Int J Adv Manuf Technol (2013) 66:1319–1326
DOI 10.1007/s00170-012-4410-y

ORIGINAL ARTICLE

Optimization of multi-pass turning operations using hybrid teaching learning-based approach

Ali R. Yildiz

Received: 6 January 2012 / Accepted: 23 July 2012 / Published online: 11 October 2012

Abstract This paper presents a novel hybrid optimization approach based on teaching–learning based optimization (TLBO) algorithm and Taguchi's method. The purpose of the present research is to develop a new optimization approach to solve optimization problems in the manufacturing area. This research is the first application of the TLBO to the optimization of turning operations in the literature The proposed hybrid approach is applied to two case studies for multi-pass turning operations to show its effectiveness in machining operations. The results obtained by the proposed approach for the case studies are compared with those of particle swarm optimization algorithm, hybrid genetic algorithm, scatter search algorithm, genetic algorithm and integration of simulated annealing, and Hooke–Jeeves patter search.

Keywords Hybrid optimization · Teaching–learning based optimization algorithm · Taguchi method · Manufacturing · Turning

1 Introduction

The machining processes have been widely used to produce high-quality products by many companies. These machining processes include large number of parameters that may affect the cost and quality of the products. Selection of optimum machining parameters is very important to satisfy all the conflicting objectives of the process. In the first study on the machining economics problems, Gilbert [1] presented theoretical analysis of the optimization of the machining process. Various research efforts have been made on single and multi-pass turning problems [2–14]. Recently, a comparison of evolutionary-based optimization techniques to solve multi-pass turning optimization problems is presented by Yildiz [14].

The convergence speed of evolutionary algorithms to the optimal results is better than those of traditional optimization algorithms. Population-based algorithms such as cuckoo search algorithm, differential evolution algorithm (DE), particle swarm optimization algorithm (PSO), and genetic algorithm (GA) have been preferred in many applications instead of conventional techniques [8, 15–30].

The population-based algorithms may have premature convergence towards a local minimum. To find a remedy the mentioned weakness, they have been integrated with other techniques [31–36]. In [36], the differential evolution algorithm was integrated with Taguchi method for optimization of multi-pass turning operations. The results of the HRDE were better than those of scatter search, the GA and the simulated annealing powered with a Hooke–Jeeves Pattern Search (SA–PS) algorithm for turning operations.

In this research, a new hybrid approach based on teaching learning-based optimization (TLBO) algorithm and Taguchi method is presented. The proposed hybrid approach (HRTLBO) is applied to the two case studies to optimize cutting parameters in multi-pass turning operations. The rest of the paper is organized as follows: Section 2 describes a detailed formulation of the objective and constraints in multi-pass turning. The TLBO algorithm and Taguchi method are presented in Section 3. In Section 4, two case studies are solved. The results and discussions for case studies are given in Section 4. The paper is concluded in Section 5.

2 Metal cutting optimization model

In multi-pass turning operations, the aim is to minimize unit production cost (C_U). The unit production cost is the sum of

A. R. Yildiz (✉)
Department of Mechanical Engineering,
Bursa Technical University,
Bursa, Turkey
e-mail: aliriza.yildiz@btu.edu.tr

the cutting cost (C_M), machine idle cost (C_I), tool replacement cost (C_R), and tool cost (C_T), respectively. The developed hybrid optimization approach is applied to optimize multi-pass turning operation for the determination of cutting parameters considering minimum production cost under a set of machining constraints which are presented and adopted in the references of Shin and Joo [5], Chen and Tsai [8], and Chen [30].

2.1 The cost function

$$C_U = C_M + C_I + C_R + C_T \tag{1}$$

$$\begin{aligned} C_U = k_0\left[\frac{\pi DL}{1{,}000V_rf_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi DL}{1{,}000V_sf_s}\right] \\ +k_0\left[t_c+(h_1L+h_2)\left(\frac{d_t-d_s}{d_r}+1\right)\right] \\ +k_0\frac{t_e}{T_p}\left[\frac{\pi DL}{1{,}000V_rf_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi DL}{1{,}000V_sf_s}\right] \\ +\frac{k_t}{T_p}\left[\frac{\pi DL}{1{,}000V_rf_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi DL}{1{,}000V_sf_s}\right] \end{aligned} \tag{2}$$

2.2 Parameter bounds and cutting condition constraints

In multi-pass turning operations, C_U is imposed by different constraints which are (1) parameter bounds cover depth of cut, cutting speed and feed; (2) tool-life constraint; (3) cutting force constraint; (4) power constraint; (5) stable cutting region constraint; (6) chip–tool interface temperature constraint; (7) surface finish constraint (only for finish machining); and (8) parameter relations. These constraints are as follow [5]:

2.2.1 Rough machining

$$\text{Depth of cut} \quad d_{rL} \le d_r \le d_{rU} \tag{3}$$

$$\text{Feed} \quad f_{rL} \le f_r \le f_{rU} \tag{4}$$

$$\text{Cutting speed} \quad V_{rL} \le V_r \le V_{rU} \tag{5}$$

$$\text{Tool}-\text{life contraint} \quad T_L \le t_r \le T_U \tag{6}$$

$$\text{Cutting force constraint} \quad k_1 f_r^{\mu} d_r^{\upsilon} \le F_U \tag{7}$$

$$\text{Power contraint} \quad \frac{k_1 f_r^{\mu} d_r^{\upsilon} V_r}{6120\eta} \le P_U \tag{8}$$

$$\text{Stable cutting region contraint} \quad V_r^{\lambda} f_r d_r^{\nu} \ge S_C \tag{9}$$

$$\begin{gathered}\text{Chip}-\text{tool interface temperature constraint} \\ Q_r = k_q V_R^{\tau} f_r^{\phi} d_r^{\delta} \le Q_U\end{gathered} \tag{10}$$

2.2.2 Finish machining

$$\text{Depthofcut} \quad ds_L \le ds \le ds_U \tag{11}$$

$$\text{Feed} \quad fs_L \le f_s \le fs_U \tag{12}$$

$$\text{Cutting speed} \quad Vs_L \le Vs \le Vs_U \tag{13}$$

$$\text{Tool}-\text{life constraint} \quad T_L \le t_s \le T_U \tag{14}$$

$$\text{Cutting force constraint} \quad \mathrm{k_1 f_s^{\mu} d_s^{\upsilon}} \le F_U \tag{15}$$

$$\text{Power constraint} \quad \frac{\mathrm{k_1 f_S^{\mu} d_S^{\upsilon}} V_S}{6120\eta} \le P_U \tag{16}$$

$$\text{Stable cutting region constraint} \quad V_S^{\lambda} f_S\, d_S^{\nu} \ge S_C \tag{17}$$

$$\begin{gathered}\text{Chip}-\text{tool interface temperature constraint} \\ Q_S = k_2 V_s^{\tau} f_s^{\phi} d_s^{\delta} \le Q_U\end{gathered} \tag{18}$$

$$\text{Surface finish constraint} \quad \frac{f_s^2}{8R} \le \mathrm{SR}_U \tag{19}$$

2.2.3 Parameter relations

$$V_s \ge k_3 V_r \tag{20}$$

$$f_r \ge k_4 f_s \tag{21}$$

$$d_r \ge k_5 d_5 \tag{22}$$

$$d_r = (d_t - d_s)/n \tag{23}$$

In addition to these constraints, the total depth of cut is another important constraint for the case study. The total depth of cut (d_t) is the sum of the depth of finish cut (d_s), and the total depth of rough cut (nd_r). The optimization algorithm does not determine the optimal depth of roughing since it can be given by the mathematical manipulation as expressed in Eq. (24). Therefore, one can eliminate the equality constraint (Eq. 23) and the decision variable (d_r) in the optimization procedure [8].

$$d_s = d_t - nd_r \tag{24}$$

Therefore, the equality constraint and the decision variable (d_r) and (n) in the optimization procedure can be eliminated. The five machining parameters (V_r, f_r, d_s, V_s, f_s) are determined for turning model optimization. Further details about the turning mathematical model and data with respect to machining can be obtained from Shin and Joo [5] and Chen and Tsai [8] and Chen [30].

3 The proposed hybrid approach

3.1 Taguchi method

The Taguchi method is a universal approach, which is widely used in robust design [37]. There are three stages to achieve Taguchi's objective: (1) concept design, (2) robust parameter design (RPD), and (3) tolerance design. The robust parameter design is used to determine the levels of factors and to minimize the sensitivity of noise. That is, a parameter setting should be determined with the intention that the product response has minimum variation while its mean is close to the desired target. Taguchi's method is based on statistical and sensitivity analysis for determining the optimal setting of parameters to achieve robust performance. The responses at each setting of parameters were treated as a measure that would be indicative of not only the mean of some quality characteristic, but also the variance of that characteristic. The mean and the variance would be combined into a single performance measure known as the signal-to-noise (S/N) ratio. Taguchi classifies robust parameter design problems into different categories depending on the goal of the problem and for each category as follows:

Smaller the better For these kind of problems, the target value of y, that is, quality variable, is zero. In this situation, S/N ratio is defined as follows:

$$S/N\,\text{ratio} = -10\log\left(\sum y_i^2/n\right) \tag{25}$$

Larger the better In this situation, the target value of y, that is, quality variable, is infinite and S/N ratio is defined as follows:

$$S\Big/N\,\text{ratio} = -10\log\left(\sum 1\big/y_i^2/n\right) \tag{26}$$

Nominal the best For these kind of problems, the certain target value is given for y value. In this situation, S/N ratio is defined as follows:

$$S\Big/N\,\text{ratio} = -10\log\left(\sum y^2/s^2\right) \tag{27}$$

Taguchi's method uses an orthogonal array and analysis of mean to analyze the effects of parameters based on statistical analysis of experiments. To compare performances of parameters, the statistical test known as the analysis of variance (ANOVA) is used. Further details and technical merits about robust parameter design can be found in [37, 38].

3.2 Teaching–learning-based optimization algorithm

TLBO is a teaching–learning process inspired algorithm proposed by Rao et al. [39], which is based on the effect of influence of a teacher on the output of learners in a class. It has been used for optimization of mechanical elements [40], structural design [41], and manuafcturing problems[42]. 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 a 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 phases is explained below.

(a) 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 room from any value M_1 to his or her level (i.e., TA). But practically, it is not possible and a teacher can move the mean of the class room M_2 to any other value M_2 which is better than M_1 depending on his or her capability. Consider M_j be as the mean and T_i as the teacher at any iteration i. Now, T_i will try to improve existing mean M_j towards it so the new mean will be T_i designated as M_{new} and the difference between the existing mean and new mean is given by Rao et al. [40].

$$\text{Difference\_Mean}_i = r_i\left(M_{\text{new}}T_F M_j\right) \tag{28}$$

where teaching factor (TF) 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 TF can be either 1 or 2 which is a heuristic step and it is decided randomly with equal probability as:

$$T_F = \text{round}[1 + \text{rand}(0,2)\{2-1\}] \tag{29}$$

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

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

$$X_{\text{new},i} = X_{\text{old},i} + \text{Difference\_Mean}_i \tag{30}$$

(b) 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. Mathematically, the learning phenomenon of this phase is expressed below.

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

$$X_{\text{new},i} = X_{\text{old},i} + r_i\left(X_i - X_j\right) \;\; \text{If}\, f\left(X_i\right) < f\left(X_j\right) \tag{31}$$

$$X_{\text{new},i} = X_{\text{old},i} + r_i\left(X_j - X_j\right) \;\; \text{If}\, f\left(X_j\right) < f\left(X_j\right) \tag{32}$$

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

- Step 1: Initialize the population (i.e., learners) and design variables of the optimization problem (i.e., number of subjects offered to the learner) with random generation and evaluate them.
- Step 2: Select the best learner of each subject as a teacher for that subject and calculate mean result of learners in each subject.
- Step 3: Evaluate the difference between current mean result and best mean result according to Eq. (28) by utilizing the TF.
- Step 4: Update the learners' knowledge with the help of teacher's knowledge according to Eq. (30).
- Step 5: Update the learners' knowledge by utilizing the knowledge of some other learner according to Eqs. (31) and (32).
- Step 6: Repeat the procedure from steps 2–5 till the termination criterion is met.

The next section presents the applications of the proposed algorithm for the parameter optimization of turning operation.

3.3 The proposed optimization approach

In this paper, a new hybrid optimization approach (hybrid robust teaching–learning based optimization; HRTLBO) is presented to define the optimal machining parameters for multi-pass turning operations. The proposed approach hybridizes teaching–learning based optimization algorithm and Taguchi method. It has an important advantage to consider hybridizing TLBO with other techniques to develop a new approach that improves the performance of TLBO to solve optimization problems.

A larger population makes the algorithm more likely to locate a good masking string, but also increases the time taken by the algorithm. Therefore, there is a need to define the efficient range of population size to achieve better optimal solutions in shorter times. In this research, this shortcoming is eliminated by introducing Taguchi's robust parameter design through the initial population generation for TLBO.

The Taguchi method is a method that chooses the most suitable combination of the levels of factors by using *S/N* table and orthogonal arrays against the factors that form the variation and are uncontrollable in product and process [37]. Hence, it tries to reduce the variation in product and process as much as possible. Taguchi's robust parameter design uses statistical performance measure which is known as *S/N* ratio that takes both medium and variation into consideration. Therefore, the current approach uses the issues of robustness to emphasize the statistical and sensitivity analysis of RPD to achieve an efficient exploration using a small population by avoiding the use of a large search space for the evolution process. The current proposed approach involves two stages of optimization: (a) refinement of search space of solutions using Taguchi's RPD and (b) TLBO search process using refined population size.

4 Example of computational machining optimization

As stated in the above sections, the metal cutting operation has a complex nature, the objectives are usually in conflict with each other, and they have uncontrollable variations in their design parameters with complex

Table 1 Data for the example of multi-pass turning

D=50 mm	L=300 mm	d_t=6.0 mm
V_{rU}=500 m/min	V_{rL}=50 m/min	f_{rU}=0.9 mm/rev
f_{rL}=0.1 mm/rev	d_{rU}=3.0 mm	d_{rL}=1.0 mm
V_{sU}=500 m/min	V_{sL}=50 m/min	f_{sU}=0.9 mm/rev
f_{sL}=0.1 mm/rev	d_{sU}=3.0 mm	d_{sL}=1.0 mm
k_o=0.5 \$/min	k_t=2.5 \$/edge	$h_1=7\times10^{-4}$
h_2=0.3	t_c=0.75 min/piece	t_e=1.5 min/edge
p=5	q=1.75	r=0.75
$C_0=6\times10^{-11}$	T_U=45 min	T_L=25 min
k_f=108	μ=0.75	υ=0.95
η=0.85	F_U=200 kg f	P_U=5 kW
λ=2	ν=−1	S_c=140
k_q=132	τ=0.4	φ=0.2
δ=0.105	Q_U=1,000 °C	R_n=1.2 mm
k^3=1.0		

nature. For example, increasing production rate may increase the production cost by increasing the rate of tool wear. As stated in Section 2, the complex nature and high nonlinearity of machining optimization problems may present some shortcomings for optimization approaches. There is a crucial need to overcome the limitations owing to the traditional optimization methods and also further to improve the strength of recent approaches to achieve better results for the machining problems in industry. In the present research, the search space is refined based on the effect of the various design variables on objective functions. An aim was to reach optimum solutions by using Taguchi's RPD approach coupled with TLBO.

Table 2 Experimental results and S/N ratio

Ex. no	X_1	X_2	X_3	X_4	X_5	F	S/N
1	50	0.1	50	0.1	1	10.3	−20.2
2	50	0.27	200	0.27	1.66	3.1	−9.7
3	50	0.53	350	0.53	2.32	1.9	−5.7
4	50	0.9	500	0.9	3	1.4	−3.5
5	200	0.1	200	0.53	3	3.6	−11.1
6	200	0.27	50	0.9	2.32	1.8	−5.3
7	200	0.53	350	0.1	1.66	3.1	−10.1
8	200	0.9	500	0.27	1	9.5	−19.5
9	350	0.1	350	0.9	1.66	17.9	−25.1
10	350	0.27	500	0.53	1	26.7	−28.5
11	350	0.53	50	0.27	3	2.7	−8.8
12	350	0.9	200	0.1	2.32	2.2	−7.2
13	500	0.1	500	0.27	2.32	33.4	−30.4
14	500	0.27	350	0.1	3	3.8	−11.8
15	500	0.53	200	0.9	1	1.8	−5.1
16	500	0.9	50	0.27	1.66	2.6	−8.5

Table 3 Results of the analysis of variance for objective (case 1 with d_t=6 mm)

	Level 1	Level 2	Level 3	Level 4	SS	%Cont.
x_1	−9.8	−11.5	−17.4	−14	127	11.95
x_2	−21.7	−13.8	−7.4	−9.7	472.4	44.45
x_3	−10.7	−8.3	−13.1	−20.5	258.6	24.33
x_4	−12.3	−15.4	−15.1	−9.7	71.7	6.74
x_5	−18.3	−13.3	−12.1	−8.8	132.8	12.44

4.1 Metal cutting example

In this section, the HRTLBO is used to find the optimum machining parameters for the multi-pass turning problem, which is described in section 2. The machining variables (factors) x_1 (V_r), x_2 (f_r), x_3 (V_s), x_4 (f_s), and x_5 (d_s) are selected as feed, cutting speed, and depth of cut in rough and finish turning. Machining data for the first example of multi-pass turning are shown in Table 1.

The equations for calculating S/N ratios for quality characteristics are logarithmic functions based on the mean square quality characteristics. For this problem, S/N ratios for objective function of first example are computed using smaller-the-better (Eq. 25) as given in Table 2 since the objective is the minimization of cost.

The relative effect of the different factors can be obtained by the decomposition of variance, which is called ANOVA. The purpose of ANOVA is to investigate the design parameters that affect significantly the quality characteristic. It is designed N using S/N ratios as shown in Table 3 for (case 1 with d_t=6 mm). The intervals of the design parameters are found regarding the effects of factors on the objective.

The intervals of design variables for case 1 are found as $50<x_1<200$, $0.53<x_2<0.9$, $50<x_3<200$, $0.1<x_4<0.9$, and $2.32<x_5<3$. The computed levels are used to generate the initial population in TLBO. The analysis of variance is applied for case 2 with d_t=8 mm and results are given in Table 4.

It can be seen that the most effective variables and their levels are the same as in case 1. Therefore, the search space limits of the parameters are $50<x_1<200$, $0.53<x_2<0.9$, $50<x_3<200$, $0.1<x_4<0.9$, and $2.32<x_5<3$. The initial population

Table 4 results of the analysis of variance for objective (case 2 with d_t=8 mm)

	Level 1	Level 2	Level 3	Level 4	S_S	%Cont.
x_1	−13.6	−14.3	−19.9	−16.3	94.5	7.9
x_2	−25.7	−17	−9.8	−11.7	599.1	50.5
x_3	−12.8	−11.4	−16.1	−24	294.5	24.8
x_4	−14.4	−18	−19.1	−13	58	4.8
x_5	−21.40	−16.1	−15.2	−11.5	139.8	11.7

Table 5 Comparison of the best computed optimum results for turning problem

	HRTLBO	PSO [31]	HRGA [35]	SS [30]	FEGA [29]	SA/PS [8]
Case 1: cost ($) ($d_t$=6 mm)	2.0460	2.0470	2.0481	2.0667	2.2988	2.2795
Case 2: cost ($) ($d_t$=8 mm)	2.4790	2.4796	2.486	2.5417	2.8170	2.7411

HRTLBO hybrid robust teaching–learning based optimization algorithm, *PSO* particle swarm optimization algorithm, *HRGA* hybrid robust genetic algorithm, *SS* scatter search, *SA/PS* simulated annealing and Hooke–Jeeves pattern search, *FEGA* float-encoding genetic algorithm

of TLBO is randomly generated for solutions within the range of $50<x_1<200$, $0.53<x_2<0.9$, $50<x_3<200$, $0.1<x_4<0.9$, and $2.32<x_5<3$. Then, TLBO evolution is processed to find the best result for objective using the refined search space of solutions.

From the comparison of best results given in Table 5, it is seen that the minimization of the unit production cost in multi-pass turning operation is achieved by proposed hybrid approach. The comparison of the results obtained by the proposed approach, against other techniques, is given in Table 5.

It can be seen that better results for the best computed solutions are achieved for the turning optimization problem compared to PSO, HRGA, scatter search, float-encoding GA (FEGA), and SA/PS as shown in Table 5. PSO, HRGA, and FEGA required 10,000, 27,000, 40,000, 60,000 function evaluations to find the best solutions, respectively.

The FEGA of Chen and Chen [29] required 60,000 function evaluations to find the best solutions 2.2988 and 2.8170 for cases 1 and 2, respectively. The use of the HRTLBO improves the convergence rate by computing the best values 2.0460 and 2.4790 for case 1 and case 2, respectively, and maintaining the less function evaluations 9000.

5 Conclusions

In this paper, a hybrid optimization algorithm is presented for the optimization of machining parameters considering minimum production cost under a set of machining constraints in turning operation. The HRTLBO is performed quite well on the optimization of machining parameters of turning operation problem finding better solutions compared to other approaches. From the above computational results and discussions, it is demonstrated that HRTLBO can be used as a powerful technique for optimization of machining problems.

Nomenclature

C_0	constant pertaining to tool-life equation
C_I	machine idle cost (dollars per piece)
C_M	cutting cost by actual time in cut (dollars per piece)
C_R	tool replacement cost (dollars per piece)
C_T	tool cost (dollars per piece)
d_r, d_s	depths of cut for each pass of rough and finish machining (millimeters)
d_{rL}, d_{rU}	lower and upper bounds of depth of rough cut (millimeters)
d_{sL}, d_{sU}	lower and upper bounds of depth of finish cut (millimeters)
d_t	total depth of metal to be removed (millimeters)
D	diameter of work piece (millimeters)
f_r, f_s	feeds in rough and finish machining (millimeters per revolution)
f_rL, f_{rU}	lower and upper bounds of feed in rough machining (millimeters per revolution)
f_{sL}, f_{sU}	lower and upper bounds of feed in finish machining (millimeters per revolution)
F_r, F_s	cutting forces during rough and finish machining (kilogram force)
F_U	maximum allowable cutting force (kilogram force)
h_1, h_2	constants pertaining to tool travel and approach/depart time (minutes)
k_1, k_2, k_3	constants for roughing and finishing parameter relations
k_f	coefficient pertaining to specific tool–work piece combination
k_o	direct labor cost overhead (dollars per minute)
k_q	coefficient pertaining to equation of chip–tool interface temperature
k_t	cutting edge cost (dollars per edge)
L	length of work piece (millimeters)
n	number of rough passes
p, q, r	constants pertaining to the tool-life equation
P_r, P_s	cutting power during roughing and finishing (kilowatt)
P_U	maximum allowable cutting power (kilowatt)
Q_r, Q_s	temperatures during roughing and finishing (degree Celcius)
Q_U	maximum allowable temperature (degree Celcius)

R_a	maximum allowable surface roughness (millimeters)
R_n	nose radius of cutting tool (millimeters)
S_c	limit of stable cutting region
t	tool life (minute)
t_c	constant term of machine idling time (minute)
t_e	tool exchange time (minute)
t_p	tool life (minute) considering roughing and finishing
t_r, t_s	tool lives (minute) for roughing and finishing
t_v	variable term of machine idling time (minute)
T_I	machine idling time (minute)
T_L, T_U	lower and upper bounds of tool life
T_M	cutting time by actual machining (minute)
T_{Mr}, T_{Ms}	cutting time by actual machining for roughing and finishing (minute)
T_R	tool replacement time (minute)
U_C	unit production cost except material cost (dollars per piece)
V_r, V_s	cutting speeds in rough and finish machining (meters per minute)
V_{rL}, V_{rU}	lower and upper bounds of cutting speed in rough machining (meters per minute)
V_{sL}, V_{sU}	lower and upper bounds of cutting speed in finish machining (meters per minute)
X	vector of machining parameters
τ, φ, δ	constants pertaining to expression of chip–tool interface temperature
η	power efficiency
λ, ν	constants pertaining to expression of stable cutting region
μ, υ	constants of cutting force equation

References

1. Gilbert WW (1950) Economics of machining machining theory and practice. American Society Metals, Cleveland
2. Okushima K, Hitomi K (1964) A study of economic machining: an analysis of maximum profit cutting speed. Int J Prod Res 3:73–78
3. Ermer DS (1971) Optimization of the constrained machining economics problem by geometric programming. Transactions of the ASME Journal of Engineering for Industry 93:1067–1072
4. Boothroyd G, Rusek P (1976) Maximum rate of profit criteria in machining. Transactions of the ASME, Journal of Engineering for Industry 98:217–220
5. Shin YC, Joo YS (1992) Optimization of machining conditions with practical constraints. Int J Prod Res 30:2907–2919
6. Iwata K, Murotsu Y, Iwatsubo T, Oba F (1977) Optimization of cutting conditions for multi-pass operations considering probabilistic nature in machining conditions. Journal of Engineering for Industry-Transactions of ASME 99:211–217
7. Lambert BK, Walvekar A (1978) Optimization of multi pass machining operations. Int J Prod Res 16:259–265
8. Chen MC, Tsai DM (1996) A simulated annealing approach for optimization of multi-pass turning operations. Int J Prod Res 34:2803–2825
9. Ermer DS, Kromodihardo S (1981) Optimization of multi pass turning with constraints. Journal of Engineering for Industry-Transactions of the ASME 103:462–468
10. Gopalkrishan B, Khayyal FA (1991) Machining parameter selection for turning with constraints, pp. an analytical approach based on geometric programming. Int J Prod Res 29:1897–1908
11. Gupta R, Batra JL, Lal GK (1995) Determination of optimal subdivision of depth of cut in multi-pass turning with constraints. Int J Prod Res 33:2555–2565
12. Hati SK, Rao SS (1976) Determination of optimum machining conditions deterministic probabilistic approaches. Transactions of the ASME-Journal of Engineering for Industry 98:354–359
13. Tan FP, Creese RC (1995) A generalized multi-pass machining model for machining parameter selection in turning. Int J Prod Res 33:1467–1487
14. Yildiz AR (2012) A comparative study of population-based optimization algorithms for turning operations. Inf Sci 210:81–88
15. Holland HJ (1975) Adaptation in natural and artificial systems an introductory analysis with application to biology control and artificial intelligence. The University of Michigan Press, Ann Arbor, USA
16. Rao RV, Pawar PJ (2010) Parameter optimization of a multi-pass milling process using non-traditional optimization algorithms. Appl Soft Comput 10:445–456
17. Rao RV, Pawar PJ, Shankar R (2008) Multi-objective optimization of electro-chemical machining process parameters using a particle swarm optimization algorithm. Journal of Engineering Manufacture 122:949–958
18. Yildiz AR (2009) Hybrid immune-simulated annealing algorithm for optimal design and manufacturing. Int J Mater Prod Tech 34 (3):217–226
19. Yildiz AR (2009) A new design optimization framework based on immune algorithm and Taguchi method. Comput Ind 60(8):613–620
20. Durgun I, Yildiz AR (2012) Structural design optimization of vehicle components using Cuckoo search algorithm. Mater Test 54(3):185–188
21. Kunakote T, Bureerat S (2011) Multi-objective topology optimization using evolutionary algorithms. Eng Optim 43 (5):541–557
22. Yildiz AR (2012) Cuckoo search algorithm for the selection of optimal machining parameters in milling operations. Int J Adv Manuf Tech. doi:10.1007/s00170-012-4013-7 (in press)
23. Srisompom S, Bureerat S (2008) Geometrical design of plate-fin heat sinks using hybridization of MOEA and RSM. IEEE Transactions on components and packaging technologies 31:351–360
24. Yildiz AR (2012) A new hybrid differential evolution algorithm for the selection of optimal machining parameters in milling operations. Appl Soft Comput. doi:10.1016/j.asoc.2011.12.016 (in press)
25. Yildiz AR, Saitou K (2011) Topology synthesis of multi-component structural assemblies in continuum domains. Transactions of ASME, Journal of Mechanical Design 133(1):011008–011009
26. Yildiz AR (2012) Hybrid Taguchi-differential evolution algorithm for optimization of multi-pass turning operations. Appl Soft Comput J. doi:10.1016/j.asoc.2012.01.012
27. Gokdag H, Yildiz AR (2012) Structural damage detection using modal parameters and particle swarm optimization. Mater Test 6:416–420

28. Vijayakumar K, Prabhaharan G, Asokan P, Saravanan R (2003) Optimization of multi-pass turning operation using ant colony system. Int J Mach Tool Manuf 43:1633–1639
29. Chen MC, Chen KY (2003) Optimization of multipass turning operations with genetic algorithms: a note. Int J Prod Res 41:3385–3388
30. Chen MC (2004) Optimizing machining economics models of turning operations using the scatter search approach. Int J Prod Res 42:2611–2625
31. Yildiz AR (2009) A novel particle swarm optimization approach for product design and manufacturing. Int J Adv Manuf Technol 40 (5–6):617–628
32. Yildiz AR, Solanki KN (2012) Multi-objective optimization of vehicle crashworthiness using a new particle swarm based approach. Int J Adv Manuf Tech 59(1–4):367–376
33. Yildiz AR (2009) A novel hybrid immune algorithm for global optimization in design and manufacturing. Robotics and Computer-Integrated Manufacturing 25(2):261–270
34. Coello CAC, Cortes NC (2004) Hybridizing a genetic algorithm with an artificial immune system for global optimization. Eng Optim 36:607–634
35. Yildiz AR, Ozturk F (2006) Hybrid enhanced genetic algorithm to select optimal machining parameters in turning operation. Proc Instn Mech Engrs, Part B, Journal of Engineering Manufacture 220(12):2041–2053
36. Yildiz AR (2013) A new hybrid artificial bee colony algorithm for robust optimal design and manufacturing. Appl Soft Comput. doi:10.1016/j.bbr.2011.03.031
37. Phadke SM (1989) Quality engineering using robust design. Prentice Hall, New York
38. Taguchi G, Chowdhury S, Taguchi S (2000) Robust engineering. McGraw-Hill, New York
39. Rao RV, Savsani VJ, Vakharia DP (2012) Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problems. Inf Sci 183(1):1–15
40. Rao RV, Savsani VJ, Vakharia DP (2011) Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Computer-Aided Design 43(3):303–315
41. Togan V (2012) Design of planar steel frames using teaching–learning based optimization. Eng Struct 34:225–232
42. RV Rao, VD Kalyankar (2011) Parameters optimization of advanced machining processes using TLBO algorithm, EPPM, Singapore, 20–21 Sep 2011.