Parameter optimization of machining processes using teaching-learning-based optimization algorithm

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Abstract: The optimum selection of process parameters plays a significant role to ensure quality of product, to reduce the machining cost and to increase the productivity of any machining process. This paper presents the optimization aspects of process parameters of three machining processes including an advanced machining process known as abrasive water jet machining process and two important conventional machining processes namely grinding and milling. A recently developed advanced optimization algorithm, teaching-learning-based optimization (TLBO), is presented to find the optimal combination of process parameters of the considered machining processes. The results obtained by using TLBO algorithm are compared with those obtained by using other advanced optimization techniques such as genetic algorithm (GA), simulated annealing (SA), particle swarm optimization (PSO), harmony search (HS), and artificial bee colony (ABC) algorithm. The results show better performance of the TLBO algorithm.

Keywords: Abrasive water jet machining; Grinding; Milling; Process parameter optimization; Teaching-learning-based optimization algorithm

1 Introduction

In today's manufacturing environment many large industries have attempted to introduce the highly automated and computer controlled machines as their strategy to adapt to the ever-changing competitive market requirement. 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.

Determination of optimum process parameters of any machining process is usually a difficult work where the following aspects are required: knowledge of manufacturing process, empirical equations to develop realistic constraints, specification of machine tool capabilities, development of effective optimization criteria, and knowledge of mathematical and numerical optimization techniques. A human process planner selects proper machining process parameters using his own experience or from the handbooks. But these parameters do not give optimal result. The selection of optimum process parameters play a significant role to ensure quality of product, to reduce the machining cost, to increase productivity in computer controlled machining processes and to assist in computer aided process planning. . The present study is mainly focused on the optimization aspects of one of the advanced machining processes namely abrasive water jet machining and two important conventional machining processes, grinding and milling.

Several attempts have been made to study the influence of different process parameters of abrasive water jet machining process such as water pressure and water flow rate, abrasive type, size, shape, and flow rate, stand-off-distance, number of passes, angle of attack, abrasive condition etc. on the important performance measures such as depth of cut and material removal rate [1-5]. However, very few efforts have been reported for optimization of process parameters

of abrasive water jet machining process parameters. Chakravarthy and Babu [6] applied genetic algorithm to achieve two conflicting objectives i.e. maximization of production rate and minimization of abrasive consumption. However, the authors had not considered any constraint and no bounds for variables were specified. To overcome above limitations, Jain et al. [7] used genetic algorithm as a tool for maximization of the material removal rate with power consumption as a constraint. Rao et al. [8] used simulated annealing algorithm to the optimization of abrasive water jet machining process and reported significant improvement in the material removal rate over that obtained by Jain et al. [7].

Previous work on the optimization of grinding process parameters has concentrated on possible approaches for optimizing constraints during grinding. Amitay [9] reported the technique of optimizing both grinding and dressing conditions for the maximum workpiece removal rate subjected to constraints on workpiece burn and surface finish in an adaptive control system. Wen et al. [10] applied successive quadratic programming (QP) approach using a multi-objective function model with a weighted approach for optimization of surface grinding process parameters. Rowe et al. [11] provided an extensive review on various approaches based on artificial intelligence to the grinding process. A genetic algorithm (GA) based optimization procedure was developed by Saravanan et al. [12] to optimize the grinding conditions. Dhavalikar et al. [13] applied combined Taguchi and dual response methodology to determine the robust condition for minimization of out of roundness error of workpiece for centerless grinding operation. Optimization was then carried out by using Monte Carlo simulation procedure. Mitra and Gopinath [14] used non-dominated sorting genetic algorithm for multi-objective optimization of industrial grinding process. Krishna [15] applied differential evolution (DE) algorithm for optimization of process parameters of grinding operation. Pawar et al. [16]

used particle swarm optimization algorithm for optimization of grinding process parameters and showed superiority of particle swarm optimization algorithm over traditional optimization techniques. For the same problem, Rao and Pawar [17] presented that artificial bee colony and harmony search algorithms provide better accuracy of solution as compared to particle swarm optimization.

Various investigators have proposed optimization techniques, both traditional and advanced, for optimization of multi-pass milling operation. Shin and Joo [18] used the dynamic programming optimization method for milling process parameter optimization. Wang [19] used a neural network based approach to optimize milling process parameters. Tolouei-Rad and Bidhendi [20] used the method of feasible direction and considered maximization of profit rate as an objective function in milling operation. Sonmez et al. [21] applied dynamic programming to determine optimum number of passes and the optimal values of the cutting conditions were found by using geometric programming. Shunmugam et al. [22] used genetic algorithm (GA) for milling process parameter optimization with total production cost as the objective function. During the past decade, different optimization methods had been integrated to improve performance of algorithms and to reach the global optimum results. In order to optimize the machining parameters, the evolutionary methods had been modified or hybridized by using other optimization techniques. Liu and Wang [23] modified the genetic algorithm by defining and changing the operating domain and used for optimization of milling parameters. Wang et al. [24] proposed a new hybrid approach, named parallel genetic simulated annealing (PGSA), based on genetic algorithm and simulated annealing to find optimal machining parameters in milling operations. Bhaskar et al. [25] used memetic algorithm for optimization of milling process parameters. Onwubolu [26] proposed a new optimization technique based on Tribes for

determination of the cutting parameters in multi-pass milling operations. Yildiz [27] developed a new hybrid optimization approach by hybridizing the immune algorithm with hill climbing local search algorithm to maximize the total profit rate in milling operations. Zarei et al. [28] presented a harmony search (HS) algorithm to determine the optimum cutting parameters for multi-pass face-milling. Rao and Pawar [29] applied various advanced optimization algorithms such as artificial bee colony, particle swarm optimization, and simulated annealing to the optimization of process parameters of multi-pass milling process.

It is observed from the literature that various traditional methods of optimization such as sequential quadratic programming, dynamic programming, and method of feasible direction have been employed to the optimization of machining processes considered in this work. However, these traditional methods of optimization and search do not fare well over a broad spectrum of problem domains. These methods are not efficient when practical search space is too large. Also these traditional methods tend to obtain a local optimum solution. To overcome these drawbacks of traditional methods of optimization, researchers are employing a commonly used evolutionary algorithm known as genetic algorithm (GA) for parametric optimization of machining processes. Although GA has advantages over the traditional optimization techniques, the successful application of GA depends on the population size or the diversity of individual solutions in the search space. If GA cannot hold its diversity well before the global optimum is reached, it may prematurely converge to a local optimum. To overcome these limitations of basic genetic algorithms, recently developed popular algorithms such as particle swarm optimization (PSO), harmony search algorithm (HS), and artificial bee colony algorithms (ABC) are also tried successfully by various researchers. However, the major difficulty in application of these algorithms lies in their selection of appropriate algorithm-specific parameters such as crossover

probability, mutation probability, scaling function, selection function, etc. in case of GA; inertia coefficient and acceleration coefficients in case of PSO; proportion of employed and scout bees in case of ABC; and harmony memory consideration rate and pitch adjusting rate in case of HS algorithm. The performance of all the above mentioned algorithms is greatly influenced by their respective algorithm-specific parameters in addition to the common control parameters such as population size and number of generations. Selection of suitable values of these algorithm-specific parameters for a particular application is itself is a complex optimization problem. To overcome this drawback of existing advanced optimization algorithms, an optimization algorithm known as teaching-learning-based optimization (TLBO) has been recently developed by Rao et al. [30,31]. TLBO requires only common controlling parameters like population size and number of generations for its working. In this way TLBO can be said as an algorithm-specific parameter-less algorithm.

Various researchers have started applying the TLBO algorithm to their research problems. Hosseinpour et al. [32] presented a multi-objective placement of Automatic Voltage Regulators (AVRs) in distribution systems in the presence of distributed generators (DGs). Satapathy and Naik [33] used TLBO algorithm for data clustering. It was shown how TLBO could be used to find the centroids of a user specified number of clusters. The TLBO algorithm was evaluated on some datasets and was compared with the performance of K-means and PSO clustering. Results showed that TLBO clustering techniques have much potential.

Krishnanand et al. [34] applied a multiobjective TLBO algorithm with non-domination based sorting to solve the environmental/economic dispatch (EED) problem containing the incommensurable objectives of best economic dispatch and least emission dispatch. The simulation result revealed that the TLBO algorithm is a competitive one to the current existing

methods for finding the best optimal pareto front of two conflicting objectives and has the better robustness.

Toğan [35] presented a design procedure employing TLBO algorithm for discrete optimization of planar steel frames. Several frame examples from the literature were examined to verify the suitability of the design procedure and to demonstrate the effectiveness and robustness of the TLBO for creating an optimal design for frame structures. The results of the TLBO were compared to those of the genetic algorithm (GA), ant colony optimization (ACO), harmony search (HS) and the improved ant colony optimization (IACO). The results had shown that TLBO is a powerful search and applicable optimization method for the problem of engineering design applications.

Niknam et al. [36] proposed θ-Multiobjective Teaching-Learning-Based optimization for Dynamic Economic Emission Dispatch. The applicability of the method was validated on three test systems, including 5-unit, 10-unit, and 120-unit test systems. In another work, Niknam et al. [37] integrated the optimal operation management of Proton Exchange Membrane FCPPs (PEM-FCPPs) and the optimal configuration of the system through an economic model of the PEM-FCPP. Azizipanah-Abarghooee [38] presented probabilistic multiobjective wind-thermal economic emission dispatch based on point estimated method and modified TLBO algorithm was proposed to determine the set of non-dominated optimal solutions.

Rao and Patel [39] described the TLBO algorithm for solving complex constrained optimization problems. The code of TLBO algorithm was also included. The distinction between the algorithm-specific control parameters and common control parameters such as population size and the number of generations was explained. TLBO algorithm can be considered as an

algorithm-specific parameter-less algorithm and it requires only the common control parameters. Thus, the total efforts required for tuning of parameters are very less in TLBO algorithm.

It is with this spirit that TLBO algorithm is considered in this work for optimization of process parameters of selected machining processes. TLBO algorithm was not applied previously for the parameter optimization of machining processes and hence an attempt is made in the present work to apply the algorithm to the selected machining processes. This paper provides the comparative performance of the TLBO algorithm with other traditional and advanced algorithms in terms of its ability to find global optimum solution, accuracy of solution, and convergence rate.

2   Teaching-learning-based optimization algorithm

Teaching-learning-based optimization algorithm (TLBO) is a teaching-learning process inspired algorithm proposed by Rao et al. [30, 31], 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 phases is explained below.

2.1 Teacher phase

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 variables), 'n' number of learners (i.e. population size, $k=1,2,…,$n) and $M_{j,i}$ be the mean result of the learners in a particular subject 'j' ($j=1,2,…,m$) The best overall result $X_{total-kbest,i}$ considering all the subjects together obtained in the entire population of learners can be considered as the result of best learner *kbest*. 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 by the algorithm 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,

$$Difference\_Mean_{j,k,i} = r_i\,(X_{j,kbest,i} -\ T_F M_{j,i}) \tag{1}$$

Where, $X_{j,kbest,i}$ is the result of the best learner (i.e. teacher) in subject j. T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. Value of T_F can be either 1 or 2. The value of T_F is decided randomly with equal probability as,

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

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 using Eq. (2). After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs

better if the value of T_F 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 Eq.(2).

Based on the *Difference_Mean$_{j,k,i}$*, the existing solution is updated in the teacher phase according to the following expression.

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,i} \tag{3}$$

Where $X'_{j,k,i}$ is the updated value of $X_{j,k,i}$. Accept $X'_{j,k,i}$ if it gives better function value. All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase. The learner phase depends upon the teacher phase.

2.2 Learner phase

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

$$X''_{j,P,i} = X'_{j,P,i} + r_i (X'_{j,P,i} - X'_{j,Q,i}), \text{ If } X'_{total-P,i} < X'_{total-Q,i} \tag{4}$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i (X'_{j,Q,i} - X'_{j,P,i}), \text{ If } X'_{total-Q,I} < X'_{total-P,i} \tag{5}$$

Accept $X''_{j,P,i}$ if it gives a better function value.

3 Examples

Now to demonstrate and validate the teaching-learning-based optimization algorithm for parameter optimization of machining processes, abrasive water jet machining, grinding, and milling processes are considered.

3.1 Optimization of abrasive water jet machining (AWJM)

The AWJM process uses a high velocity water jet in combination with abrasive particles for cutting different types of materials. A stream of small abrasive particles is introduced and entrained in the water jet in such a manner that water jet's momentum is partly transferred to the abrasive particles. The role of carrier water is primarily to accelerate large quantities of abrasive particles to a high velocity and to produce a highly coherent jet. Important process parameters of abrasive water jet machining can be categorized as hydraulic parameters: water pressure, and water flow rate, abrasive parameters: type, size, shape, and flow rate of abrasive particles; cutting parameters: traverse rate and stand-off-distance. The model is based on the analysis given by Hashish [2]. The decision variables, objective function, and constraint considered in the present work are given below.

3.1.1 Optimization model of abrasive water jet machining process

The five decision variables considered for this model are, water jet pressure at the nozzle exit (P_w), diameter of abrasive water jet nozzle (d_{awn}), feed rate of nozzle (f_n), mass flow rate of water (M_w), and mass flow rate of abrasives (M_a). The objective function and constraint are discussed below:

Objective function:

The objective is to maximize the material removal rate (Z_1) as given by equation (6).

$$Maximize\ Z_1 = d_{awn} f_n (h_c + h_d) \tag{6}$$

Where, 'h_c' is the indentation depth due to cutting wear as given by equation (7).

$$h_c = \left[\left(\frac{1.028 \times 10^{4.5} \xi}{C_k \rho_a^{0.4}} \right) \left(\frac{d_{awn}^{0.2} M_a^{0.4}}{f_n^{0.4}} \right) \left(\frac{M_w P_w^{0.5}}{M_a + M_w} \right) - \left(\frac{18.48 K_a^{2/3} \xi^{1/3}}{C_k^{1/3} f_r^{0.4}} \right) \left(\frac{M_w P_w^{0.5}}{M_a + M_w} \right) \right]^{1/3} ; \text{ if } \alpha_t \leq \alpha_0. \tag{7}$$

$$h_c = 0, \text{ if } \alpha_t \geq \alpha_0. \tag{8}$$

'h_d' is the indentation depth due to deformation wear as given by equation (9).

$$h_d = \frac{\eta_a d_{awn} M_a \left[K_1 M_w P_w^{0.5} - (M_a + M_w) v_{ac} \right]^2}{(1570.8 \sigma_{fw}) d_{awn}^2 f_n (M_a + M_w)^2 + (K_1 C_{fw} \eta_a) \left[K_1 M_w P_w^{0.5} - (M_a + M_w) v_{ac} \right] M_a M_w P_w^{0.5}} \tag{9}$$

$$\alpha_0 \approx \left(\frac{0.02164\ C_K^{1/3} f_r^{0.4}}{K_a^{2/3} \xi^{1/3}} \right) \left(\frac{\dot{M}_a + \dot{M}_w}{\dot{M}_w P_w^{0.5}} \right)^{1/3} \text{ (degrees).} \tag{10}$$

$$\alpha_t \approx \left(\frac{0.389 \times 10^{-4.5} \rho_a^{0.4} C_K}{\xi} \right) \left(\frac{d_{awn}^{0.8} f_n^{0.4} \left(\dot{M}_a + \dot{M}_w \right)}{M_a^{0.4} \dot{M}_w P_w^{0.5}} \right) \text{ (degrees).} \tag{11}$$

$$v_{ac} = 5\pi^2 \frac{\sigma_{cw}^{2.5}}{\rho_a^{0.5}} \left[\frac{1-v_a^2}{E_{Ya}} + \frac{1-v_w^2}{E_{Yw}} \right]^2 \text{ (mm/s)} \tag{12}$$

$$K_1 = \sqrt{2} \times 10^{4.5} \xi. \tag{13}$$

$$C_K = \sqrt{3000 \sigma_{fw} f_r^{0.6} / \rho_a} \text{ (mm/s)} \tag{14}$$

$$K_a = 3.$$

Constraint:

Constraint is on power consumption as given by equation (15).

$$1.0 - \frac{P_w M_w}{P_{\max}} \geq 0 \tag{15}$$

Description of various symbols appeared in equation (6) to (15) is provided in Table 1.

Variable bounds:

The bounds for the five variables are given in equations (16) to (20).

$$50 \leq P_w \leq 400 \text{ (MPa)} \tag{16}$$

$$0.5 \leq d_{awn} \leq 5 \text{ (mm)} \tag{17}$$

$$0.2 \leq f_n \leq 25 \text{ (mm/s)} \tag{18}$$

$$0.02 \leq M_w \leq 0.2 \text{ (Kg/s)} \tag{19}$$

$$0.0003 \leq M_a \leq 0.08 \text{ (Kg/s)} \tag{20}$$

3.1.2 Optimization using TLBO algorithm

As TLBO algorithm is an algorithm-specific parameter-less algorithm, only population size and number of generations need to be specified to run the algorithm. Based on several trial runs, the population size decided for the present example is 20 and the number of generations is 50. The results of optimization of AWJM process using TLBO algorithm are presented in Table 2 along with those obtained by using other optimization algorithms.

For abrasive water jet machining, if angle of impingement at the top of the machined surface 'α_t' exceeds the critical impact angle 'α_0' then no material removal is assumed to occur by cutting wear (i.e. h_c=0) and the material removal occurs only due to the deformation wear (h_d), which results into relatively less material removal rate [4]. As shown in Table 2, for the solution obtained by using GA [7], as 'α_t' exceeds 'α_0', indentation depth of cutting wear (h_c) becomes zero and hence results in very poor material removal rate as compared to the solution

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obtained by using TLBO algorithm for which, as 'α_t'< 'α_0' significant amount of material removal rate is contributed by cutting wear. Besides that, the optimum values of process variables obtained by using TLBO algorithm also results in higher value of depth of deformation wear (h_d) than that obtained by using genetic algorithm, which further increases the material removal rate. The combined effect thus leads to the significant improvement in material removal rate by from 90.257 mm^3/s to 239.54 mm^3/s. It can also be observed that TLBO algorithm provides better solution accuracy as compared to the solution obtained by using SA algorithm. TLBO algorithm provides an improvement of about 9% in objective function over that obtained by using SA algorithm. The convergence of TLBO algorithm is shown in Fig. 1. From Fig. 1, it is observed that the algorithm requires only 30 generations to achieve the global optimum solution.

3.2   Optimization of grinding process

Grinding is one of the important and widely used manufacturing processes in engineering industries. The success of grinding process in terms of cost and quality depends on proper selection of various operating conditions in grinding process such as wheel speed, work piece speed, depth of dressing and lead of dressing, area of contact, grinding fluid etc. However, owing to the complexity in process dynamics, problems related to determination of optimal cutting conditions in grinding process are faced with discrete and continuous parameter spaces with multi-modal, differentiable, as well as non-differentiable objective functions.

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3.2.1 Optimization model of grinding process

The optimization model for grinding process formulated in the present work based on the analysis given by Wen et al. [10]. The four decision variables considered for this model are, wheel speed 'V_s' (m/min), work piece speed 'V_w' (m/min), depth of dressing 'doc' (mm) and lead of dressing 'L' (mm/rev).

Objectives:

The two objectives considered in this example are:

a) Minimize production cost as given by Equation (21).

$$C_T = \frac{M_c}{60p}\left(\frac{L_w+L_e}{V_w 1000}\right)\left(\frac{b_w+b_e}{f_b}\right)\left(\frac{a_w}{a_p}+S_p+\frac{a_w b_w L_w}{\pi D_e b_s a_p G}\right)+\frac{M_c}{60p}\left(\frac{S_d}{V_r}+t_1\right)+\frac{M_c t_{ch}}{60N_t}+\frac{M_c \pi b_s D_e}{60pN_d LV_s 1000}+C_s\left(\frac{a_w b_w L_w}{pG}+\frac{\pi(doc)b_s D_e}{pN_d}\right)+\frac{C_d}{pN_{td}} \quad (21)$$

Where, M_c is cost per hour labor and administration, L_w is length of workpiece, L_e is empty length of grinding, b_w is width of workpiece, b_e is empty width of grinding, f_b is cross feed rate, a_w is total thickness of cut, a_p is down feed of grinding, S_p is number of spark out grinding, D_e is diameter of wheel, b_s is width of wheel, G is grinding ratio, S_d is distance of wheel idling, p is number of workpieces loaded on the table, V_r is speed of wheel idling, t_1 is time of loading and unlading workpieces, t_{ch} is time of adjusting machine tool, N_t is batch size of the workpieces, N_d is total number of workpieces to be ground between two dressing, N_{td} is total number of workpieces to be ground during life of dressing, C_d is cost of dressing.

b) Maximize the production rate in terms of workpiece removal parameter 'WRP' given by

$$WRP = 94.4\frac{(1+(2\,doc\,/3\,L))L^{11/19}(V_w/V_s)^{3/19}V_s}{D_e^{43/304}VOL^{0.47}d_g^{5/38}R_c^{27/19}} \quad (22)$$

Where, VOL= wheel bond percentage, d_g =grind size, R_c= workpiece hardness.

The combined objective function (Z_R) is formulated as given in equation (23).

$$Min\,Z_R = W_1\times\frac{C_T}{C_T^*}-W_2\times\frac{WRP}{WRP^*} \quad (23)$$

Where, W_1 and W_2 are the weighting factors for production cost and workpiece removal parameter respectively. In the present example equal weights are considered for both objectives. Thus $W_1 = W_1 = 0.5$. $C_T^* = 10(\$/pc), WRP^* = 20\,mm^3/\min.N$.

Constraints:

Following four constraints are considered.

a) Thermal damage constraint

The grinding process requires very high energy per unit volume of material removed. Whatever the energy that is concentrated within the grinding zone, it is converted into heat. The high thermal energy causes damage to the work piece, and it leads to the reduced production rate. The specific energy U is calculated by equation (24).

$$U = 13.8 + \frac{9.64 \times 10^{-4} V_s}{a_p V_w} + \left(6.9 \times 10^{-3} \frac{2102.4 V_w}{D_e V_s}\right) \times \left(A_0 + \frac{K_u V_s L_w a_w}{V_w D_e^{1/2} a_p^{1/2}}\right) \frac{V_s D_e^{1/2}}{V_w a_p^{1/2}} \tag{24}$$

K_u=wear constant.

The critical specific energy U^* at which burning starts is expressed in terms of the operating parameters as

$$U^* = 6.2 + 1.76 \left(\frac{D_e^{1/4}}{a_p^{3/4} V_w^{1/2}}\right) \tag{25}$$

The thermal damage constraint is then specified as

$$U^* - U \geq 0 \tag{26}$$

b) Wheel wear parameter constraint

Wheel wear parameter *WWP* (mm3/min.*N*) is related directly to the grinding conditions. For single-point diamond dressing, it is given by Eq. (27).

$$WWP = \left(\frac{k_p a_p d_g^{5/38} R_c^{27/29}}{D_c^{1.2/VOL-43/304} VOL^{0.38}} \right) \times \frac{(1+(doc/L))L^{27/19}(V_s/V_w)^{3/19} V_w}{(1+(2doc/3L))} \tag{27}$$

The wheel wear constraint is obtained as

$$\frac{WRP}{WWP} - G \geq 0 \tag{28}$$

c) Machine tool stiffness constraint

Chatter results in poorer surface quality and lowers machining production rate. Chatter avoidance is therefore a significant constraint in selection of machining parameters. The relationship between grinding stiffness K_c (N/mm), wheel wear stiffness Ks (N/mm) and operating parameters during grinding is given below:

$$K_c = \frac{1000 V_w f_b}{WRP} \tag{29}$$

$$K_s = \frac{1000 V_s f_b}{WWP} \tag{30}$$

To avoid chatter during machining, the constraint given by equation (31) has to be fulfilled:

$$MSC - \frac{|R_{em}|}{K_m} \geq 0 \tag{31}$$

Where,

$$MSC = \frac{1}{2K_c} \left(1 + \frac{V_w}{V_s G} \right) + \frac{1}{K_s}, \tag{32}$$

R_{em}=dynamic machine characteristics, K_m=Static machine stiffness.

d) Surface roughness constraint

The surface roughness constraint is as given by equation (33) below.

$$R_a \leq 1.8 \ \mu m \tag{33}$$

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$$R_a = 0.4587T_{ave}^{0.30} \quad \text{for} \quad 0 < T_{ave} < 0.254 \quad \text{else,}$$

$$R_a = 0.78667T_{ave}^{0.72} \quad \text{for} \quad 0.254 < T_{ave} < 2.54 \tag{34}$$

$$T_{ave} = 12.5 \times 10^3 \frac{d_g^{16/27} a_p^{19/27}}{D_e^{8/27}} \left(1 + \frac{doc}{L}\right) L^{16/27} \left(\frac{V_w}{V_s}\right)^{16/27} \tag{35}$$

Values of the constants and parameters considered in the present example are as given below:

M_c=30 \$/hr, L_w = 300 mm, L_e = 150 mm, b_w = 60 mm, b_e = 25 mm, f_b =2 mm/pass, a_w = 0.1mm,

a_p = 0.0505 mm/pass, S_p = 2, D_e = 355 mm, b_s = 25mm, G = 60, S_d = 100 mm, p = 1, V_r = 254

mm/min, t_1 = 5 min, t_{ch} = 30 min, N_t = 12, N_d = 20, N_{td} = 2000, C_d =25 \$, VOL=6.99 %, d_g =0.3

mm, R_c=58 HRC, K_u=3.937×10⁻⁷ mm⁻¹, R_{em}=1, K_m=100000 N/mm, K_a=0.0869.

3.2.2   Optimization using TLBO

Results of optimization of grinding process using TLBO algorithm are presented in Table 3 along with those obtained with other advanced optimization algorithms such as genetic algorithm, simulated annealing, particle swarm optimization, artificial bee colony, and harmony search algorithm. It is observed from Table 3 that TLBO algorithm shows significant improvement in the combined objective function value over quadratic programming by about 77% and that over genetic algorithm by about 16%. The TLBO algorithm also shows better solution accuracy as compared to SA, PSO, and HS algorithms. The solutions obtained by using TLBO and ABC algorithms are equally better although they provide different combinations of variables to achieve optimum performance. The convergence of TLBO algorithm along with other advanced algorithms is shown in Fig. 3. It is observed from Fig. 3, that TLBO algorithm requires only 30 iterations to converge to optimum solution as compared to other algorithms which requires 60-80 iterations.

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A real case study of grinding operations of an industry located in Nasik city of India was taken up and the mathematical models given by Equations (21) to (35) were considered and the TLBO algorithm was applied. The results of application of TLBO algorithm have been found more suitable and useful to the concerned industry.

3.3 Optimization of milling process

The optimization model for grinding process formulated in the present work based on the analysis given by Sonmez et al. [4]. The decision variables considered for this model are feed per tooth (f_z), cutting speed (V) and depth of cut (a).

3.3.1 Optimization model of milling process

The objective function in this model is to minimize the production time (T_{pr}) as given by the equation (36).

$$T_{Pr} = \frac{T_s}{N_b} + T_L + N_p T_a + \sum_{i=1}^{N_p} \frac{\pi D L}{f_{zi} z 1000 V_i} + \frac{T_d \pi L V_i^{\left(\frac{1}{m}-1\right)} a_i^{e_v/m} f_{zi}^{\left(\frac{u_v}{m}-1\right)} a_r^{r_v/m} z^{\left(\frac{n_v}{m}-1\right)} \lambda_s^{q_v/m}}{1000 C_v^{1/m} D^{\left(\frac{b_v}{m}-1\right)} \times \left(B_m B_h B_p B_t\right)^{1/m}} \tag{36}$$

Where, T_s = setup time; N_b = total number of components in batch; T_L = loading and unloading time; N_p = total number of passes and subscript 'i' denotes i^{th} pass; T_a = process adjusting and quick return time; T_d = tool changing time; f_z = feed per tooth; z = Number of teeth on milling cutter; D = cutter diameter; L = length of the cut; a_r = width of the cut; a = depth of cut; V = cutting speed; $B_m, B_k, B_p, B_t, m, e_v, u_v, r_v, n_v, q_v, C_v, b_v, C_{zp}, b_z, u_z,$ are process constants.

Following three constraints are considered in this optimization model:

a) Arbour strength:

$$F_s - F_c \geq 0 \tag{37}$$

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Where, Mean peripheral cutting force $= F_c = C_{zp} a_r z D^{b_z} a^{e_z} f_z^{u_z}$ (38)

Permissible force for arbour strength (Kg) $= F_s$

$$F_s = \frac{0.1 k_b d_a^3}{0.08 L_a + 0.65\sqrt{\left((0.25 L_a)^2 + (0.5\alpha D)^2\right)}}$$ (39)

where, k_b = permissible bending strength of arbor; d_a = arbor diameter=27 mm; L_a = arbor length between supports; $\alpha = k_b / (1.3\ k_t)$; k_t = permissible torsional strength of arbor.

b) Arbour deflection:

$$F_d - F_c \geq 0$$ (40)

Where, Permissible force for arbour deflection (Kg) $= F_d = \frac{4 E e d_a^4}{L_a^3}$ (41)

Where, E = modulus of elasticity of arbor material; e = permissible value of arbor deflection.

For roughing operation 'e'=0.2 mm and for finishing operation 'e'=0.05 mm.

c) Power:

$$P_c - \frac{F_c V}{6120} \geq 0$$ (42)

where, P_c = Cutting power (KW) = $P_m \times \eta$

P_m = nominal motor power; η = overall efficiency.

The three process variables and their bounds considered in this work are as given below.

a) Feed per tooth:

$0.000875 \leq f_z \leq 3.571$ (43)

b) Cutting speed:

$6.234 \leq V \leq 395.84$ (44)

c) Depth of cut:

$$0.5 \leq a \leq 4 \text{ (mm)} \tag{45}$$

Values of the constants and parameters considered in the present example are as given below:

$P_m = 5.5$ kW, $\eta = 0.7$, $d_a = 27$ mm, $L_a = 210$ mm, k_b: 140 MPa, k_t: 120 MPa, $E = 200$ GPa, $D = 63$ mm, $z = 8$, $L_a = 160$ mm, $a_r = 50$ mm, $a = 5$ mm, $T_L = 1.5$ min, $T_s = 10$ min, $T_c = 5$ min, $T_a = 0.1$ (min/part), $N_b = 100$; 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 $u_z = 0.72$.

3.3.2 Optimization using TLBO

Results of optimization of milling process using TLBO algorithm are presented in Table 4 for the optimum cutting strategy indicating 3 rough passes each of 1.5 mm and one finishing pass of 0.5 mm. Table 5 provides the results of optimization of milling process obtained by various algorithms. As shown in Table 5, the results obtained by using geometric programming (GP), genetic algorithm (GA), parallel genetic simulated annealing (PGSA), and Tribes are inappropriate, as these results violates the specified constraints. It can be seen from Table 5 that, the solution obtained by using TLBO algorithm is slightly better in terms of accuracy of solution as compared to ABC, PSO, and SA algorithms.

4 Conclusion

In the present work, optimization aspects of process parameters of three machining processes are considered using a recently developed advanced algorithm known as teaching-learning–based optimization (TLBO) algorithm. The three machining processes considered are abrasive water jet machining, grinding and milling. The performance of the TLBO algorithm is studied in terms of convergence rate and accuracy of the solution. Compared to other advanced optimization

methods, TLBO algorithm does not require selection of the algorithm-specific parameters. It makes this algorithm to apply to the real life optimization problems easily and effectively. The TLBO algorithm requires only 20 to 30 iterations for convergence to the optimal solution. The algorithm outperformed GA and SA in all three examples in terms of accuracy of solution. The results obtained by TLBO also show slight superiority over those obtained by using PSO, HS, and ABC algorithms. This is mainly due to the fact that TLBO uses the best solution of the iteration to modify the existing solution as in PSO and it does not divide the population as in case of ABC. The algorithm can also be easily modified to suit optimization of process parameters of other machining processes such as turning, drilling, advanced machining processes, etc. Also the presented algorithm can efficiently handle the multi-objective optimization models.

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Table 1. Values of the constants and parameters for abrasive water jet machining process

Notation	Description	Unit	Value
ρ_a	Density of abrasive particles	Kg/mm^3	3.95x10-6
v_a	Poisson ratio of abrasive particles		0.25
E_{Ya}	Modulus of elasticity of abrasive particles	MPa	350000
f_r	Roundness factor of abrasive particles		0.35
f_s	Sphericity factor of abrasive particles		0.78
η_a	Proportion of abrasive grains effectively participating in machining		0.07
v_w	Poisson ratio of work material		0.20
E_{Yw}	Modulus of elasticity of work material	MPa	114000
σ_{ew}	Elastic limit of work material	MPa	883
σ_{fw}	Flow stress of work material	MPa	8142
C_{fw}	Drag friction coefficient of work material		0.002
ξ	Mixing efficiency between abrasive and water		0.8
P_{max}	Allowable power consumption value	kW	56

Table 2. Results of optimization of AWJM process using TLBO

Method	d_{awn} (mm)	f_n (mm/s)	M_w (Kg/s)	P_w (MPa)	M_a (Kg/s)	α_0 (°)	α_t (°)	h_c (mm)	h_d (mm)	MRR (mm³/s)	Power (kW)
GA [1]	3.726	23.17	0.141	398.3	0.079	0.384	0.572	0.00	1.045	90.257	56
SA [2]	2.9	15	0.138	400	0.08	0.385	0.378	2.97	2.04	218.19	56
TLBO	5.0	5.404	0.141	400	0.07	0.379	0.350	5.694	3.238	239.54	56

Table 3. Results of optimization for grinding process using TLBO

Method	V_s	V_w	doc	L	C_T	WRP	R_a	Z_R
Quadratic Programming [10]	2000	19.96	0.055	0.044	6.2	17.47	1.74	-0.127
Genetic algorithm [12]	1998	11.30	0.101	0.065	7.1	21.68	1.79	-0.187
PSO [16]	2023	10.00	0.110	0.137	8.33	25.63	1.798	-0.224
Simulated annealing [17]	2023	11.48	0.089	0.137	7.755	24.45	1.789	-0.223
Harmony search Algorithm [17]	2019.35	12.455	0.079	0.136	7.455	23.89	1.796	-0.225
Artificial bee colony Algorithm [17]	2023	10.973	0.097	0.137	7.942	25.00	1.80	-0.226
TLBO	2023	11.537	0.0899	0.137	7.742	24.551	1.798	-0.226

Table 4. Results of optimization of milling process using TLBO

Cutting strategy	f_z mm/tooth	V m/min	T_2 (per pass) min	T_2 min	T_1 min	T_{pr} (T_1+T_2) (min)
$a_{rough}=1.5$	0.341	46.641	0.342			
$a_{rough}=1.5$	0.341	46.641	0.342			
$a_{rough}=1.5$	0.341	46.641	0.342	**1.237**	**2.0**	**3.237**
$a_{finish}=0.5$	0.434	66.8576	0.211			

Where, a_{rough} = depth of cut for rough pass (mm); a_{finish} = depth of cut for finish pass (mm);

$$T_1 = \frac{T_s}{N_b} + T_L + N_p T_a \; ; \quad T_2 = \sum_{i=1}^{N_p} \frac{\pi D L}{f_{zi} z 1000 V_i} + \frac{T_d \pi L V_i^{\left(\frac{1}{m}-1\right)} a_i^{e_v/m} f_{zi}^{\left(\frac{u_v}{m}-1\right)} a_r^{r_v/m} z^{\left(\frac{n_v}{m}-1\right)} \lambda_s^{q_v/m}}{1000 C_v^{1/m} D^{\left(\frac{b_v}{m}-1\right)} \times \left(B_m B_h B_p B_t\right)^{1/m}}$$

Table 5. Results of optimization of milling process by using various optimization algorithms

Method	Cutting strategy	f_z mm/tooth	V m/min	SC	DC	PC	T_2 min	T_{pr} (T_1+T_2) (min)
GP [21]	a_{rough} = 3	0.338	26.40	**-405**	24.92	**-0.08**	0.813	2.614
	a_{finish} =2	0.570	25.16	**-430**	**-702**	0		
GA[24]	a_{rough} = 3	0.366	24.69	**-459**	**-28.81**	**-0.04**	0.8102	2.61
	a_{finish} =2	0.5667	25.16	**-427**	**-698**	0		
PGSA[24]	a_{rough} = 3	0.3693	24.25	**-465**	**-35**	0.2	0.8	2.60
	a_{finish} =2	0.5886	24.58	**-452**	**-74**	0		
Tribes[26]	a_{rough} = 3	0.587	36.27	**-8.50**	**-420**	**-4.18**	0.512	2.212
	a_{finish} =2	0.902	30.16	**-797**	**-1069**	**-2.57**		
ABC[29]	a_{rough} = 1.5	0.337	46.982	4.708	435.02	0.0047	1.240	3.240
	a_{rough} = 1.5	0.337	46.982	4.708	435.02	0.0047		
	a_{rough} = 1.5	0.337	46.982	4.708	435.02	0.0047		
	a_{finish} =0.5	0.432	64.410	271.97	1.131	1.400		
PSO[29]	a_{rough} = 1.5	0.340	46.610	1.5	431.9	0.01	1.240	3.240
	a_{rough} = 1.5	0.340	46.610	1.5	431.9	0.01		
	a_{rough} = 1.5	0.340	46.610	1.5	431.9	0.01		
	a_{finish} =0.5	0.434	63.580	271.9	0.35	1.422		
SA[29]	a_{rough} = 1.5	0.336	44.633	5.779	436.09	0.204	1.263	3.263
	a_{rough} = 1.5	0.336	44.633	5.779	436.09	0.204		
	a_{rough} = 1.5	0.336	44.633	5.779	436.09	0.204		
	a_{finish} =0.5	0.429	57.230	273.91	2.296	1.683		
TLBO	a_{rough} = 1.5	0.341	46.641	0.435	430.755	0.0001	1.237	3.237
	a_{rough} = 1.5	0.341	46.641	0.435	430.755	0.0001		
	a_{rough} = 1.5	0.341	46.641	0.435	430.755	0.0001		
	a_{finish} =0.5	0.434	66.8576	271.975	0.355	1.297		

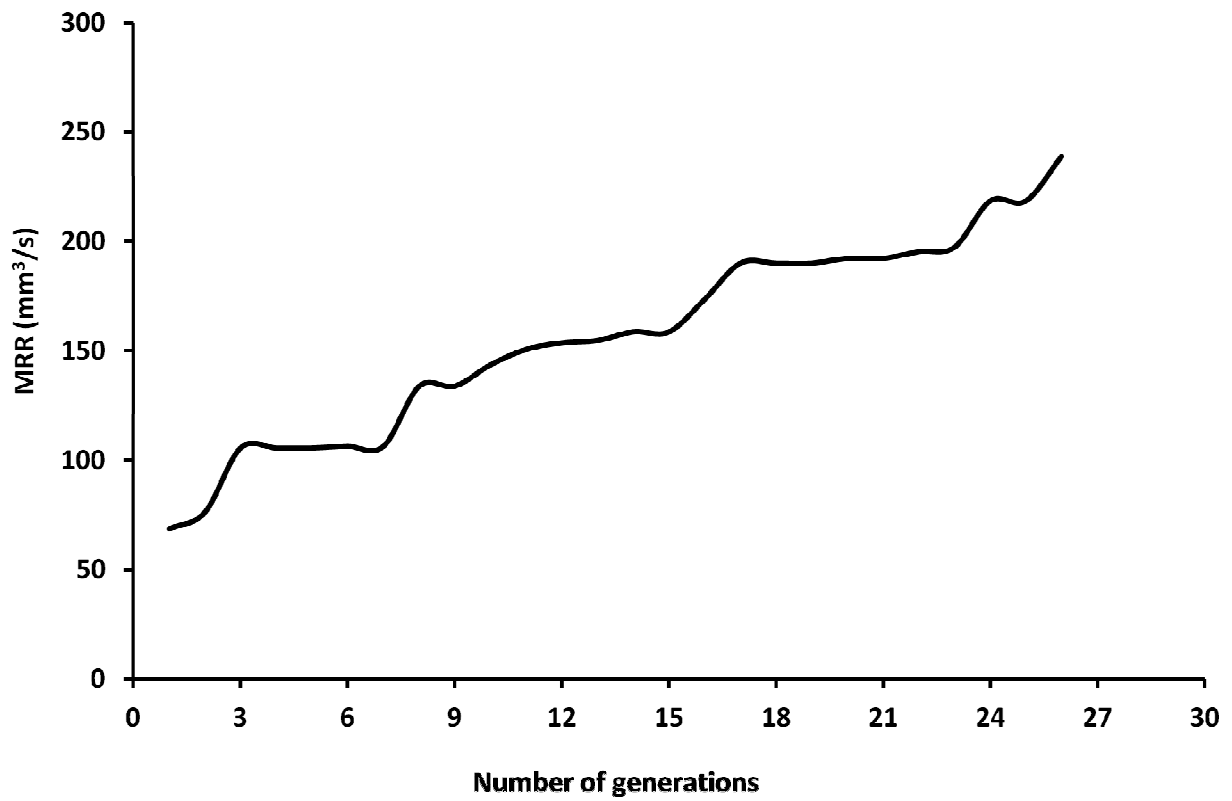SC: Arbor strength constraint, DC: Arbor deflection constraint, and PC: Power constraint

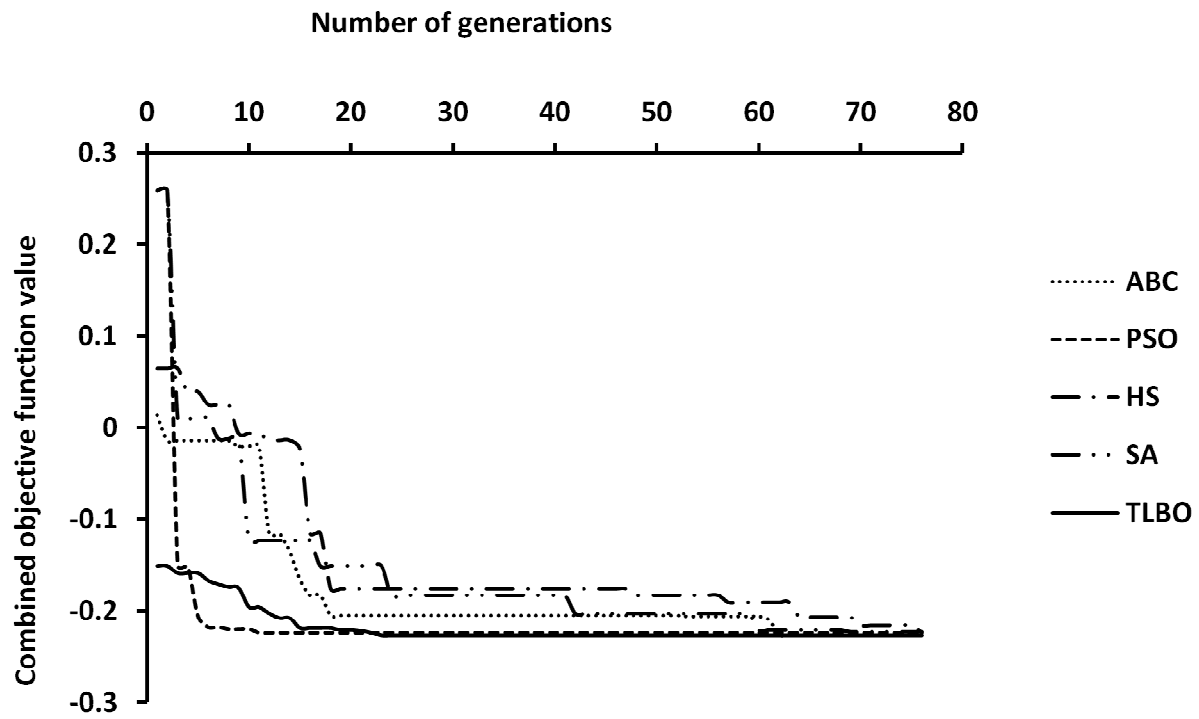**Fig. 1.** Convergence of TLBO algorithm for optimization of abrasive water jet machining process

Fig. 2. Convergence of TLBO algorithm for optimization of grinding process