Int J Adv Manuf Technol (2015) 76:647–656
DOI 10.1007/s00170-014-6309-2

ORIGINAL ARTICLE

Cuckoo optimization algorithm for unit production cost in multi-pass turning operations

Mohamed Arezki Mellal · Edward J. Williams

Received: 17 June 2014 / Accepted: 20 August 2014 / Published online: 5 September 2014

Abstract The multi-pass turning process is one of the most used machining methods in manufacturing industry. The minimization of the unit production cost is considered the key objective of this operation. In this work, the cutting parameters are carried out using a recently developed advanced bio-inspired optimization algorithm, called the cuckoo optimization algorithm (COA). The obtained results are compared with previously published results available in the literature. It has been proven that the COA competes robustly with a wide range of optimization algorithms.

Keywords Multi-pass turning operations · Cutting parameters · Unit production cost · Cuckoo optimization algorithm

Nomenclature

UC	Unit production cost, excluding material cost ($/piece)
C_M	Cutting cost by actual time in cutting ($/piece)
C_I	Machine idle cost due to loading and unloading operations and tool idle motion time ($/piece)
C_R	Tool replacement cost ($/piece)
C_T	Tool cost ($/piece)
V_r, V_s	Cutting speeds in rough and finish machining, respectively (m/min)
V_{rL}, V_{rU}	Lower and upper bounds of cutting speed in rough machining, respectively (m/min)
V_{sL}, V_{sU}	Lower and upper bounds of cutting speed in finish machining, respectively (m/min)
f_r, f_s	Feed rates in rough and finish machining, respectively (mm /rev)
f_{rL}, f_{rU}	Lower and upper bounds of feed rate in rough machining, respectively (mm/rev)
f_{sL}, f_{sU}	Lower and upper bounds of feed rate in finish machining, respectively (mm/rev)
d_r, d_s	Depths of cut for each pass of rough and finish machining, respectively (mm)
d_{rL}, d_{rU}	Lower and upper bounds of depth of roughing cut, respectively (mm)
d_{sL}, d_{sU}	Lower and upper bounds of depth of finishing cut, respectively (mm)
n	Number of rough cuts (rough passes)
d_t	Total depth of metal to be removed (mm)
D, L	Diameter and length of work piece, respectively (mm)
k_0	Direct labor cost, including overheads ($/min)
k_t	Cutting edge cost ($/edge)
t_{mr}, t_{ms}, t_m	Rough machining time, finish machining time, and actual machining time, respectively (min)
t_c, t_e, t_i	Constant term of machine idling time, tool exchange time, and total machine idle time, respectively (min)
h_1, h_2	Constants pertaining to tool travel and approach/depart time, respectively (min)
T_r, T_s	Expected tool life for rough and finish machining, respectively (min)
T_P	Tool life of weighted combination of T_r and T_s (min)

M. A. Mellal (✉)
Faculty of Engineering Sciences (FSI),
M'Hamed Bougara University, Boumerdes 35000, Algeria
e-mail: mellal.mohamed@gmail.com

M. A. Mellal
e-mail: mellal-mohamed@umbb.dz

E. J. Williams
Industrial and Manufacturing Systems Engineering Department,
College of Engineering and Computer Science,
University of Michigan, Dearborn 48126, USA

E. J. Williams
Decision Sciences, College of Business, University of Michigan,
Dearborn 48126, USA

θ	Weight for T_p
T_L, T_U	Lower and upper bounds for tool life, respectively (min)
α, β, γ, C	Constants of the tool life equation
p, q, r, C_0	$p=1/\alpha$, $q=\beta/\alpha$, $r=\gamma/\alpha$, and $C_0=C^{1/\alpha}$
SR	Maximum allowable surface roughness (mm)
SC	Limit of stable cutting region
R	Nose radius of the cutting tool (mm)
F_r, F_s	Cutting forces during rough and finish machining, respectively (kgf)
F_U	Maximum allowable cutting force (kgf)
k_1, u, v	Constants of the cutting force equation
P_r, P_s	Cutting powers during rough and finish machining, respectively (kW)
P_U	Maximum allowable cutting power (kW)
η	Power efficiency
λ, υ	Constants related to expression of the stable cutting region
Q_r, Q_s	Limit of stable cutting region constraint chip-tool interface temperatures during rough and finish machining, respectively (°C)
Q_U	Maximum allowable chip-tool interface temperature (°C)
k_2, τ, ϕ, δ	Constants related to the equation of chip-tool interface temperature
k_3, k_4, k_5	Constants for roughing and finishing parameter relations
X	$\{x_1, x_2, \ldots, x_{NCOA}\}$ Set of cutting parameters, i.e. design variables

1 Introduction

The process of metal removal using multi-pass turning operations involves two separated stages, the rough machining stage and the finish machining stage. Several variables should be considered to achieve products that meet the specifications. These can be categorized as input variables, such as cutting speed, feed rate, depth of cut, number of passes, work material and its properties, tool material and tool geometry, and cutting fluid properties and characteristics and output variables, such as production cost, production time, tool life, dimensional accuracy, surface roughness, cutting forces, cutting temperature, and power consumption [1–3].

The present work focuses on the well-known multi-pass turning optimization problem which consists of selecting the optimal cutting parameters, i.e., cutting speeds, feed rates, depths of cut, and number of passes, for minimizing a production cost-based objective function [3–9]. The first application of a prevailing metaheuristic called the cuckoo optimization algorithm (COA) to the optimization of turning operations in the literature is addressed for this purpose.

The reminder of the paper is organized as follows. A brief overview of the literature on the multi-pass turning operations is presented in the next section. Section 3 presents the optimization problem of unit production cost in multi-pass turning operations. Section 4 describes the basic idea behind the cuckoo optimization algorithm and presents pseudocode summarizing its fundamental steps. Section 5 is devoted to the results obtained by the implemented COA and the discussion. Section 6 concludes this work.

2 Literature review

The overview of the literature shows that several researchers from different backgrounds have investigated the optimization of cutting parameters in turning operations. Generally, the authors used traditional mathematical programming techniques, probabilistic or heuristic/metaheuristic methods, and hybrid approaches to optimize the machining conditions. It should be noted that evolutionary algorithms were the most powerful approach, and this constitutes their advantages: an efficient way to produce acceptable solutions by trial-and-error in reasonably practical time, diversified solutions, and the possibility of handling the constraints.

After the pioneer works developed in [10–14], Shin and Joo [4] proposed a comprehensive mathematical model solved by a dynamic programming approach. Later, several researchers have relied on the data of this model to improve the results using different resolution methods.

Chen and Tsai [5] solved the optimization problem by combining the simulated annealing algorithm and a Hook-Jeeves pattern search technique (SA-PS), whereas Chen and Su [15] solely used a simulated annealing. Gupta et al. [16] proposed an approach based on linear programming. Onwubolu and Kumalo [6] investigated the use of the genetic algorithm (GA) to optimize the parameters of multi-pass turning operations. However, M. Chen and K. Chen [17] applied a float-encoding genetic algorithm (FEGA) and revealed that Onwubolu and Kumalo [6] incorrectly manipulated the machining model presented by Chen and Tsai [5]. Similarly, the results found by Aryanfar and Solimanpur [18] using GA exceed the bound of some constraints.

Vijayakumar et al. [19] proposed an approach based on ant colony optimization (ACO). In the technical note [20], Wang revealed that Vijayakumar et al. [19] did not provide the optimal values they found for the depth of the rough cuts and the finishing cut and the constraint related to the number of passes.

A hybrid approach by combining genetic algorithm and artificial immune system (GA-AIS) has been implemented by Zheng and Ponnambalam [21] without considering the bounds on the number of passes.

In [22], a comparison of six non-traditional methods, the genetic algorithm (GA), simulated annealing algorithm (SA), Tabu search algorithm (TS), ant colony optimization (ACO), memetic algorithm (MA), and particle swarm optimization (PSO), has been performed to determine the optimal machining parameters for turning cylindrical stocks into various continuous finished profiles and different data. It has been shown that the results were outperformed by the PSO.

Yildiz implemented several optimization techniques for solving the multi-pass turning operations problem, such as differential evolution algorithm and receptor editing (DERE), artificial bee algorithm (ABC), differential evolution algorithm (DE) [23], hybrid artificial bee colony algorithm [8], hybrid robust differential evolution algorithm (HRDE), artificial immune algorithm (AIA) [24], and hybrid robust teaching-learning-based optimization algorithm (HRTLBO) [25]. It should be noted that the minimum production cost was provided without any information about the optimal values of the machining parameters. Hence, the constraint violations cannot be fully investigated from these works.

Venkata Rao and Kalyankar [3] applied the teaching-learning-based optimization algorithm (TLBO). The authors showed that the TLBO requires a lower number of iterations for convergence to the optimal solution.

Belloufi et al. [26] used a firefly algorithm (FA) and a hybrid genetic algorithm-sequential quadratic programming (GA-SQP) [27]. The obtained numerical value of the cost was better than that of other optimization techniques. However, the constraints have been incorrectly handled.

In [7], Srinivas et al. used the particle swarm optimization (PSO) with a carefully detailed comparison of the constraint violations found in ACO [19], GA [6], and SA-PS [5]. Later, Costa et al. [9] improved the results of Srinivas et al. [7] by applying a hybrid particle swarm optimization technique (HPSO) which combines the PSO and SA.

The next section presents the comprehensive mathematical model for minimizing the unit production cost in multi-pass turning operations.

3 Optimization model of multi-pass turning operations

In this paper, the detailed mathematical model presented in [3, 7–9] is adopted. The numerical data are reported in Table 1.

3.1 Objective function: Unit production cost

The aim considered here is to minimize the unit production cost (UC) in multi-pass turning operations. The UC is divided into four basic cost elements:

(1) Cutting cost by actual time, C_M;
(2) Machine idle cost due to loading and unloading operations and idling tool motion, C_I;
(3) Tool replacement cost, C_R;
(4) Tool cost C_T.

Thus, the objective function is defined as follows:

$$F(X) = \mathrm{Min}(\mathrm{UC}) = \mathrm{Min}(C_M + C_I + C_R + C_T) \tag{1}$$

The expression of each cost element is given below.

3.1.1 Machining cost

The machining cost involves the multi-pass roughing and a single-pass finishing, respectively:

$$\begin{aligned} C_M &= k_0\left[\frac{\pi DL}{1,000V_r f_r}n + \frac{\pi DL}{1,000V_s f_s}\right] \\ &= k_0\left[\frac{\pi DL}{1,000V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1,000V_s f_s}\right] \\ &= k_0(t_{mr} + t_{ms}) \end{aligned} \tag{2}$$

Finally,

$$C_M = k_0 t_m \tag{3}$$

where t_m is the actual machining time.

3.1.2 Machine idling cost

The machine idling cost is defined by the sum of a constant term related to the loading/unloading operations and a variable term representing the idle tool motion:

$$\begin{aligned} C_I &= k_0[t_c + (h_1 L + h_2)(n+1)] \\ &= k_0\left[t_c + (h_1 L + h_2)\left(\frac{d_t - d_s}{d_r} + 1\right)\right] \end{aligned} \tag{4}$$

Finally,

$$C_I = k_0 t_i \tag{5}$$

where t_i is total machine idle time.

3.1.3 Tool replacement cost

From Taylor's tool-life equation, the life of a tool is given by:

$$T = \frac{C^{1/\alpha}}{V^{1/\alpha} f^{\beta/\alpha} d^{\gamma/\alpha}} = \frac{C_0}{V^p f^q d^r} \tag{6}$$

Table 1 Machining model data

Parameter	Value	Parameter	Value	Parameter	Value
D	500 mm	L	300 mm	d_t	6 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 mm	d_{rL}	1 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 mm	d_{sL}	1 mm
p	5	q	1.75	r	0.75
u	0.75	v	0.95	η	0.85
λ	2	υ	−1	τ	0.4
ϕ	0.2	δ	0.105	R	1.3 mm
C_0	6×10^{11}	h_1	7×10^{-4}	h_2	0.3
T_L	25 min	t_c	0.75 min/piece	t_e	1.5 min/edge
P_U	5 kW	T_U	45 min	F_U	200 kgf
SC	140	SR_U	10 μm	Q_U	1,000 °C
k_0	\$0.5 per minute	k_1	108	k_2	132
k_3	1	k_4	2.5	k_5	1
k_t	\$2.5 per edge	θ	0.8		

It has been considered that the same tool is used for the entire machining operation process of both roughing and finishing. Furthermore, the wear rate of tools differs between the operations. Thus, the tool life can be expressed as:

$$T_p = \theta T_r + (1-\theta) T_s, \quad \theta \in [0,1] \tag{7}$$

where:

$$T_r = \frac{C_0}{V_r^p f_r^q d_r^r}, \quad T_r = \frac{C_0}{V_s^p f_s^q d_s^r} \tag{8}$$

It should be noted that the majority of authors simplify T_p (Eq. (7)) by ignoring the weight θ:

$$T_p = T_r + T_s \tag{9}$$

The tool replacement time depends on the tool life (T_p), time required to exchange a tool (t_e), and machining time (t_m):

$$\begin{aligned} C_R &= \frac{t_e}{T_p}\left[\frac{\pi DL}{1,000 V_r f_r}\left(\frac{d_t - d_s}{d_r}\right) + \frac{\pi DL}{1,000 V_s f_s}\right] \\ &= t_e \frac{t_m}{T_p} \end{aligned} \tag{10}$$

The tool replacement cost C_R is given by:

$$C_R = k_0 t_e \frac{t_m}{T_p} \tag{11}$$

3.1.4 Tool cost

The tool cost C_T is given by:

$$C_T = k_t \frac{t_m}{T_p} \tag{12}$$

3.2 Machining constraints

The unit production cost (UC) defined by Eq. (1) is subject to several constraints during the roughing and finishing operations. These constrains can be classified as follows:

(1) Parameter bounds;
(2) Tool-life constraint;
(3) Operating constraints consisting of surface finish constraint (only for finish machining), cutting force constraint, and power constraint;
(4) Stable cutting region constraint;
(5) Chip-tool interface temperature constraint;
(6) Roughing and finishing parameter relations;
(7) Bounds on the number of rough passes.

3.2.1 Rough machining

(a) Parameter bounds:
The range of cutting speeds is:

$$V_{rL} \le V_r \le V_{rU} \tag{13}$$

The feed rate is restricted as:

$$f_{\mathrm{rL}} \le f_{\mathrm{r}} \le f_{\mathrm{rU}} \tag{14}$$

Bounds on the depth of cut are:

$$d_{\mathrm{rL}} \le d_{\mathrm{r}} \le d_{\mathrm{rU}} \tag{15}$$

(b) Tool-life constraint:

$$T_{\mathrm{L}} \le T_{\mathrm{r}} \le T_{\mathrm{U}} \tag{16}$$

(c) Operating constraints:

(i) Cutting force constraint:
The cutting force constraint is given in terms of maximum force F_{U} according to:

$$F_{\mathrm{r}} = k_1 (f_{\mathrm{r}})^u (d_{\mathrm{r}})^v \le F_{\mathrm{U}} \tag{17}$$

(ii) Power constraint:
The power required during the cutting operation should not exceed the available power P_{U} of the machine tool:

$$P_{\mathrm{r}} = \frac{F_{\mathrm{r}} V_{\mathrm{r}}}{6,120\eta} = \frac{k_1 (f_{\mathrm{r}})^u (d_{\mathrm{r}})^v V_{\mathrm{r}}}{6,120\eta} \le P_{\mathrm{U}} \tag{18}$$

(iii) Stable cutting region constraint:
The constraint on the stable cutting region in turning is expressed as:

$$(V_{\mathrm{r}})^{\lambda} (f_{\mathrm{r}}) (d_{\mathrm{r}})^{\nu} \ge SC \tag{19}$$

(iv) Chip-tool interface temperature constraint:
The temperature generated at the chip-tool interface should not exceed the permissible limit:

$$Q_{\mathrm{r}} = k_2 (V_{\mathrm{r}})^{\tau} (f_{\mathrm{r}})^{\phi} (d_{\mathrm{r}})^{\delta} \le Q_{\mathrm{U}} \tag{20}$$

3.2.2 Finish machining

For all the constraints defined in Eqs. (13)–(20), the suffix r is replaced by s for the finish machining constraints:

$$V_{\mathrm{sL}} \le V_{\mathrm{s}} \le V_{\mathrm{sU}} \tag{21}$$

$$f_{\mathrm{sL}} \le f_{\mathrm{s}} \le f_{\mathrm{sU}} \tag{22}$$

$$d_{\mathrm{sL}} \le d_{\mathrm{s}} \le d_{\mathrm{sU}} \tag{23}$$

$$T_{\mathrm{L}} \le T_{\mathrm{s}} \le T_{\mathrm{U}} \tag{24}$$

$$F_{\mathrm{s}} \le F_{\mathrm{U}} \tag{25}$$

$$P_{\mathrm{s}} \le P_{\mathrm{U}} \tag{26}$$

$$Q_{\mathrm{s}} \le Q_{\mathrm{U}} \tag{27}$$

$$(V_{\mathrm{s}})^{\lambda} (f_{\mathrm{s}}) (d_{\mathrm{s}})^{\nu} \ge SC \tag{28}$$

The surface finish constraint is given by:

$$\frac{f_{\mathrm{s}}^2}{8R} \le (SR)_{\mathrm{U}} \tag{29}$$

The cutting parameter relation constraints are:

$$V_{\mathrm{s}} \ge k_3 V_{\mathrm{r}} \tag{30}$$

$$f_{\mathrm{r}} \ge k_4 f_{\mathrm{s}} \tag{31}$$

$$d_{\mathrm{r}} \ge k_5 d_{\mathrm{s}} \tag{32}$$

The number of rough passes ($n = \frac{d_{\mathrm{t}} - d_{\mathrm{s}}}{d_{\mathrm{r}}}$) should be an integer and is restricted as follows:

$$\frac{d_{\mathrm{t}} - d_{\mathrm{sL}}}{d_{\mathrm{rL}}} \le \frac{d_{\mathrm{t}} - d_{\mathrm{s}}}{d_{\mathrm{r}}} \le \frac{d_{\mathrm{t}} - d_{\mathrm{sU}}}{d_{\mathrm{rU}}} \tag{33}$$

4 Cuckoo optimization algorithm

The cuckoo optimization algorithm (COA) is a bio-inspired and a population-based stochastic optimization technique recently proposed by Ramin Rajabioun [28]. COA can deal with several otherwise intractable problems, such as multivariable controller design [28], replacement of obsolete components in industrial plants [29, 30], job scheduling [31], statistical process control [32], fractional-order hyperchaotic system [33], analyzing the electrochemical machining process [34], unconventional machining processes [35], and determination of the warranty period [36].

The COA uses the biological inspiration of the social behavior of a bird species called cuckoos. The cuckoos have the ability to lay eggs in the nest of another species and the cuckoo chicks will be fed by the host birds. As some of the eggs are dissimilar to the host bird's eggs, they are detected and destroyed by the host birds (Fig. 1).

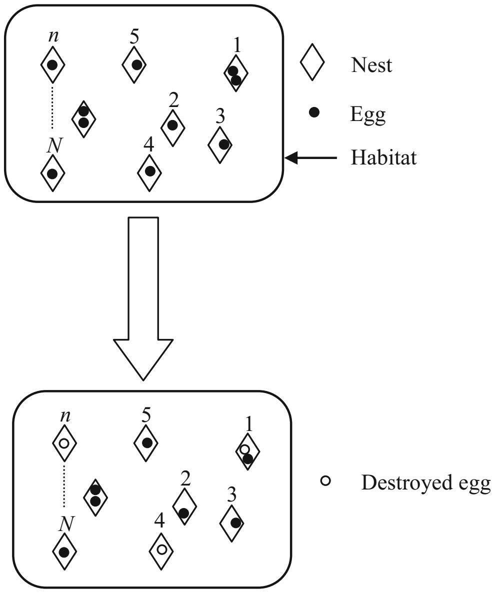

Fig. 1 Egg laying of cuckoos

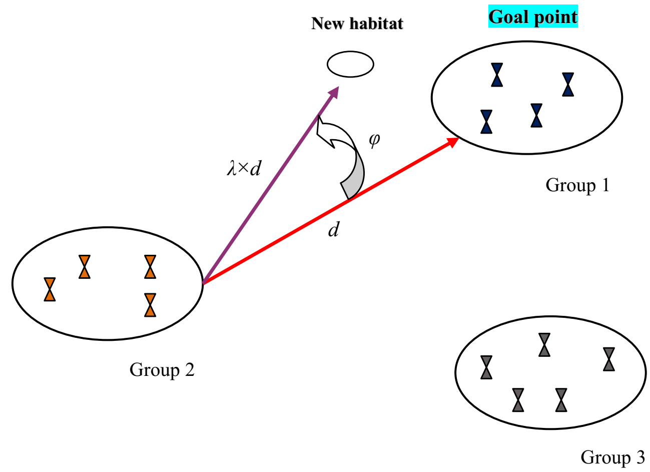

Fig. 2 Migration of the cuckoos toward goal habitat

First, a given population of mature cuckoos starts to lay eggs in their habitat:

$$\text{Habitat} = [x_1, x_2, \ldots, x_{N_{COA}}] = [V_r, f_r, d_r, V_s, f_s, d_s] \quad (34)$$

where $(x_1, x_2, \ldots, x_{N_{COA}})$ represent the design variables.

The value of the cost function is obtained by evaluating the profit of a habitat:

$$\text{Profit} = -f_{COA}(\text{Habitat}) = -f_{COA}(V_r, f_r, d_r, V_s, f_s, d_s) \quad (35)$$

where the sign (−) is attributed to generate a cost minimization because the cuckoos try to maximize the number of surviving cuckoo eggs. Therefore, a candidate habitat matrix $N_{pop} \times N_{COA}$ is randomly generated.

The eggs will be laid within a distance ELR (egg laying radius):

$$ELR = \alpha \times \frac{\text{Number of current cuckoos' eggs}}{\text{Total number of eggs}} \times (\text{var}_{hi} - \text{var}_{low}) \quad (36)$$

where α is an integer imposed to accommodate the value of ELR, var_{hi} and var_{low} are the upper limit and the lower limit for variables, respectively.

When the eggs hatch, the cuckoo chicks will eat most of the food of the host birds and the food is insufficient for all the chicks. Thus, some chick cuckoos will starve. Once the cuckoos mature and the reproduction period approaches, they migrate toward best habitat. To recognize which cuckoo belongs to which group, the algorithm uses K-clustering method.

Figure 2 shows an illustrative outline of the cuckoo's migration. Each cuckoo flies only λ% of all way toward goal with a deviation φ (rad):

$$\begin{aligned} &\lambda \sim U(0, 1) \\ &\varphi \sim U\left(-\frac{\pi}{6}, \frac{\pi}{6}\right) \end{aligned} \quad (37)$$

where λ is a random number uniformly distributed between 0 and 1.

After the migration step, a new egg-laying process restarts. Thus, the cuckoo optimization algorithm is summarized as follows [28]:

Step 1: Initialize the habitats with some random points on the profit function;
Step 2: Dedicate some eggs to each cuckoo;
Step 3: Define ELR for each cuckoo;
Step 4: Let cuckoos lay eggs inside their corresponding ELR;
Step 5: Destroy those eggs that are recognized by host birds;
Step 6: Let eggs hatch and chicks grow;
Step 7: Evaluate the habitat of each newly grown cuckoo;
Step 8: Limit cuckoos' maximum number in environment and kill those who live in worst habitats;
Step 9: Cluster cuckoos, find best group and select goal habitat;
Step 10: Let new cuckoo population migrate toward goal habitat;
Step 11: If stop condition is satisfied, stop; otherwise, go to Step 2.

Figure 3 shows the flowchart of the cuckoo optimization algorithm (COA). The pseudocode of the proposed approach is as follows:

%Parameters
Habitat size = N
Number of initial cuckoos = InitCuck
Maximum number of eggs for each initial cuckoo = MaxEggs

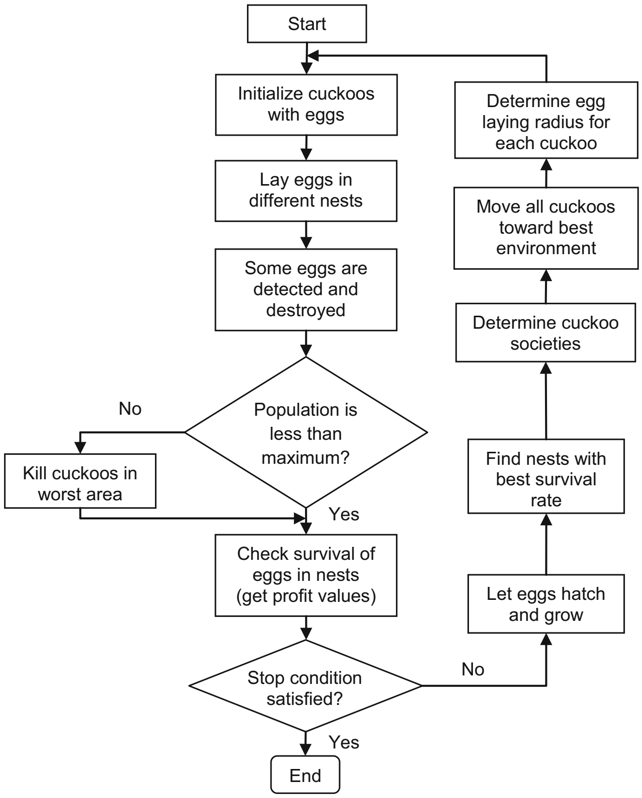

Fig. 3 Flowchart of COA [28]

Minimum number of eggs for each initial cuckoo = MinEggs
Maximum cuckoos may live at the same time = MaxCuck
Maximum iterations = CuckIter
Begin
%Initialization
Generate some random points;
%Loop until the termination condition
For Iter = CuckIter **Do**
Dedicate some eggs to each cuckoo;
Calculate the ELR for each cuckoo according to Eq. (36);
Laying eggs inside the calculated ELR;
End

Table 2 COA property and value

COA property	Value
Dimension of the problem to optimize (number of cutting parameters)	6
Number of initial population of cuckoos	5
Minimum number of eggs for each initial cuckoo	2
Maximum number of eggs for each initial cuckoo	9
Maximum number of cuckoos that can live at the same time	50
Maximum iterations of the algorithm	70

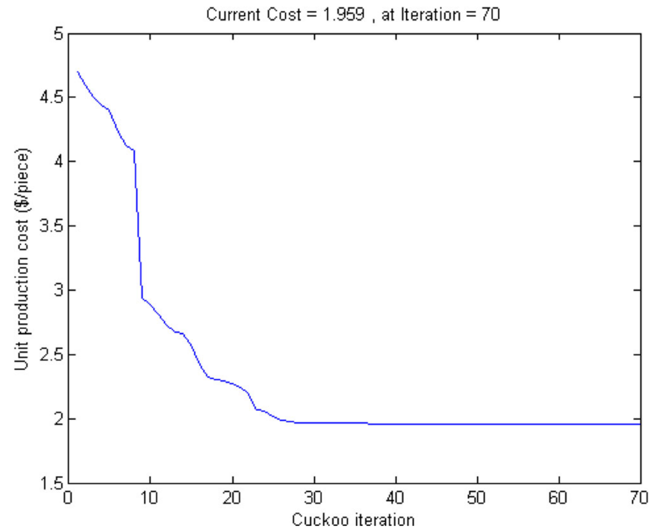

Fig. 4 Convergence of unit production cost (case $T_p = T_r + T_s$)

Destroy some eggs;
Let eggs hatch and chicks grow;
Evaluate the fitness function according to Eq. (1) and implemented by Eq. (35);
Constraint handling with violation terms by considering Eqs. (13)–(33);
Limit the number of cuckoos;

Table 3 Results obtained by COA (case $T_p = T_r + T_s$)

	Variable	Range/Limit	COA result
Cutting parameters	V_r	50–500	123.1462 (m/min)
	f_r	0.1–0.9	0.5655 (mm/rev)
	d_r	1.0–3.0	3.0 (mm)
	V_s	50–500	169.9876 (m/min)
	f_s	0.1–0.9	0.2262 (mm/rev)
	d_s	1.0–3.0	3.0 (mm)
Constraints for rough cut	T_r	25–45	25.2028 (min)
	F_r	≤200	199.9924 (kgf)
	P_r	≤5	4.7344 (kW)
	SC	≥140	2.8586e+003
	Q_r	≤1,000	906.4140 (°C)
Constraints for finish cut	T_s	25–45	25 (min)
	F_s	≤200	100.5908 (kgf)
	P_s	≤5	3.2870 (kW)
	SC	≥140	2.1787e+003
	Q_s	≤1,000	858.4936 (°C)
	$(SR)_U$	10	0.0053 (μm)
Constraint on variable relations	$\geq k_3$	1.0	1.38
	$\geq k_4$	2.5	2.5
	$\geq k_5$	1.0	1.0
Unit production cost			1.959 ($/piece)

Table 4 Comparison of different optimization methods (case $T_p = T_r + T_s$)

Method	Cutting speed (m/min)		Feed rate (mm/rev)		Depth of cut (mm)		UC ($/piece)	Constraint violation
	V_r	V_s	f_r	f_s	d_r	d_s		
COA (present study)	123.1462	169.9876	0.5655	0.2262	3	3	1.959	0
GA [6]	114.22	164.369	0.7	0.2978	2.9745	2.9863	1.8450	(16), (17), (18), (24) (31), (32)
PSO [7]	106.69	155.89	0.897	0.28	2	2	2.272	0
ACO [19]	103.05	162.02	0.9	0.24	–	–	1.626	(33): not considered
HPSO [9]	123.3424	169.9783	0.5655	0.2262	3	3	1.959	0
SA–PS [5]	–	–	–	–	–	–	2.313	–
TLBO [3]	110	170	0.565	0.225	3	3	1.973	0
HRDE [24]	–	–	–	–	–	–	2.046	–
AIA [24]	–	–	–	–	–	–	2.12	–
DERE [23]	–	–	–	–	–	–	2.046	–
ABC [23]	–	–	–	–	–	–	2.118	–
DE [23]	–	–	–	–	–	–	2.136	–
HABC [8]	–	–	–	–	–	–	2.046	–
HRTLBO [25]	–	–	–	–	–	–	2.046	–
GA–SQP [27]	94.464	162.289	0.866	0.258	3	3	1.814	(16), (17)
FA [26]	98.4102	162.2882	0.820	0.2582	3	3	1.824	(17)

Apply K-means clustering, find best group, and select goal habitat by considering Eq. (37);
Migrate toward goal habitat;
End For
Generate the optimal cutting parameters
Generate the minimum unit production cost

5 Results and discussion

The goal is to minimize the unit production cost (UC) in multi-pass turning operations using the cuckoo optimization algorithm. The problem is defined by the object function (Eq. (1)) and subject to the constraints (Eqs. (13)–(33)). Table 2 contains

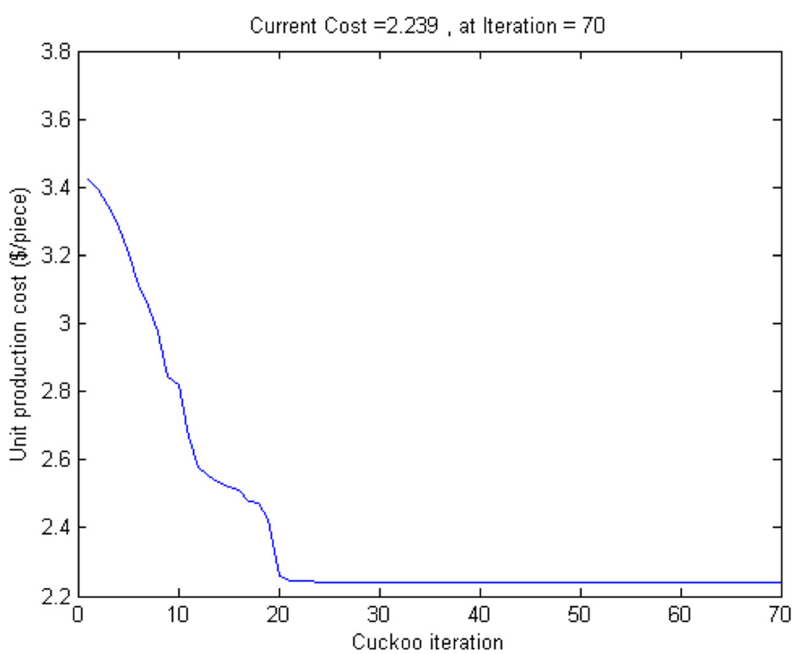

Fig. 5 Convergence of unit production cost (case $T_p = \theta T_r + (1-\theta) T_s$)

Table 5 Results obtained by COA (case $T_p=\theta T_r+(1-\theta)T_s$)

	Variable	Range/Limit	COA result
Cutting parameters	V_r	50–500	117.9322 (m/min)
	f_r	0.1–0.9	0.5655 (mm/rev)
	d_r	1.0–3.0	3.0 (mm)
	V_s	50–500	123.1993 (m/min)
	f_s	0.1–0.9	0.2262 (mm/rev)
	d_s	1.0–3.0	3.0 (mm)
Constraints for rough cut	T_r	25–45	25.031 (min)
	F_r	≤200	199.992 (kgf)
	P_r	≤5	4.533 (kW)
	SC	≥140	2.6217e+003
	Q_r	≤1,000	890.863 (°C)
Constraints for finish cut	T_s	25–45	25 (min)
	F_s	≤200	100.590 (kgf)
	P_s	≤5	2.382 (kW)
	SC	≥140	1.1444e+003
	Q_s	≤1,000	754.768 (°C)
	$(SR)_U$	10	0.005 (μm)
Constraint on variable relations	$\geq k_3$	1.0	1.044
	$\geq k_4$	2.5	2.5
	$\geq k_5$	1.0	1.0
Unit production cost			2.239 ($/piece)

the rules and parameters for the COA implemented to solve this optimization problem. These values were chosen by trial-and-error and based on experience. The algorithm has been run on Intel Pentium Processor G620 (3Mo Cache, 2.60GHz, Sandy Bridge) PC with 4 GB memory (Windows 7, 64 bits).

The optimization process of the COA is shown in Fig. 4, whereas the results are reported in Table 3. The algorithm used 3,500 function evaluations and the execution time was 22.58 s of CPU time.

From Table 3, it can be observed that the minimum unit production cost value is 1.959 ($/piece). It should be noted that the results were obtained at the 37th iteration of the COA.

From the comparison of the results given in Table 4, it is seen that the minimum of the UC in multi-pass turning operations is achieved by the COA with feasible solutions compared to the published works. The results which should be considered as competitive from the literature are the particle swarm optimization (PSO) of Srinivas et al. [7], teaching-learning-based optimization algorithm (TLBO) of Venkata Rao and Kalyankar [3], and hybrid particle swarm optimization (HPSO) of Costa et al. [9]. It can be seen also that the HPSO provided the same UC with COA (1.959 $/piece). However, the COA has outperformed the HPSO since the COA required 3,500 function evaluations and the convergence iteration was 37, whereas the HPSO required 62,500 function evaluations and the convergence iteration was 202.

As mentioned in Section 3, some authors consider $T_p=\theta T_r+(1-\theta)T_s$. The COA has been implemented to consider this case using the same number of function evaluations fixed in Table 2, where the execution time here was 24.74 s of CPU time. Figure 5 shows the optimization process of the COA, whereas the optimal results are given in Table 5.

From Table 5, it can be observed that the minimum unit production cost value is 2.239 ($/piece). The results were obtained at the 24th iteration. Table 6 reveals that the COA has outperformed the results obtained by the HPSO [9].

6 Conclusions and future research

In this paper, the prevailing cuckoo optimization algorithm (COA) has been implemented for the optimization of cutting parameters in the multi-pass turning operations. The goal was to minimize the unit production cost (UC). Several authors tried to solve this problem using other optimization techniques without overlooking on the constraint violations. Furthermore, it has been observed that the optimal parameters were not reported in many works; only the UC value was provided.

The results showed that the COA is highly competitive to other published optimization techniques available in the literature. The COA required a lower number of function evaluations, improved the convergence rate, and showed its ability to handle different constraint forms.

For future work, another optimization technique may be applied to perhaps provide better results. Another point to explore is to propose a hybrid and/or multi-objective COA.

Table 6 Comparison of different optimization methods (case $T_p=\theta T_r+(1-\theta)T_s$)

Method	Cutting speed (m/min)		Feed rate (mm/rev)		Depth of cut (mm)		UC ($/piece)	Constraint violation
	V_r	V_s	f_r	f_s	d_r	d_s		
COA (present study)	117.9322	123.1993	0.5655	0.2262	3	3	2.239	0
HPSO [9]	109.663	169.97	0.5655	0.226	3	3	2.035	(24)

References

1. Zadshakoyan M, Pourmostaghimi V (2013) Genetic equation for the prediction of tool-chip contact length in orthogonal cutting. Eng Appl Artif Intell 26(7):1725–1730
2. Rao RD, Kalyankar VD (2013) Parameter optimization of modern machining processes using teaching-learning-based optimization algorithm. Eng Appl Artif Intell 26(1):524–531
3. Venkata Rao R, Kalyankar VD (2013) Multi-pass turning process parameter optimization using teaching-learning-based optimization algorithm. Scientia Iranica 20(3):967–974
4. Shin YC, Joo YS (1992) Optimization of machining conditions with practical constraints. Int J Prod Res 30(12):2907–2919
5. Chen MC, Tsai DM (1996) A simulated annealing approach for optimization of multi-pass turning operations. Int J Prod Res 34(10):2803–2825
6. Onwubolu GC, Kumalo T (2001) Optimization of multi-pass turning operations with genetic algorithms. Int J Prod Res 39(16):3727–3745
7. Srinivas J, Giri R, Yang SH (2009) Optimization of multi-pass turning using particle swarm intelligence. Int J Adv Manuf Technol 40(1–2):56–66
8. Yildiz AR (2013) Optimization of cutting parameters in multi-pass turning using artificial bee colony-based approach. Inf Sci 220:399–407
9. Costa A, Celano G, Fichera S (2011) Optimization of multi-pass turning economies through a hybrid particle swarm optimization technique. Int J Adv Manuf Technol 53(5–8):421–433
10. Crookall JR, Venkataramani N (1971) Computer optimization of multi-pass turning. Int J Prod Res 9(2):247–259
11. Iwata K, Iwatsubo T, Fujii S, Iwatsubo Y (1972) A probabilistic approach to the determination of the optimum cutting conditions. J Eng Ind 94(4):1099–1107
12. Ermer DS, Kromodihardjo S. Optimization of multipass turning with constraints. Journal of Engineering for Industry Transactions of the ASME 1981;103(4):462–468
13. Alberti N. Optimization of multi-pass turning, in: Proceedings of the 14th North American Manufacturing Research Conference, USA, 1986
14. Gopalakrishnan B, Al-Khayyal F (1991) Machine parameter selection for turning with constraints: an analytical approach based on geometric programming. Int J Prod Res 29(9):1897–1908
15. Chen MC, Su ST (1998) Optimization of machining conditions for turning cylindrical stocks into continuous finished profiles. Int J Prod Res 36(8):2115–2130
16. 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(9):2555–2565
17. Chen MC, Chen KY (2003) Optimization of multi-pass turning operations with genetic algorithms: a note. Int J Prod Res 41(14): 3385–3388
18. Aryanfar A, Solimanpur M (2012) Optimization of multi-pass turning operations using genetic algorithms, in: Proceedings of the 2012 International Conference on Industrial Engineering and Operations Management. Istanbul, Turkey
19. Vijayakumar K, Prabhaharan G, Asokan P, Saravanan R (2003) Optimization of multi-pass turning operations using ant colony system. Int J Mach Tools Manuf 43(15):1633–1639
20. Wang YC (2007) A note on 'optimization of multi-pass turning operations using ant colony system'. Int J Mach Tools Manuf 47(12–13):2057–2059
21. Zheng LY, Ponnambalam SG (2010) A hybrid GA-AIS heuristic for optimization of multi-pass turning operations. In: Intelligent robotics and applications. Springer Berlin Heidelberg, Germany, pp 599–611
22. Saravanan R, Siva Sankar R, Asokan P, Vijayakumar K, Prabhaharan G (2005) Optimization of cutting conditions during continuous finished profile machining using non-traditional techniques. Int J Adv Manuf Technol 26(1–2):30–40
23. Yildiz AR (2012) A comparative study of population-based optimization algorithms for turning operations. Inf Sci 210:81–88
24. Yildiz AR (2013) Hybrid Taguchi differential evolution algorithm for optimization of multi-pass turning operations. Appl Soft Comput 13(3):1433–1439
25. Yildiz AR (2013) Optimization of multi-pass turning operations using hybrid teaching learning based approach. Int J Adv Manuf Technol 66(9–12):1319–1326
26. Belloufi A, Assas M, Rezgui I. Intelligent selection of machining parameters in multi-pass turnings using firefly algorithm. Modeling and Simulation in Engineering 2013; In Press
27. Belloufi A, Assas M, Rezgui I (2012) Optimization of cutting conditions in multi-pass turning using hybrid genetic algorithm-sequential quadratic programming. J Appl Mech Eng 1(1):3–7
28. Rajabioun R (2011) Cuckoo optimization algorithm. Appl Soft Comput 11(8):5508–5518
29. Mellal MA, Adjerid S, Williams EJ (2013) Optimal selection of obsolete tools in manufacturing systems using cuckoo optimization algorithm. Chem Eng Trans 33:355–360
30. Mellal MA, Adjerid S, Williams EJ, Benazzouz D (2012) Optimal replacement policy for obsolete components using cuckoo optimization algorithm based approach: Dependability context. J Sci Ind Res 71(11):715–721
31. Rabiee M, Sajedi H (2013) Job scheduling in grid computing with cuckoo optimization algorithm. Int J Comput Appl 62(16):38–44
32. Addeh J, Ebrahimzadeh A, Azarbad M, Ranaee V. Statistical process control using optimized neural networks: A case study. ISA Transactions 2013;DOI: 10.1016/j.isatra.2013.07.018
33. Sahab AR, Ziabari MT, Modabbernia MR (2012) A novel fractional-order hyperchaotic system with a quadratic exponential nonlinear term and its synchronization. Adv Differ Equ 2012:1–21
34. Teimouri R, Sohrabpoor H (2013) Application of adaptive neuro-fuzzy inference system and cuckoo optimization algorithm for analyzing electro chemical machining process. Front Mech Eng 8(4): 429–442
35. Mellal MA, Williams EJ. Parameter optimization of advanced machining processes using cuckoo optimization algorithm and hoopoe heuristic. Journal of Intelligent Manufacturing 2014;DOI: 10.1007/s10845-014-0925-4
36. Roozitalab A, Asgharizadeh E (2013) Optimizing the warranty period by cuckoo meta−heuristic algorithm in heterogeneous customers' population. J Ind Eng Int 9(27):1–6