application Examples

It is observed from the literature that very few advanced optimization algorithms such as genetic algorithm, particle swarm optimization and artificial bee colony algorithm had been applied for the parameter optimization of ECM and ECDM process. However, to check whether any further improvement is possible, the proposed TLBO algorithm is now attempted for the following multiobjective problems of ECM and ECDM process each. Example 1 describes the details of the model for ECM process along with the result and discussions, whereas Example 2 is for ECDM process.

Example 1

The ECM process model presented by Samanta and Chakraborty (2011) has been used in this example. In this work, the ECM process was modeled as maximization of material removal rate (MRR) and minimization of radial overcut (ROC). Four input parameters were involved in this multiobjective problem viz. electrolyte concentration (g/l), electrolyte flow rate (l/min), applied voltage (V) and inter-electrode gap (mm). The RSM based mathematical models for MRR and ROC as given by Samanta and Chakraborty (2011) are given in equations (6)-(7) respectively.

Z_{MRR}, (g/min) = $1.19263 + 0.05688x_1 - 0.13590x_2 + 0.09215x_3 - 5.45671x_4 - 0.00004x_1^2 + 0.01232x_2^2 + 0{:}00029x_3^2 - 0.36444x_4^2 - 0.00365x_1x_2 - 0.00067x_1x_3 + 0.01407x_1x_4 - 0.01045x_2x_3 + 0{:}26505x_2x_4 + 0.09247x_3x_4$ (6)

Z_{ROC} (mm) = $- 2.10705 + 0.01065x_1 + 0.31849x_2 + 0{:}00266x_3 + 0.48742x_4 - 0.00002x_1^2 - 0.01223x_2^2 + 0.00011x_3^2 + 0.08501x_4^2 - 0.00040x_1x_2 - 0.00006x_1x_3 - 0.00199x_1x_4 + 0.00044x_2x_3 - 0.02656x_2x_4 - 0.00781x_3x_4$ (7)

Where, x_1 is the electrolyte concentration, x_2 is the electrolyte flow rate, x_3 is the applied voltage and x_4 is the inter-electrode gap. The bounds for these parameters are given as:
Electrolyte concentration (g/l) = 15 – 75
Electrolyte flow rate (l/min) = 10 – 14
Applied voltage (V) = 10 – 30
Inter-electrode gap (mm) = 0.4 – 1.2

Bhattacharya and Sorkhel (1999) investigated the electrochemical machining through response surface methodology-based approach. Samanta and Chakraborty (2011) had applied artificial bee colony algorithm to the models developed by Bhattacharya and Sorkhel (1999) for obtaining the optimized parameters of this example of ECM process. The maximum MRR obtained by Samanta and Chakraborty (2011) was 1.4551 (g/min) and the minimum ROC was 0.0824 mm. For this purpose, Samanta and Chakraborty (2011) had used a large population size of 2000 and had taken 100 iterations to obtain the optimum results.

However, the same mathematical models given by equations (6) and (7) are now attempted by the TLBO algorithm to check for improvement in the result. Initially both the models are attempted individually as a single objective function. The population size is used randomly starting with the low value and a promising result is shown by a population size of 10. The TLBO algorithm has given a maximum MRR of 1.4551 (g/min) and minimum ROC of 0.0818 mm. The optimized parameters obtained for this result is given in Table 1 along with its comparison with the other results.

Table 1. Single objective optimization results for ECM process.

Process parameters	Results of Bhattacharya and Sorkhel (1999)		ABC algorithm		TLBO algorithm	
	MRR	Overcut	MRR	Overcut	MRR	Overcut
Electrolyte conc. (g/l)	57.88	17.55	75	15	75	15
Electrolyte flow rate (l/min)	11.98	11.05	10	10	10	10
Applied voltage (V)	22.04	21.65	30	10	30	10
Inter-electrode gap (mm)	1	0.87	1.2	0.4	1.2	0.4
Optimal value	0.7245	0.2702	1.4551	0.0824	1.4551	0.0824

Even though the results of TLBO algorithm are similar to that of the ABC algorithm, but the TLBO algorithm has used a very low population size of 10 as compared to that of 2000 in case of ABC algorithm. Similarly, the TLBO algorithm need only 20 iterations for consistency and has converged the optimum result in fifth iteration only. Whereas, ABC algorithm had taken 100 iterations in both the models. Thus, TLBO algorithm has proved its superiority in terms of faster convergence rate.

Samanta and Chakraborty (2011) had combined both the objectives and obtained a multi-objective optimization problem, as given by equation (8). By combining all the objectives, common process parameters can be obtained which satisfies all the conflicting objectives (Rao 20101).

$$\mathrm{Min}(Z_1) = w_1 Z_{ROC}/ROC_{min} - w_2 Z_{MRR}/MRR_{max} \quad (8)$$

Where, ROC_{min} and MRR_{max} are the minimum and the maximum values of ROC and MRR respectively which can be obtained by attempting an individual objective function, and w_1 and w_2 are the weight values assigned to ROC and MRR, respectively. In the present case, same weightage of 0.5 each is used as considered by Samanta and Chakraborty (2011) and the results obtained by artificial bee colony algorithm is given in Table 2. The objective function values reported by Samanta and Chakraborty (2011) were wrong. The same is rectified in this work and the corrected values are given in Table 2.

This multi objective optimization problem is now attempted by the TLBO algorithm and the result obtained by TLBO algorithm is given in Table 2 along with its comparison with earlier result.

Table 2. Multi-objective optimization of the ECM process.

Parameters and objective function	ABC result	TLBO result
Electrolyte concentration (g/l)	15	15
Electrolyte flow rate (l/min)	10	10
Applied voltage (V)	10	10
Inter-electrode gap (mm)	0.4	0.4
Metal removal rate (g/min)	0.4408*	0.4408
Radial overcut (mm)	0.0818*	0.0818
Z_1	0.3488*	0.3488
Number of iterations	100	20

*Corrected values

The TLBO algorithm has given a compromising result for both the conflicting objectives by satisfying all the parameter bounds. TLBO algorithm has taken a very small population size of 20 for such a multiobjective problem compared to that of 2000 in case of ABC algorithm. The results are also converged very fast.

Example 2

This example is taken from the work of Sarkar et al. (2006) who had carried out parametric analysis on electro- chemical discharge machining of silicon nitride ceramics using steepest ascent method. Samanta and Chakraborty (2011) attempted the same problem using artificial bee colony algorithm. The example considered was a multiobjective problem which involves maximization of material removal rate (MRR) and minimization of radial overcut (ROC) and heat affected zone (HAZ). The input parameters involved in the model were applied voltage (V), electrolyte concentration (wt %) and inter-electrode gap (mm). The individual mathematical model for material removal rate, radial overcut and heat affected zone is given below by the equations (9) - (11) respectively.

$$Z_{MRR}, \text{(mg/hr)} = 4.96423 - 0.20418x_1 + 0.09862x_2 + 0.00851x_3 + 0.00249x_1^2 - 0.00086x_2^2 + 0.00039x_3^2 - 0.00181x_1x_2 - 0.00104x_1x_3 + 0.00125x_2x_3 \quad (9)$$

$$Z_{ROC}, \text{(mm)} = 3.15622 - 0.08019x_1 - 0.07678x_2 - 0.00356x_3 + 0.00069x_1^2 + 0.00048x_2^2 + 0.00016x_3^2 + 0.00072x_1x_2 - 0.00026x_1x_3 + 0.00041x_2x_3 \quad (10)$$

$$Z_{HAZ}, \text{(mm)} = 0.940335 - 0.019541x_1 - 0.028638x_2 - 0.003122x_3 + 0.000147x_1^2 + 0.000242x_2^2 + 0.000017x_3^2 + 0.000251x_1x_2 - 0.000017x_1x_3 + 0.000106x_2x_3 \quad (11)$$

Where x_1 is the applied voltage (V), x_2 is the electrolyte concentration (wt %) and x_3 is the inter-electrode gap. The bounds for these parameters are given as:

Applied voltage (V) = 50 – 70

Electrolyte concentration (wt %) = 10 – 30

Inter-electrode gap (mm) = 20 – 40

Samanta and Chakraborty (2011) showed the maximum MRR of 1.62603 mg/h using 100 generations. Similarly the minimum ROC and HAZ obtained by Samanta and Chakraborty (2011) was 0.05912 mm and 0.05409 respectively. However, it is observed that the obtained MRR of 1.62603 mg/h is wrong and the corrected MRR should be 1.3372 mg/h. Now to check for the improvement in result, the proposed TLBO algorithm is applied to the mathematical models of MRR, ROC and HAZ as given by the equations (9) – (11) respectively.

The settings for population size and iterations are done initially by trial runs and finally the consistent results are obtained by using population size of 10 and 20 iterations are sufficient to get optimum and consistent result. Samanta and Chakraborty (2011) used a population size of 2000 and the number of iterations was 100 in the case of artificial bee colony algorithms; whereas a population size of 10 and 20 numbers of iterations are sufficient for TLBO algorithm to give the consistent result in this case. Table 3 gives the result obtained by TLBO algorithm and its comparison with the previous results.

Table 3. Comparative results for single objective optimization of ECDM process.

Process parameters	Steepest ascent method			ABC algorithm			TLBO algorithm		
	MRR	ROC	HAZ	MRR	ROC	HAZ	MRR	ROC	HAZ
Voltage (V)	70	50	50	70	50	50	70	50	50
Electrolyte conc (wt%)	18	24	22	20	30	24.5	10	30	25
IEG (mm)	27	30	39	20	20	40	21	20	38
Optimal value	1.24453	0.11138	0.055874	1.3372*	0.05912	0.05409	1.5902	0.0591	0.0541

* Corrected result.

TLBO algorithm has increased the MRR from 1.3372 mg/h to 1.5902 mg/h thereby giving improvement over 18 %. Convergence curve given by Samanta and Chakraborty (2011) shows that number of iterations used was 100 and maximum MRR was converged after 30 iterations. However, TLBO algorithm has converged the maximum MRR in fifth iteration. In case of minimization of ROC and HAZ, any improvement in the result is not observed, but in this case also, TLBO algorithm has converged faster result and needs population size of 10 and 20 iterations, whereas algorithm used by Samanta and Chakraborty (2011) had taken population size of 2000 and 100 iterations. Thus TLBO algorithm has proved its effectiveness in terms of faster convergence rate as compared to other advanced algorithm. Samanta and Chakraborty (2011) had also attempted the multiobjective problem by considering all the three models simultaneously. The multiobjective model used by Samanta and Chakraborty (2011) is given by equation (12).

$$\text{Min}(Z_2) = w_1 Z_{ROC}/ROC_{min} + w_2 Z_{HAZ}/HAZ_{min} - w_3 Z_{MRR}/MRR_{max} \quad (12)$$

Where, Z_{MRR}, Z_{ROC} and Z_{HAZ} are the RSM-based equations, as given in equations (9)–(11), respectively. ROC_{min}, HAZ_{min} and MRR_{max} are the minimum, minimum and maximum values of ROC, HAZ and MRR, respectively when these are attempted individually. w_1, w_2 and w_3 are the weights assigned to ROC, HAZ and MRR, respectively. In this case, same weightages of equal priority is considered as used by Samanta and Chakraborty (2011) i.e. $w_1=w_2=w_3=1/3$.

For this multiobjective model, Samanta and Chakraborty (2011) had given the maximum MRR of 1.4860 mg/h, minimum ROC of 0.0591 mm and minimum HAZ of 0.0569 mm. The optimized parameters obtained for this are given in Table 4. The proposed TLBO algorithm is now applied to this multiobjective model with a population size of 50 and the results are checked for 50 iterations. The results obtained for this combined objective function using TLBO algorithm are given in Table 4 along with its comparison with the artificial bee colony algorithm.

Table 4. Multi-objective optimization of the ECDM process.

Parameters and objective function	ABC result	TLBO result
Applied voltage (V)	50	50
Electrolyte concentration (wt %)	30	30
Inter-electrode gap (mm)	20	20
Metal removal rate (mg/h)	0.4860*	0.4860
Radial overcut (mm)	0.0591	0.0596
HAZ thickness (mm)	0.0569	0.0569
Z_2	0.5843	0.5733
Number of iterations	100	20

* Corrected value

The combined objective function always gives compromising result by satisfying all the objectives. In the present case also, the optimized parameters setting obtained by using the TLBO algorithm has given the compromising solution for the combined objective function, as compared to the individual function solution. In this example, the results obtained by the TLBO algorithm have proved its capability over the artificial bee colony algorithm in terms of handling the multiobjective problem.

Conclusions

In this work two advanced machining processes, ECM and ECDM, are considered for the process parameters optimization using a new algorithm. Two examples are considered, one for each process, having multiobjective models. The same models were earlier attempted by other researchers using ABC algorithm. The newly developed TLBO algorithm is successfully applied to both these examples. In some cases, the TLBO algorithm has given the similar results to that of ABC algorithm, but in all those cases, TLBO algorithm uses very small population size and less number of iterations to converge to the optimum result. In few cases TLBO has proved its superiority over ABC algorithm and has given improvement over ABC algorithm. Thus the TLBO algorithm is proved superior over the other advanced optimization algorithm. In the similar way, the TLBO can be effectively applied to other advance machining processes.

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