Optimization of Machining Processes using Teaching Learning Based Optimization Technique

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Abstract- *In this work, 'teaching–learning-based optimization (TLBO) algorithm' is tested and applied on various Benchmark functions and Machining Operations. 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 classroom. The machining operations like Electrochemical Machining, Electrochemical Discharge Machining, Multi-pass milling and Abrasive water jet machining are optimized using TLBO algorithm. The results are optimized to the limit of maximum efficiency.*

Keywords- Abrasive water jet machining, Electrochemical Discharge Machining, Electrochemical Machining, Multi-pass milling, Teaching Learning Based Algorithm, TLBO, Optimization.

I. INTRODUCTION

With the passage of time various machining processes have been used and worked along with ~~modifica~~tion, in industries but to ensure smooth processing and efficiency in operation. Different types of optimization algorithm have been developed such as Genetic Algorithm(GA),Harmony Search (HS), Artificial Bee Colony (ABC),particle swarm optimization, Shuffled frog leaping etc.

These work were previously attempted by various ~~researche~~rs using different optimization techniques and in the present work, advanced optimization algorithm named 'teaching–learning-based optimization (TLBO)' is applied to various machining operations to justify.
These are the following are machining operations which are optimized:-

- Electrochemical Machining,
- Electrochemical Discharge Machining,
- Multi-pass milling
- Abrasive water jet machining

The next section describes a detailed review of the algorithm named 'Teaching–learning-based optimization algorithm'.

II. TEACHING-LEARNING BASED OPTIMIZATION ALGORITHM

Teaching–learning-based optimization algorithm (TLBO) is a teaching–learning process inspired algorithm recently proposed by Rao et al. (2011, 2012) and Rao and Patel (2012) based on the effect of influence of a teacher on the output of learners in a class. The algorithm mimics 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). A high quality 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 algorithm a group of learners are considered as population and different subjects offered to the learners are considered as different design para-meters and a learner's result is analogous to the 'fitness' value of the optimization problem. The best solution in the entire population is considered as the teacher. The design parameters are actually the parameters involved in the objective function of the given optimization problem and the best solution is the best value of the objective function. The working of TLBO is divided into two parts, 'Teacher phase' and 'Learner phase'. Working of both the phase is explained below.

Teacher phase

It is the 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 in the subject taught by him or her depending on his or her capability. At any iteration i, assume that there are 'm' number of subjects (i.e., design parameters), 'n' number of learners (i.e., population size, k¼1,2, y, n) and $M_{j,i}$ be the mean result of the learners in a particular subject 'j' (j¼1,2, y, m) The best overall result $X_{total-kbest,i}$, obtained in the entire population of learners considering all the subjects together can be considered as 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.

T_F is not a parameter of the TLBO algorithm. The value of T_F is not given as an input to the algorithm and its value is randomly decided by the algorithm. After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if its value is between 1 and 2. However, the algorithm is found to perform much better if the value of T_F is either 1 or 2 to simplify the algorithm All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase.

Learner phase

It is the 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. Considering a population size of 'n', the learning phenomenon of this phase is expressed below.

Randomly select two learners P and Q such that $X^0_{total-P,i}$ a $X^0_{total-Q,i}$ (where, $X^0_{total-P,i}$ and $X^0_{total-Q,i}$ are the updated values of 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

For i = 1: Pn
Randomly select two learners X_i and X_j, where i is not equal to j
If $f(X_i) < f(X_j)$
$X_{new}, i = X_{old}, i + r_i (X_i – X_j)$
Else
$X_{new}, i = X_{lod}, i + r_i (X_j – X_i)$
End
End
Accept X_{new} if it gives a better function value.

III. OPTIMISATION OF VARIOUS MACHINING OPERATIONS USING TLBO ALOGRITHM

Now it is the time to articulate the research work with ideas gathered in above steps by adopting any of below suitable approaches:

A. Electrochemical Discharge Machining

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. 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.

ECDM is a very recent technique in the field of advanced machining to machine electrically non conductive materials using electrochemical discharge phenomenon. 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.

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.

Objective function-

ZMRR, (mg/hr) = 4.96423 – 0.20418x1 + 0.09862x2 + 0.00851x3 + 0.00249x12 – 0.00086x + 0.00039x32 – 0.00181x1x2 – 0.00104x1x3 + 0.00125x2x3

ZROC, (mm) = 3.15622 – 0.08019x1 - 0.07678x2 – 0.00356x3 + 0.00069x12 + 0.00048x22 + 0.00016x32 + 0.00072x1x2 – 0. 00026x1x3 + 0.00041x2x3

ZHAZ, (mm) = 0.940335 – 0.019541x1 – 0.028638x2 – 0.003122x3 + 0.000147x12+ 0.000242x22 +0.000017x32 + 0.000251x1x2 – 0.000017x1x3 + 0.000106x2x3

Where x1 is the applied voltage (V), x2 is the electrolyte concentration (wt %) and x3 is the inter-electrode gap.

Constraints –

Applied voltage (V) = 50 – 70
Electrolyte concentration (wt %)
Inter-electrode gap (mm) = 20 – 40

Table 1. Comparison of results of Electrochemical Discharge Machining

Process Parameter	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	1.24	0.11	0.05	1.33	0.05	0.05	1.59	0.05	0.05

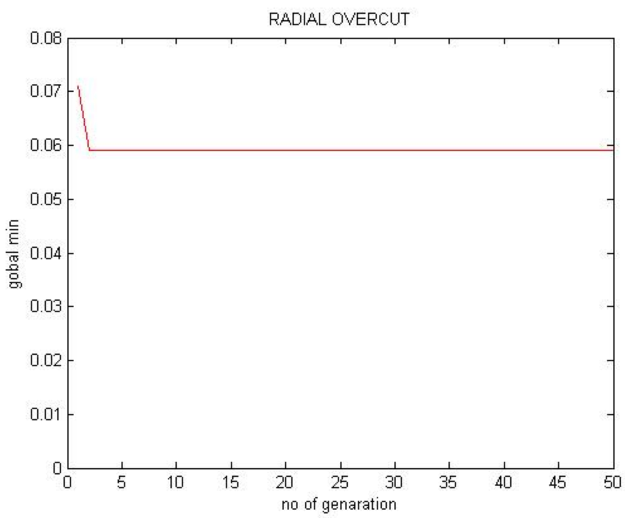

Fig 1. Convergence global minimum of Radial Overcut v/s Number of generations

TLBO algorithm has increased the MRR from 1.3372 mg/h to 1.6202 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 at the maximum MRR in tenth 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.

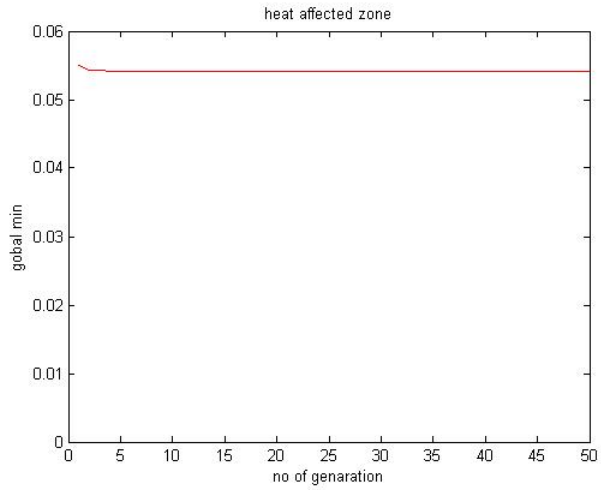

Fig 2. Convergence global minimum of Heat Affected Zone v/s Number of generations

B. Electro-Chemical Machining Process

Electrochemical machining (ECM) is a modern machining process that relies on the removal of workpiece atoms by electrochemical dissolution (ECD) in accordance with the principles of Faraday (1833).

Electrolysis occurs when an electric current passes between two electrodes dipped into an electrolyte solution. The system of the electrodes and the electrolyte is referred to as the electrolytic cell. The chemical reactions, which occur at the electrodes, are called the anodic or cathodic reactions. ED of the anodic workpiece forms the basis for ECM of metals. The amount of metal dissolved (removed by machining) or deposited is calculated from Faraday's laws of electrolysis, which state that

1. The amount of mass dissolved (removed by machining), m, is directly proportional to the amount of electricity.

$$m \propto It$$

2. The amount of different substances dissolved, m, by the same quantity of electricity (It) is proportional to the substances' chemical equivalent weight e.

$$m \propto e$$

where
I = electrolyzing current, A
t = machining time, min
e = chemical equivalent weight, g
A = atomic weight
Z = workpiece valence

ECM uses a direct current at a high density of 0.5 to 5 A/mm2 and a low voltage of 10 to 30 V. The machining current passes through the electrolytic solution that fills the gap between an anodic workpiece and a preshaped cathodic tool. The electrolyte is forced to flow through the interelectrode gap at high velocity, usually more than 5 m/s, to intensify the mass and charge transfer through the sub layer near the anode. The electrolyte removes the dissolution products, such as metal hydroxides, heat, and gas bubbles, generated in the interelectrode gap. When a potential difference is applied across the electrodes, several possible reactions occur at the anode and the cathode the dissolution reaction of iron in a sodium chloride (NaCl) water solution as an electrolyte. The result of electrolyte dissociation and NaCl dissolution leads to

$H2O \rightarrow H+ + OH-$
$NaCl \rightarrow Na+ + Cl-$

The negatively charged anions OH− and Cl− move toward the anode, and the positively charged cations of H+ and Na+ are directed to the cathode. At the anode, Fe changes to Fe++ by losing two electrons

$Fe \rightarrow Fe++ + 2e$

At the cathode, the reaction involves the generation of hydrogen gas and the hydroxyl ions.

$2H_2O + 2e \rightarrow H_2 + 2(OH)-$

The outcome of these electrochemical reactions is that iron ions combine with other ones to precipitate out as iron hydroxide, $Fe(OH)_2$.

$Fe + 2H_2O \rightarrow Fe(OH)_2 + H_2$

The ferrous hydroxide may react further with water and oxygen to form ferric hydroxide, $Fe(OH)_3$.

$4Fe(OH)_2 + 2H_2O + O2 \rightarrow 4Fe(OH)_3$

With this metal-electrolyte combination, electrolysis has involved the dissolution of iron, from the anode, and the generation of hydrogen, at the cathode.

Objective function:

ZMRR, (g/min) = 1.19263 + 0.05688x1 – 0.13590x2 + 0.09215x3 – 5.45671x4 – 0.00004x12 + 0.01232x22 + 0:00029x32 – 0.36444x42 – 0.00365x1x2 – 0.00067x1x3 + 0.01407x1x4 – 0.01045x2x3 + 0:26505x2x4 + 0.09247x3x4

ZROC (mm) = - 2.10705 + 0.01065x1 + 0.31849x2 + 0:00266x3 + 0.48742x4 – 0.00002x12 – 0.01223x22 + 0.00011x32 + 0.08501x42 – 0.00040x1x2 – 0.00006x1x3 – 0.00199x1x4 + 0.00044x2x3 – 0.02656x2x4 – 0.00781x3x4

Where, x1 is the electrolyte concentration, x2 is the electrolyte flow rate, x3 is the applied voltage and x4 is the inter-electrode gap. The bounds for these parameters are given as:

Constraints

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

Samanta and Chakraborty (2011) had applied artificial bee colony algorithm for obtaining the optimized parameters 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. The population size is used randomly starting with the low value and a promising result is shown by a population size of 10.

Table.2 Comparison of TLBO for Electro-Chemical Machining Process

Process Parameter	Results of Bhattacharya and Sorkhel(1999)		ABC Algorithm		TLBO Algorithm	
	MRR	Overcut	MRR	Overcut	MRR	Overcut
Electrolyte Conc. (g/f)	57.88	17.55	75	15	75	15
Electrolyte flowrate(1/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 valve	0.7245	0.2702	1.4551	0.0824	1.4551	0.0818

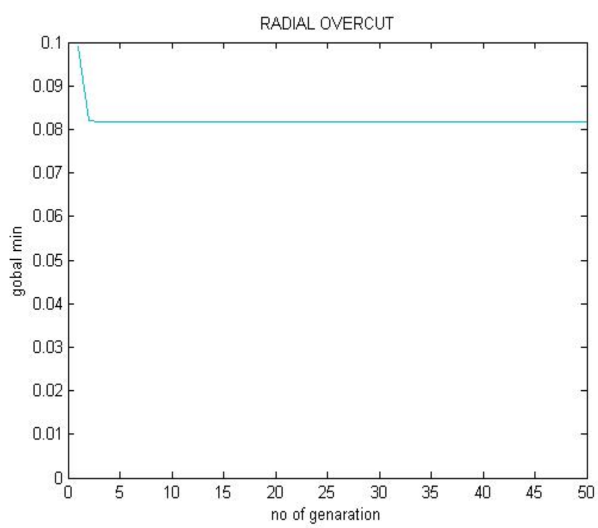

Fig 3. Convergence global minimum of Radial Overcut v/s Number of generations

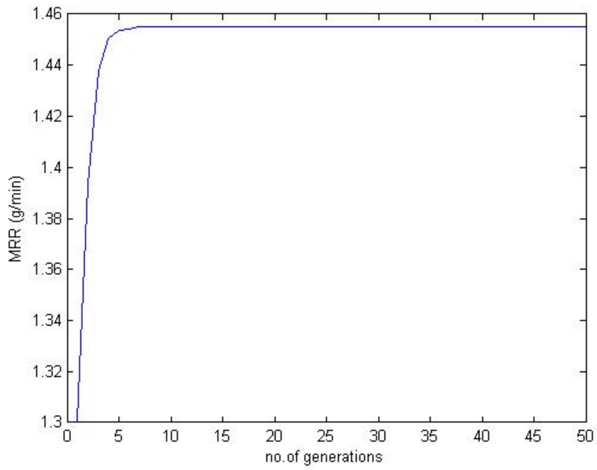

Fig 4. Convergence material removal rate v/s Number of generations

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 along with its comparison with the other results. 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 at the optimum result in fifth iteration only. Thus, TLBO algorithm has proved its superiority in terms of faster convergence rate.

C. Multi-pass milling process

In today's manufacturing environment many large industries have attempted to introduce the flexible manufacturing system (FMS) as a strategy to adapt to the ever-changing competitive market requirement. The flexible manufacturing system involves highly automated and computer controlled machines. Due to high capital and machining costs, there is an economic need to operate these machines as efficiently as possible in order to obtain the required pay back. The success of the machining operation depends on the selection of machining process parameters. Proper selection of process parameters plays a significant role to ensure quality of product, to reduce the machining cost, to increase Productivity.

Milling is the machining process in which the metal is removed by a rotating multiple tooth cutter. As the cutter rotates, each tooth removes a small amount of material from the advancing work for each spindle revolution. The relative motion between cutter and the work piece can be in any direction and hence surfaces having any orientation can be machined in milling. Milling operation can be performed in a single pass or in multiple passes. Multi-pass operations are often preferred to single pass operations for economic reasons and are generally used to machine stocks that cannot be removed in a single pass.

The optimization model of milling process formulated in the present work is based on the analysis given by Sonmez et al. The decision variables (i.e. process parameters) considered for this model are feed per tooth (fz), cutting speed (V) and depth of cut (a).In this case we optimized the process time required.

The objective function and the constraints are formulated as discussed:

For a milling operation the total production time (Tpr) is composed of the following items:

(a) Machine preparation time (Tp)
(b) Loading–unloading time (TL).
(c) Process adjusting and quick return time (Ta).
(d) Machining time (Tm).
(e) Tool changing time per component (Tc)

Objective function

The objective function for multi-pass milling operation is expressed as given

$$\mathrm{T_{pr}} = \frac{\mathrm{T_s}}{\mathrm{N_b}} + \mathrm{T_L} + \mathrm{N_p}\,\mathrm{T_a} + \sum_{i=1}^{\mathrm{N_p}} \frac{\pi \mathrm{DL}}{\mathrm{f_{z_i}} \mathrm{z} \times 1000 \times \mathrm{V_i}} +$$

$$\frac{\mathrm{T_d}\,\pi \mathrm{L} \mathrm{V_i}^{(1/m-1)} \mathrm{a_i}^{e_v/m} \mathrm{f_{z_i}}^{(u_v/m-1)} \mathrm{a_r}^{r_v/m} \mathrm{z}^{(n_v/m-1)} \lambda_s^{q_v/m}}{1000 \times \mathrm{C_v}^{1/m} \mathrm{D}^{(b_v/m-1)} \times \left(\mathrm{B_m} \times \mathrm{B_h} \times \mathrm{B_p} \times \mathrm{B_t}\right)^{1/m}}$$

Constraints-

Following three constraints are considered in this optimization model.

a) Arbor strength

$F_s - F_c = 0$

b) Arbor deflection

$F_d - F_c = 0$

Where,

Permissible force for arbor deflection (kg) = $F_d = \frac{4Eed_a{}^4}{L_a{}^3}$

c) Power

$$P_c - \frac{F_c V}{6120} \geq 0$$

where Pc = cutting power (kW) = $P_m \eta$,

P_m = nominal motor power,

η = overall efficiency.

Process parameters-

The three process parameters and their bounds considered in this work are given in the following sections.

a) Feed per tooth

$$f_{z\,min} \le f_z \le fz_{max}$$

b) Cutting speed

Vmin≤V≤Vmax

Where

$$V_{max} = \frac{\pi D N_{max}}{1000}$$

$$V_{min} = \frac{\pi D N_{min}}{1000}$$

c) Depth of cut

amin≤ a ≤amax (mm)

Where, a_{min} is the minimum depth of cut

a_{max} is the maximum depth of cut.

Specifications of the required parameters and values of the constants considered by Sonmez et al. and used in the present work are as follows:

Type of machining: plain milling.
Motor power (Pm) = 5.5 kW, efficiency, h = 0.7.
Arbor diameter, d_a = 27 mm, arbor length between supports, L_a= 210 mm.
Permissible bending stress of arbor, k_b: 140 MPa.
Permissible torsional stress of arbor, k_t: 120 MPa
Modulus of elasticity of arbor material, E = 200 GPa.
Spindle speed range: (31.5–2000) rpm, feed rate range: (14–900) mm/min.
Tool material: HSS, tool diameter, D = 63 mm,
Number of teeth, z = 8. Material: structural carbon steel (C # 0.6%).
Tensile strength: 750 MPa, Brinell hardness number = 150.

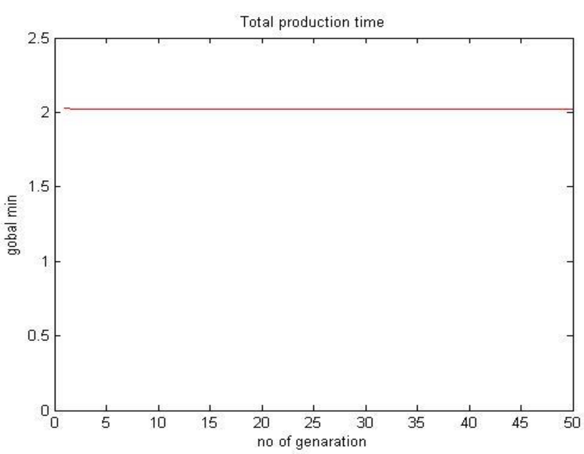

Fig 5. Convergence of Total production time v/s Number of generations

Length of cut, L_a = 160 mm, width of cut, a_r = 50 mm, depth of cut, a = 5 mm. Loading and unloading time of one work piece, T_L = 1.5 min. Set-up time of fixtures and machine tool, T_s = 10 min. Tool change time, T_c = 5 min. Process adjusting and quick return time, T_a = 0.1 (min/part). Lot size (number of parts in the batch), N_b= 100. Cutting inclination = 308. Constants: B_m= 1, B_k = 1, B_p = 0.8, B_t= 0.8, m = 0.33, e_v= 0.3, U_v = 0.4, r_v = 0.1, n_v= 0.1, q_v= 0, C_v= 35.4, b_v = 0.45, C_{zp}= 68.2, b_z= 0.86, e_z = 0.86, and u_z = 0.72.

$$f_{z_{min}} = \frac{f_{min}}{zN_{max}} = \frac{14}{8 \times 2000} = 0.000875(mm/tooth)$$

$$f_{z_{max}} = \frac{f_{max}}{zN_{min}} = \frac{900}{8 \times 31.5} = 3.571(mm/tooth)$$

Thus

$0.000875 \le f_z \le 3.571$

$$V_{max} = \frac{\pi D N_{max}}{1000} = \frac{\pi D N_{max}}{1000} = \frac{\pi \times 63 \times 2000}{1000} = 395.84(m/min)$$

$$V_{min} = \frac{\pi D N_{min}}{1000} = \frac{\pi D N_{min}}{1000} = \frac{\pi \times 63 \times 31.5}{1000} = 6.234(m/min)$$

Thus

Upper and lower boundaries of cutting velocity
6.234≤V≤395.84 (m/min)

Upper and lower boundaries of depth of cut
0.5≤a≤4 (mm)

Table.3 Overall result comparison of multi-pass milling process

Method	ABC	PSO	TLBO
T_{pr}(T_1+T_2;min)	3.240	3.240	2.0165

From table 3 ad figure 5 it is clear that the optimized value obtained by TLBO method is better than ABC and PSO methods. Also the optimum value obtained in less no. of iterations by TLBO method than ABC and PSO methods.

D. Abrasive water jet machining

This case study Azlan Mohd Zain et al. optimized the abrasive water jet machining by Simulated Annealing (SA), Genetic Algorithm (GA), integrated SA–GA-type1 and integrated SA–GA type2. Simulated Annealing (SA) and Genetic Algorithm (GA) soft computing techniques are integrated to estimate optimal process parameters that lead to a minimum value of machining performance. The objectives of the proposed TLBO algorithm estimate the minimum value of the machining performance compared to the machining performance value of the experimental data, regression modeling, to estimate the optimal process parameters values that has to be within the range of the minimum and maximum process parameter values of experimental design, and to estimate the optimal solution of process parameters with a small number of iteration.

The target of the optimization process in this study is to determine the optimal values of the process parameters that lead to the minimum value of Roughness (R_a) using TLBO algorithm.

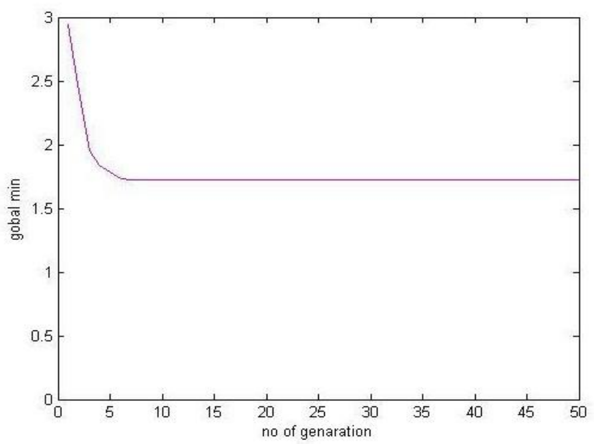

Fig 6. Convergence of Roughness (R_a) v/s Number of generations

The used objective function is expressed as follows.
Minimize

$R_a = cV^q p^r h^s d^r m^u \varepsilon$

$=\min(-5.07976+0.08169V+0.07912P-0.34221h-0.08661d-0.34866m-0.00031V^2-0.00012P^2+0.10575h^2+0.00041d^2+0.07590m^2-0.00008Vm-0.00009Pm+0.03089hm+0.00513dm)$

Where,
V is the traverse cutting speed in mm/min
P is the water jet pressure in MPa
h is the standoff distance in mm
d is abrasive grit size in m,
m is the abrasive flow rate in g/s
ε is experimental error

Limits taken are as follows-
$50 \le V \le 150$
$125 \le P \le 250$
$1 \le h <\le 4$
$60 \le d \le 120$
$0.5 \le m \le 3.5$

Table.5 Results comparison of AWJ machining process

Approach	Min. R_a	No. of iterations
Experimental	2.124	-
Regressive	2.62915	-
GA	1.5549	57
SA	1.5553	2711
Integrated SA-GA type 1	1.5242	51
Integrated SA-GA type 2	1.5234	2631
TLBO	1.5223	10

Form results comparison it is seen that results obtained by TLBO, are very much better than previous methods. Also obtained in very less no. of iterations. Obtained roughness value (1.5223) is more optimized than previous optimum solution.

VI. CONCLUSION

Teaching Learning Based Optimization technique is one of the nature-inspired population based advance optimization method and it is found that Teaching Learning Based Optimization (TLBO) algorithm is fast, correct and effective than other optimization techniques.

The tested four cases show the obtained result by TLBO algorithm is optimized better than the previous results. Roughness value (Ra) in Abrasive water jet machining optimized from 1.5234 to 1.5223. It is observed that result obtained is much better than all previous methods compared. In ECM process the result are almost same and sometimes better than the previous result. The TLBO algorithm needs only 10 iterations for consistency and has converged the optimum result within 5 iterations

In ECDM process, minimization of ROC and HAZ, gives sufficient improvement. It had reached the optimum result within 5-10 iterations by using population size of 10 only .Hence, TLBO algorithm has proved its effectiveness in terms of faster convergence rate. In multi pass milling process milling time is optimized to 2.0165 min from 3.24 min. Hence, it is clear that the optimized value obtained by TLBO method is better than ABC and PSO methods. Also the optimum value is obtained within less no. of iterations

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