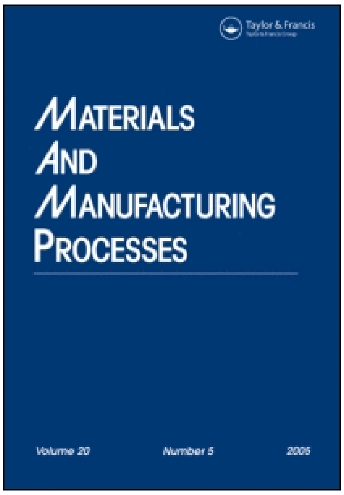

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Multiobjective Optimization of Grinding Process Parameters Using Particle Swarm Optimization Algorithm

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Grinding is one of the very important machining operations in engineering industries. Optimization of grinding processes still remains as one of the most challenging problems because of its high complexity and non-linearity. This makes the application of traditional optimization algorithms quite limited. Hence, there is a need to apply most recent and powerful optimization techniques to get desired accuracy of optimum solution. In this paper, a recently developed nontraditional optimization technique, particle swarm optimization (PSO) algorithm is presented to find the optimal combination of process parameters of grinding process. The objectives considered in the present work are, production cost, production rate, and surface finish subjected to the constraints of thermal damage, wheel wear, and machine tool stiffness. The process variables considered for optimization are wheel speed, workpiece speed, depth of dressing, and lead of dressing. The results of the algorithm are compared with the previously published results obtained by using other traditional optimization techniques.

Keywords Differential evolution; Genetic algorithm; Grinding process; Multiobjective optimization; Particle swarm optimization; Production cost; Production rate; Quadratic programming.

Introduction

Grinding is one of the important and widely used manufacturing processes in engineering industries. The success of any grinding process in terms of cost and quality depends on proper selection of various operating conditions in grinding process such as wheel speed, workpiece speed, depth of dressing and lead of dressing, area of contact, grinding fluid, etc. A significant improvement in the process efficiency may be obtained by optimization of these process parameters that identifies and determines the regions of critical process control factors leading to desired outputs with acceptable variations ensuring lowest cost of manufacturing.

Previous work on the optimization of grinding parameters has concentrated on possible approaches for optimizing constraints during grinding. Amitay [1] reported in his work 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. [2] applied successive quadratic programming (QP) approach using a multiobjective function model with a weighted approach for optimization of surface grinding process parameters. However, by this approach the convergence to an optimal solution depends on the chosen initial solution. Also the algorithm tends to get stuck to the local optimal solution. Rowe et al. [3] provided an extensive review on various approaches based on artificial intelligence to the grinding process. A genetic algorithm (GA)-based optimization procedure has been developed by Saravanan et al. [4] to optimize the grinding conditions. However, the GA has its own limitations such as 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. Also the results of GA presented by the authors are erroneous. Dhavalikar et al. [5] 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. Gopala [6] applied differential evolution (DE) algorithm for optimization of process parameters of grinding operation. However, the solution obtained using differential algorithm are erroneous for rough grinding operation whereas, for finish grinding operation the optimum values suggested by the author lies outside their respective bounds, and hence the solution is not valid.

In the present work, an effort is made to verify if any improvement in the solution is possible by employing more recent optimization techniques such as particle swarm optimization to the optimization model proposed by Wen et al. [2]. Particle swarm optimization (PSO) is reported to be the better algorithm for continuous optimization as well as discrete optimization problems [7]. PSO algorithm has been used for identification of constitutive material model parameters for high-strain rate metal cutting conditions [8] and for process parameter optimization of few manufacturing processes such as pulsed laser micromachining [9], electro-chemical machining [10], friction welding [11], and boring [12]. Hence, PSO algorithm is considered in this work for multiobjective optimization of surface grinding process parameters.

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The next section provides the details of optimization model of the grinding process used in the present work.

Optimization model of grinding process

As numerous process parameters are involved in grinding process, it is difficult and complex to optimize each and every parameter. Various process parameters, such as wheel speed, wokpiece speed, cutting depth, infeed, traverse feed, area of contact, dressing, etc., affect significantly the performance measures such as production cost, production rate, and surface finish. However, to compare the performance of PSO algorithm with that of QP [2], GA [4], and DE [7], the same process parameters, i.e., wheel speed 'V_s' (m/min), workpiece speed 'V_w' (m/min), depth of dressing '*doc*' (mm), and lead of dressing '*L*' (mm/rev) as considered by Wen et al. [2], Saravanan et al. [4], and Gopala [6] are considered in this work also. The objective functions and the constraints are formulated as discussed below.

Objectives

The three objectives considered in this work are the following ones:

a) Minimization of production cost 'C_T' (\$/pc);
b) Maximize the production rate in terms of workpiece removal parameter '*WRP*' (mm^3/min.N);
c) Minimization of surface roughness 'R_a' (μm).

However, keeping in view the specific requirement of finish grinding and rough grinding operation, these three objective functions are divided into two groups as follows. For rough grinding operation following two objective functions are considered with the condition that the surface roughness value should not exceed 1.8 μm:

a) Minimization of production cost (C_T) in \$/piece;
b) Maximize the production rate in terms of workpiece removal parameter '*WRP*' (mm^3/min.N).

For the finish grinding operation, the following two objective functions are considered with the condition that the workpiece removal parameter should not be less than 20 mm^3/min N:

a) Minimization of production cost 'C_T' (\$/pc);
b) Minimization of surface roughness 'R_a' (μm).

These three objective functions 'C_T', '*WRP*', 'R_a' can be expressed in terms of the process variables as given by Eqs. (1)–(3), respectively [2]:

$$C_T = \frac{M_c}{60p}\left(\frac{L_w + L_e}{V_w 1000}\right)\left(\frac{b_w + b_e}{f_b}\right)\left(\frac{a_w}{a_p} + S_p + \frac{a_w b_w L_w}{\pi D_e b_s a_p G}\right) + \frac{M_c}{60p}\left(\frac{S_d}{V_r} + t_1\right) + \frac{M_c t_{ch}}{60N_t} + \frac{M_c \pi b_s D_e}{60pN_d L V_s 1000} + C_s\left(\frac{a_w b_w L_w}{pG} + \frac{\pi(doc) b_s D_e}{pN_d}\right) + \frac{C_d}{pN_{td}}, \tag{1}$$

where M_c is cost per hour labor and administration, L_w is length of workpiece, L_e is the empty length of grinding, b_w is width of workpiece, b_e is the empty width of grinding, f_b is cross-feed rate, a_w is total thickness of cut, a_p is the down-feed of grinding, S_p is the number of spark out grinding, D_e is the diameter of wheel, b_s is the width of wheel, G is the grinding ratio, S_d is the distance of wheel idling, p is the number of workpieces loaded on the table, V_r is the speed of wheel idling, t_1 is the time of loading and unloading workpieces, t_{ch} is the time of adjusting machine tool, N_t is the batch size of the workpieces, N_d is the total number of workpieces to be ground between two dressing, N_{td} is the total number of workpieces to be ground during the life of dresser, C_s is the cost of wheel per mm^3, and C_d is the cost of dressing;

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

where VOL = wheel bond percentage, d_g = grind size, R_c = workpiece hardness;

$$R_a = 0.4587T_{ave}^{0.30}, \quad \text{for } 0 < T_{ave} < 0.254 \text{ else,}$$
$$R_a = 0.78667T_{ave}^{0.72} \quad \text{for } 0.254 < T_{ave} < 2.54, \tag{3}$$

where

$$T_{ave} = 12.5 \times 10^3 \frac{d_g^{16/27} a_p^{19/27}}{D_e^{8/27}}\left(1 + \frac{doc}{L}\right)L^{16/27}\left(\frac{V_w}{V_s}\right)^{16/27}. \tag{4}$$

Constraints

Various constraints considered in the optimization model [2] are discussed below.

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 workpiece, and it leads to the reduced production rate. The specific energy U is calculated by Eq. (5)

$$U = 13.8 + \frac{9.64 \times 10^{-4} V_s}{a_p V_w} + \left(6.9 \times 10^{-3}\frac{2102.4V_w}{D_e V_s}\right) \times \left(A_0 + \frac{K_u V_s L_w a_w}{V_w D_e^{1/2} a_p^{1/2}}\right)\frac{V_s D_e^{1/2}}{V_w a_p^{1/2}} \tag{5}$$

K_u = wear constant.

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

$$U^* = 6.2 + 1.76\left(\frac{D_e^{1/4}}{a_p^{3/4}V_w^{1/2}}\right) \tag{6}$$

The thermal damage constraint is then specified as

$$U^* - U \geq 0. \tag{7}$$

Wheel Wear Parameter Constraint. Wheel wear parameter WWP ($\text{mm}^3/\text{min}N$) is related directly to the grinding conditions. For single-point diamond dressing, it is given by Eq. (8):

$$WWP = \left(\frac{k_p a_p d_g^{5/38} R_c^{27/29}}{D_c^{1.2/VOL-43/304} VOL^{0.38}} \right) \times \frac{(1+(doc/L))L^{27/19}(V_s/V_w)^{3/19}V_w}{(1+(2doc/3L))}. \tag{8}$$

From Eqs. (2) and (8), the wheel wear constraint is obtained as

$$\frac{WRP}{WWP} - G \geq 0. \tag{9}$$

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:

$$K_c = \frac{1000 V_w f_b}{WRP} \tag{10}$$

$$K_s = \frac{1000 V_s f_b}{WWP}. \tag{11}$$

To avoid chatter during machining, the constraint given by Eq. (12) has to be fulfilled:

$$MSC - \frac{|R_{em}|}{K_m} \geq 0, \tag{12}$$

where

$$MSC = \frac{1}{2K_c}\left(1 + \frac{V_w}{V_s G}\right) + \frac{1}{K_s}, \tag{13}$$

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

The next section briefly describes the particle swarm optimization algorithm.

PSO

PSO is an evolutionary computation technique developed by Kennedy and Eberhart [13]. It exhibits common evolutionary computation attributes including initialization with a population of random solutions and searching for optima by updating generations. Potential solutions, called particles, are then "flown" through the problem space by following the current optimum particles. The particle swarm concept was originated as a simulation of a simplified social system. The original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) it has achieved so far. This value is called '*pBest.*' Another "best" value that is tracked by the *global* version of the PSO is the overall best value, and its location obtained so far by any particle in the population. This location is called '*gBest.*' The PSO concept consists of, at each step, changing the velocity (i.e., accelerating) of each particle toward its '*pBest*' and '*gBest*' locations (global version of PSO). Acceleration is weighted by a random term with separate random numbers being generated for acceleration toward '*pBest*' and '*gBest*' locations. The updates of the particles are accomplished as per the following equations:

$$V_{i+1} = w \times V_i + c_1 \times r_1 \times (pBest_i - X_i) + c_2 \times r_2 \times (gBest_i - X_i) \tag{14}$$

$$X_{i+1} = X_i + V_{i+1}. \tag{15}$$

Equation (14) calculates a new velocity (V_{i+1}) for each particle (potential solution) based on its previous velocity, the best location it has achieved ('*pBest*') so far, and the global best location ('*gBest*'), the population has achieved. Equation (15) updates individual particle's position (X_i) in solution hyperspace. The two random numbers 'r_1' and 'r_2' in Eq. (14) are independently generated in the range 0–1.

The acceleration constants 'c_1' and 'c_2' in Eq. (14) represent the weighting of the stochastic acceleration terms that pull each particle towards 'pBest' and 'gBest' positions. 'c_1' represents the confidence the particle has in itself (cognitive parameter) and 'c_2' represents the confidence the particle has in swarm (social parameter). Thus, adjustment of these constants changes the amount of tension in the system. Low values of the constants allow particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past through target regions [14]. The inertia weight 'w' plays an important role in the PSO convergence behavior since it is employed to control the exploration abilities of the swarm. The large inertia weights allow wide velocity updates allowing to globally explore the design space while small inertia weights concentrate the velocity updates to nearby regions of the design space. The optimum use of the inertia weight "w" provides improved performance in a number of applications. The effect of w, c_1, and c_2 on convergence for standard numerical benchmark functions is provided by Bergh and Engelbrecht [15].

To achieve the dimensional consistency of Eqs. (14) and (15), the dimension of the term '$c \times r$' in Eq. (14) could be taken as $(\text{time})^{-2}$. This way, the second and the third terms in Eq. (14) assume the dimension of acceleration. To get the correct dimension of velocity, as required by the left-hand side, one needs to multiply them by Δt, the time step, which becomes unity in the present case, denoting changes from iteration i to i+1. Similarly, the second term in Eq. (15) assumes the correct dimension when taken as $V_{i+1}\Delta t$ and the present form results through the implicit assumption that $\Delta t = 1$ [16, 17].

Particle's velocities on each dimension are confined to a maximum velocity parameter $V_{\max}$, specified by the user.

If the sum of accelerations would cause the velocity on that dimension to exceed V_{max}, then the velocity on that dimension is limited to V_{max}.

Unlike genetic algorithm, PSO algorithm does not need complex encoding and decoding process and special genetic operator. PSO takes real number as a particle in the aspect of representation solution and the particles update themselves with internal velocity. In this algorithm, the evolution looks only for the best solution and all particles tend to converge to the best solution. In the implementation process, particles randomly generated at the beginning or generated by internal velocity during the evolutionary process usually violate the system constraints resulting in infeasible particles. Therefore, the handling of system constraints, particularly nonlinear equation constraints, and the measurement and evaluation of infeasible particles is very important. To cope with constrained problems with evolutionary computation, various approaches such as rejection of infeasible individuals, repair of infeasible individuals, replacement of individuals by their repaired versions, and penalty function methods can be adopted. Among them, the penalty function methods are particularly promising [14] as evidenced by recent developments.

The next section presents an application example to demonstrate and validate the particle swarm optimization algorithm with constant values of inertia weight and acceleration coefficient. The values of inertia weight and acceleration coefficients, for which the algorithm shows better performance in terms of convergence rate, are obtained through several trials with initial guess as given by Bergh and Engelbrecht [15].

Examples

Now two examples are considered for the optimization of grinding process parameters using the PSO algorithm.

Example 1

This example presents the multiobjective optimization of rough grinding process. The combined objective function (to be minimized) formulated for rough grinding operation (Z_R) is given in Eq. (16):

$$Min\ Z_R = W_1^*(C_T/C_T^*) - W_2^*(WRP/WRP^*), \tag{16}$$

where W_1 and W_2 are the weighing factors with value 0.5 each.

$$C_T^* = 10\ (\$/pc);\ \ WRP^* = 20\,\text{mm}^3/\text{min.N},$$

subjected to the constraints specified by Eqs. (7), (9), and (12).

Parameters bounds for the four process variables are as follows:

$$1000 \le V_s \le 2023\,\text{m/min}$$

$$10 \le V_w \le 22.70\,\text{m/min}$$

$$0.01 \le doc \le 0.1370\,\text{mm}$$

$$0.01 \le L \le 0.1370\,\text{mm/rev.}$$

The optimum selection of operating parameters of PSO algorithm like acceleration constants 'c_1' and 'c_2' as well as inertia coefficient 'w' is very essential for convergence of the algorithm. Considering the velocity and positions of a particle at discrete time steps, by substitution of Eq. (14) into Eq. (15), the following non-homogeneous recurrence relation is obtained:

$$\begin{aligned} X_{i+1} = {} & (1 + w - \phi_1 - \phi_2)X_i - wX_{i-1} \\ & + \phi_1 \times pBest_i + \phi_2 \times gBest_i, \end{aligned} \tag{17}$$

where $\phi_1 = c_1 \times r_1$ and $\phi_2 = c_2 \times r_2$.

This recurrence relation can be written in matrix-vector notation as the product

$$\begin{aligned} \begin{bmatrix} X_{i+1} \\ X_i \\ 1 \end{bmatrix} & = \begin{bmatrix} 1 + w - \phi_1 - \phi_2 & -w & \phi_1 \times pBest_i + \phi_2 \times gBest_i \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ & \times \begin{bmatrix} X_i \\ X_{i-1} \\ 1 \end{bmatrix}. \end{aligned} \tag{18}$$

The characteristics polynomial of the matrix in Eq. (18) is

$$(1 - \lambda)(w - \lambda(1 + w - \phi_1 - \phi_2) + \lambda^2). \tag{19}$$

The solution to this polynomial gives eigen values

$$\lambda_1 = \frac{1 + w - \phi_1 - \phi_2 + \gamma}{2}, \tag{20}$$

$$\lambda_2 = \frac{1 + w - \phi_1 - \phi_2 - \gamma}{2}, \tag{21}$$

where,

$$\gamma = \sqrt{(1 + w - \phi_1 - \phi_2)^2 - 4w}. \tag{22}$$

Now, to ensure the convergence of algorithm, the values of λ_1 and λ_2 should be such that

$$\max(|\lambda_1|, |\lambda_2|) < 1. \tag{23}$$

This can be achieved only when the condition given by Eq. (24) is satisfied [11].

$$w > 0.5(\phi_1 + \phi_2) - 1. \tag{24}$$

As the feasible range for w is 0–1, and for c_1 and c_2 is 0–2, the selected values of w, c_1, and c_2 should be such that Eq. (24) is satisfied for all possible values of random numbers r_1 and r_2 in the range 0–1. Keeping in view of this, considerable number of trials is conduced, and the values

TABLE 1.—Values of the constants and parameters used in process parameter optimization of grinding process.

Notation	Description	Unit	Value
M_c	Cost per hour labor and administration	\$/hr	30
L_w	Length of workpiece	mm	300
L_e	Empty length of grinding	mm	150
b_w	Width of workpiece	mm	60
b_e	Empty width of grinding	mm	25
f_b	Cross-feed rate	mm/pass	2
a_w	Total thickness of cut	mm	0.1
a_p	Down-feed of grinding	mm/pass	0.0505
S_p	Number of spark out grinding		2
D_e	Diameter of wheel	mm	355
b_s	Width of wheel	mm	25
G	Grinding ratio		60
S_d	Distance of wheel idling	mm	100
p	Number of workpieces loaded on the table		1
V_r	Speed of wheel idling	mm/min	254
t_1	Time of loading and unlading workpieces	min	5
t_{ch}	Time of adjusting machine tool	min	30
N_t	Batch size of the workpieces		12
N_d	Total number of workpieces to be ground between two dressings		20
N_{td}	Total number of workpieces to be ground during the life of dresser		2000
C_s	Cost of wheel per mm^3	\$	0.003
C_d	Cost of dressing	\$	25
VOL	Wheel bond percentage		6.99
d_g	Grind size	mm	0.3
R_c	Workpiece hardness HRC		58
K_u	Wear constant	mm^{-1}	3.937×10^{-7}
R_{em}	Dynamic machine characteristics		1
K_m	Static machine stiffness.	N/mm	100000
K_a	Constant dependent on coolant and grain type		0.0869

of w, c_1, and c_2 are finally selected as 0.65, 1.65, and 1.55, respectively. Hence, the selected values of w, c_1, and c_2 in the present work are appropriate for convergence of the algorithm.

Values of the constants and parameters considered in the present work are as provided in Table 1. The optimum process parameter values obtained by using PSO algorithm are given in Table 2.

For the selected values of optimization parameters, the convergence of the PSO algorithm is shown in Fig. 1.

Optimality of the above mentioned solution could be confirmed from Figs. 2–5. Figure 2 shows variation of wheel wear parameter constraint, surface roughness constraint, and combined objective function with wheel speed. Since

TABLE 2.—Optimum process parameter values for rough grinding operation obtained by using PSO algorithm.

V_s (m/min)	R_a (m/min)	V_w (mm)	doc (mm/rev)	L (\$/piece)	C_T (mm^3/min-N)	WRP (μm)
2023	10	0.110	0.137	8.33	25.63	1.798

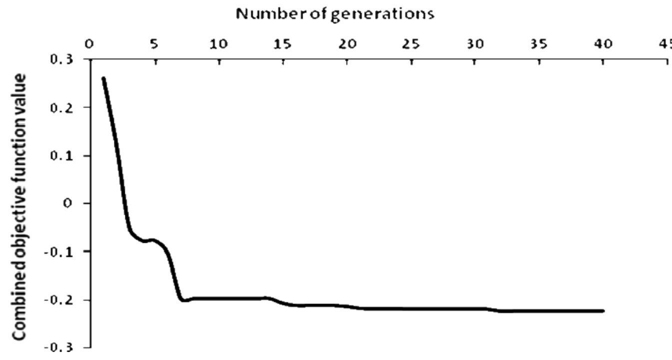

FIGURE 1.—Convergence of PSO algorithm for rough grinding.

the thermal damage constraint and machine tool stiffness constraint are having almost constant positive values for all values of wheel speed, Fig. 2 is plotted neglecting thermal damage constraint and machine tool stiffness constraint to indicate more clearly the variation of other two constraints with wheel speed. As shown in Fig. 2, the combined objective function value reduces with increase in wheel speed. This is due to the fact that with increase in wheel speed, the workpiece removal parameter increases without affecting cost. The constraints are also well satisfied at

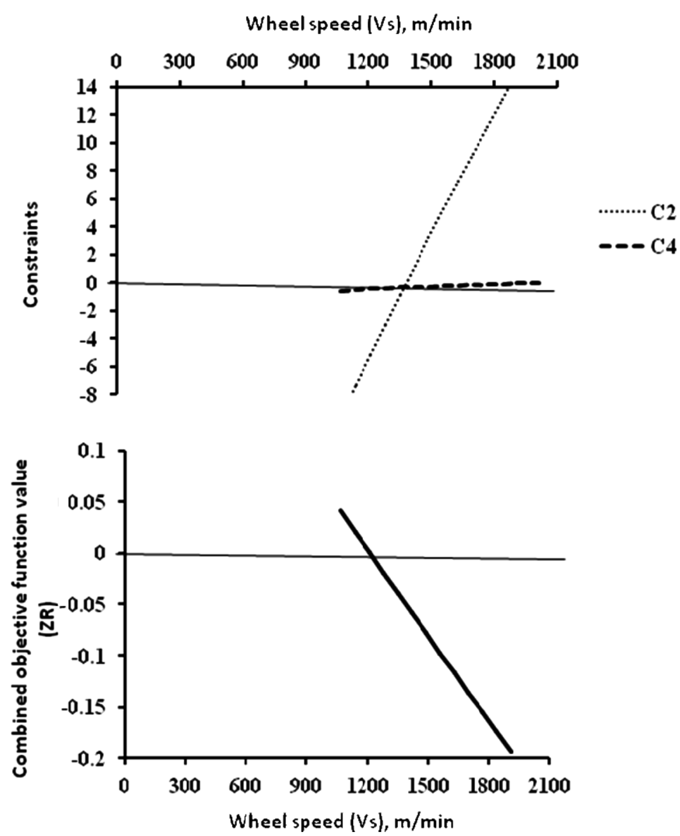

FIGURE 2.—Variation of wheel wear parameter constraint (C2), surface roughness constraint (C4), and combined objective function (Z_R) with wheel speed (V_s).

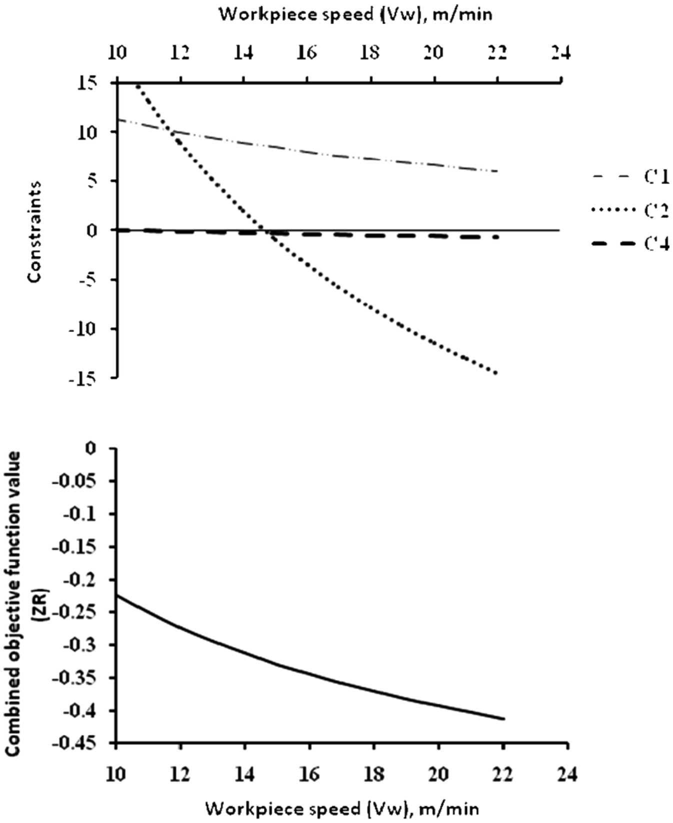

FIGURE 3.—Variation of thermal damage constraint (C1), wheel wear parameter constraint (C2), surface roughness constraint (C4), and combined objective function (Z_R) with workpiece speed (V_w).

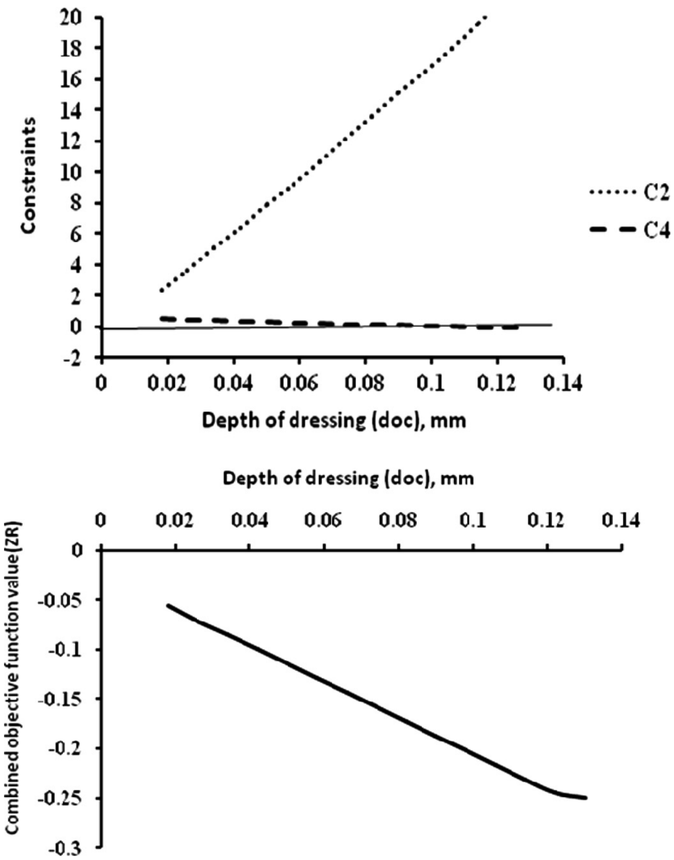

FIGURE 4.—Variation of wheel wear parameter constraint (C2), surface roughness constraint (C4), and combined objective function (Z_R) with depth of dressing.

higher values of wheel speed. Hence the optimum value of wheel speed selected at its upper bound value of 2023 m/min is appropriate. If the wheel speed is increased the size of the chips removed by a single abrasive grain is reduced which in turn reduces the wear of the wheel. Thus from the point of view of wear also, it is better to operate at higher wheel speed.

Figure 3 shows the variation of thermal damage constraint, wheel wear parameter constraint, surface roughness constraint, and combined objective function with workpiece speed. Figure 3 is plotted neglecting the machine tool stiffness constraint as it has almost constant positive values for all values of workpiece speed. As shown in Fig. 3, the combined objective function value reduces (as workpiece removal parameter increases and cost reduces) with increase in workpiece speed. Thus, higher value of workpiece speed is desirable. However, at any value of workpiece speed higher than 10 m/min (i.e., lower bound value), the surface roughness constraint is violated. This is due to the fact that if the workpiece speed is high, then the wheel wear increases.

Figure 4 shows the variation of wheel wear parameter constraint, surface roughness constraint, and combined objective function with depth of dressing. Since the thermal damage constraint and machine tool stiffness constraint are having almost constant positive values for all values of wheel speed, Fig. 4 is plotted neglecting thermal damage constraint and machine tool stiffness constraint. As shown in Fig. 4, the combined objective function value decreases with the increase in depth of dressing. Thus the higher value of depth of dressing is desirable. However, for any value of depth of dressing higher than 0.11 mm, the surface roughness constraint is violated. This confirms the optimum value depth of dressing selected using particle swarm optimization algorithm for rough grinding operation.

Figure 5 shows variation of wheel wear parameter constraint, surface roughness constraint, and combined objective function with lead of dressing. Since the thermal damage constraint and machine tool stiffness constraint are having almost constant positive values for all values of wheel speed, Fig. 5 is plotted neglecting thermal damage constraint and machine tool stiffness constraint. As shown in Fig. 5, the combined objective function value initially increases up to a certain value and thereafter decreases with increase in lead of dressing. Thus, the minimum value of combined objective function occurred at both, lower bound and upper bound values of lead of dressing. However, the upper bound value of lead of dressing should be selected, as at lower bound value of lead of dressing, surface roughness constraint is violated.

Table 3 shows the optimum process parameter data for above example, along with the previously published results using other methods. As shown in Table 3, although

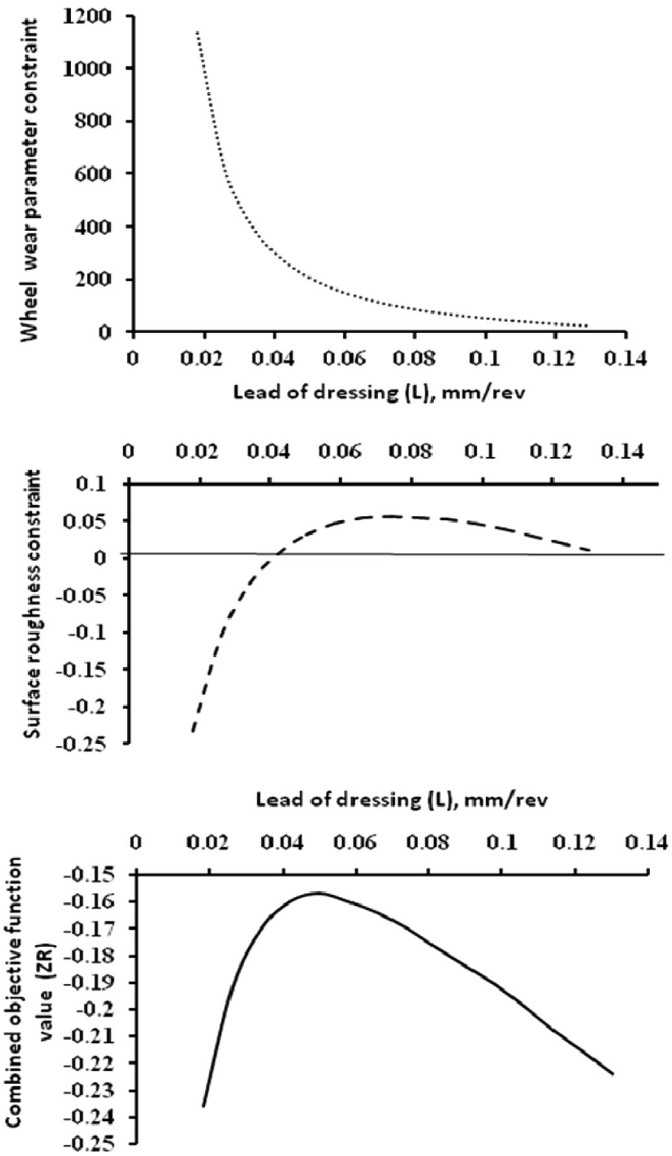

FIGURE 5.—Variation of wheel wear parameter constraint, surface roughness constraint, and combined objective function (Z_R) with lead of dressing (L).

the result of optimization using differential evolution algorithm [7] seems to be better than that using PSO, is erroneous and the corrected result is not valid as the surface roughness value (1.87 μm) exceeds than the specified value (1.8 μm). Using PSO algorithm, the improvement in combined objective function for rough grinding over that of QP [2] is 76% and GA [4] is 19.78%. This improvement is mainly due to use of better optimization technique.

TABLE 4.—Optimum process parameter values for finish grinding operation obtained by using PSO algorithm.

V_s (m/min)	R_a (m/min)	V_w (mm)	doc (mm/rev)	L ($/piece)	C_T (mm^3/min-N)	WRP (μm)
2023	22.7	0.01	0.137	7.11	20.01	0.79

Example 2

This example presents the multiobjective optimization of finish grinding process. The combined objective function formulated for finish grinding operation (Z_F) is given in Eq. (25):

$$\text{Min.} Z_F = W_1^*(C_T/C_T^*) + W_3^*(R_a/R_a^*),] \tag{25}$$

where W_1 and W_3 are the weighting factors with value 0.3 and 0.7, respectively; subjected to the constraints specified by Eqs. (7), (9), and (12).

Parameters bounds for the four process variables are same as given in Example 1. For finish grinding, the values of operating parameters of PSO algorithm 'w,' 'c_1,' and 'c_2' selected are: inertia weight factor $(w) = 0.65$; acceleration coefficients: $c_1 = 1.65$ and $c_2 = 1.55$.

The optimum process parameter values obtained by using PSO algorithm are given in Table 4.

For the selected values of optimization parameters, the convergence of the PSO algorithm is shown in Fig. 6.

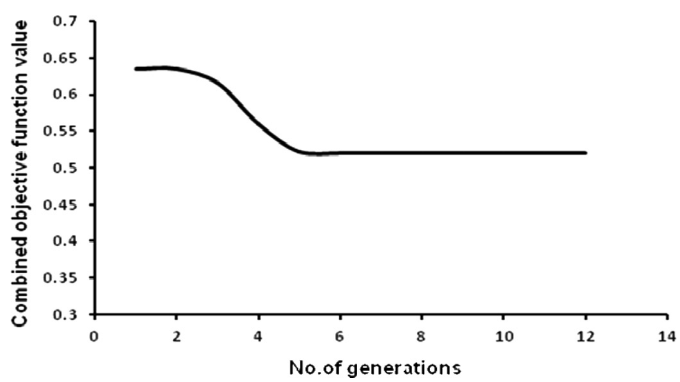

FIGURE 6.—Convergence of PSO algorithm for finish grinding.

TABLE 3.—Results of optimization for rough grinding operation.

Method	Author(s) COF		V_s	V_w	doc	L	C_T	WRP	R_a
Q.P.	Wen et al. [2]	2000	19.96	0.055	0.044	6.2	17.47	1.74	−0.127
GA	Saravanan et al. [4]	1998	11.30	0.101	0.065	7.1	21.68	1.79	−0.187
DE	Gopala [6]	2023	10.00	0.130	0.109	7.9	26.57	1.80**a**	−0.249
DE		2023	10.00	0.130	0.109	7.9	26.57	1.87**b**	−0.249
PSO		2023	10.00	0.110	0.137	8.33	25.63	1.798	−0.224

a: Values wrongly calculated by Gopala [6]; **b**: Corrected values.

Table 5.—Results of optimization for finish grinding operation.

Method	Author(s) COF		V_s	V_w	doc	L	C_T	WRP	R_a
Q.P.	Wen et al. [2]	2000	19.99	0.052	0.091	7.7	20.00	0.83	0.554
GA	Saravanan et al. [4]	1986	21.40	0.024	0.136	6.6**a**	20.08	0.83	0.521**a**
GA		1986	21.40	0.024	0.136	7.36**b**	20.08	0.83	0.542**b**
DE	Gopala [6]	2170	17.49	0.008	0.137	7.48	20.33	0.65	0.497
PSO		2023	22.7	0.01	0.137	7.11	20.01	0.79	0.520

a: Values wrongly calculated by Saravanan et al. [4], **b**: Corrected values.

Table 5 shows the optimum process parameter data for the above example, along with the previously published results using other methods. As shown in Table 5, although the result of optimization using differential evolution algorithm [7] seems to be better than that using PSO, is not valid as the values of some process parameters like wheel speed (*Vs*) and depth of dressing (doc) lies outside their respective bounds, ($Vs = 2170 > 2023$ and $\text{doc} = 0.008 < 0.01$). The result obtained by using genetic algorithm [4] is erroneous. By using PSO algorithm, the improvement in combined objective function for finish grinding over that of QP [2] is 6.54% and genetic algorithm [4] is 4.23%.

Conclusions

In the present work, multiobjective optimization aspects of rough grinding as well as finish grinding process parameters are considered using a PSO algorithm. The three objectives considered are, minimization of production cost, maximization of production rate and maximization of surface finish subjected to the constraints of thermal damage, wheel wear parameter, and machine tool stiffness. It is observed that the results obtained by using particle swarm optimization algorithm outperformed other optimization techniques such as QP, GA, and DE algorithm for both rough grinding as well as finish grinding operations.

The performance of the PSO in terms of convergence rate and accuracy of the solution is studied. Compared to other nonconventional optimization methods, few trials are required to predict the best and worst operating parameters of particle swarm optimization algorithm. The proposed algorithm requires only 30 to 40 iterations for convergence to the optimal solution. The algorithm can also be easily modified to suit optimization of process parameters of other machining processes such as milling, turning, drilling, etc. Also the proposed algorithm can efficiently handle the multiobjective optimization models.

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