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ORIGINAL ARTICLE

# Total production time minimization of a multi-pass milling process via cuckoo optimization algorithm

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**Abstract** The milling process is a widely used conventional machining operation. Due to economic reasons, the multi-pass milling process is more convenient. However, the required time for machining increases and an optimization solution must be undertaken. In this paper, the total production time is minimized by resorting to a powerful bio-inspired algorithm, called the cuckoo optimization algorithm. The constraints are successfully handled and the optimal results are compared with those available in the literature. It is shown that the present results are better.

**Keywords** Multi-pass milling process · Total production time · Machining parameters · Cuckoo optimization algorithm

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**Nomenclature**

| | |
|---|---|
| $T_{pr}$ | Total production time (min) |
| $f_{z_i}$ | Feed per tooth (mm/tooth) |
| $V_i$ | Cutting speed (m/min) |
| $a_i$ | Depth of cut (mm) |
| $T_1$ | $= \frac{T_s}{N_b} + T_L + N_p T_a$ |
| $T_2$ | $= \sum_{i=1}^{N_p} \left( \frac{\pi D L}{f_{z_i} z 1000 V_i} + \frac{T_d \pi L V_i^{\left(\frac{1}{m}-1\right)} a_i^{\left(\frac{e_v}{m}\right)} f_{z_i}^{\left(\frac{u_v}{m}-1\right)} a_r^{\left(\frac{r_v}{m}\right)} z^{\left(\frac{n_v}{m}-1\right)} \lambda_s^{\left(\frac{q_v}{m}\right)}}{1000 C_v^{\left(\frac{1}{m}\right)} D^{\left(\frac{b_v}{m}-1\right)} \left(B_m B_h B_p B_t\right)^{\left(\frac{1}{m}\right)}} \right)$ |
| $T_s$ | Set up time of the machine for a new batch (min) |
| $N_b$ | Total number of components in the batch |
| $T_L$ | Loading and unloading time (min) |
| $N_p$ | Total number of passes |
| $T_a$ | Process adjusting time and quick return time (min/part) |
| $E$ | Permissible values of arbor deflection (mm) |
| $D$ | Outer diameter of the cutter (mm) |
| $B_m$, $B_h$, $B_p$, $B_t$ | Correction coefficient of tool life equation |
| $e_v$, $e_z$, $u_v$, $u_z$, $r_v$, $r_z$, $n_v$, $n_z$, $q_v$, $b_z$, $b_v$, $m$ | Exponents determined empirically |
| $L$ | Length of cut (mm) |
| $Z$ | Number of teeth on the cutter |
| $T_d$ | Time for changing a dull cutting edge or tool (min) |
| $\lambda_s$ | Cutting inclination angle (°) |
| $C_{zp}$ | Constant of the cutting force equation |
| $a_r$ | Milling width (mm) |

| | |
|---|---|
| $C_v$ | A constant taking into account the influence of all factors that are appearing |
| $k_b$ | Permissible bending stress of the arbor material (kg/mm$^2$) |
| $d_a$ | Arbor diameter (mm) |
| $L_a$ | Arbor length between supports (mm) |
| $k_t$ | Permissible torsional stress of the arbor material (kg/mm$^2$) |
| $E$ | Modulus of elasticity of arbor material (kg/mm$^2$) |
| $P_m$ | Nominal motor power (W) |
| $\eta$ | Overall efficiency of machine tool |

## 1 Introduction

In manufacturing, a finite piece may require different kinds of machining processes, such as turning, milling, drilling, and grinding. A competitive manufacturer needs high-performance machining processes according to the considered objective, namely a minimum unit production cost, minimum surface roughness, minimum production time, maximum material removal rate, etc. The input machining parameters must be carefully fixed to achieve these aims.

In the multi-pass milling operation, the metal is removed by a rotating multi-tooth cutter [1]. Various methods have been proposed for optimizing the multi-pass milling process, including experimental, analytical, and soft computing. Sonmez et al. [2] used dynamic programming for determining the number of passes and applied geometric programming (GP) in order to find the optimal values of the cutting parameters. Wang et al. [3] proposed a hybrid approach based on the genetic algorithm (GA) and simulated annealing (SA), called parallel genetic simulated annealing (PGSA). However, the constraint limits have not been investigated. Onwubolu [4] introduced a new technique called Tribes inspired by the particle swarm optimization (PSO). The production time have been minimized for ten various depths of cut. In [5], Gao et al. analyzed the particle swarm optimization with individuals which can exchange information only with other individuals near them. This optimization technique is called cellular particle swarm optimization (CPSO), and the results were improved. Venkata Rao et al. [6], Yang et al. [7], and Pawar and Venkata Rao [8] applied the artificial bee colony (ABC), imperialist competitive algorithm (ICA), and teaching-learning-based optimization algorithm (TLBO), respectively. The applied ICA has not heretofore been investigated relative to the machining limits. Recently, Huang et al. [9] determined the machining parameters by hybridizing the teaching-

**Table 1** Machining parameters

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $T_s$ | 10 min | $C_{zp}$ | 68.2 |
| $N_b$ | 100 | $a_r$ | 50 mm |
| $T_L$ | 1.5 min | $b_z$ | −0.86 |
| $T_a$ | 0.1 min/part | $e_z$ | 0.86 |
| $e$ (roughing operation) | 0.2 mm | $u_z$ | 0.72 |
| $e$ (finishing operation) | 0.05 mm | $C_v$ | 35.4 |
| $D$ | 63 mm | $b_v$ | 0.45 |
| $B_m$ | 1 | $k_b$ | 140 MPa = 14.27 kg/mm$^2$ |
| $B_h$ | 1 | $k_t$ | 120 MPa = 12.23 kg/mm$^2$ |
| $B_p$ | 0.8 | $E$ | 200 GPa = 20,387 kg/mm$^2$ |
| $B_t$ | 0.8 | $P_m$ | 5500 W |
| $e_v$ | 0.3 | $d_a$ | 27 mm |
| $u_v$ | 0.4 | $L_a$ | 210 mm |
| $r_v$ | 0.1 | $m$ | 0.33 |
| $n_v$ | 0.1 | $\eta$ | 0.7 |
| $q_v$ | 0 | $f_{z_i}$ | [0.000875, 3.571] mm/tooth |
| $L$ | 160 mm | $V_i$ | [6.234, 395.84] m/min |
| $z$ | 8 | $a_i$ | [0.5, 4] mm |
| $T_d$ | 5 min | | |
| $\lambda_s$ | 30° | | |

**Table 2** Comparison results for strategy 1 ($a_{\text{rough}_1} = 1.5,\ a_{\text{rough}_2} = 1.5,\ a_{\text{rough}_3} = 1.5,\ a_{\text{finish}} = 0.5$)

| Method | $f_z$ (mm/tooth) | $V$ (m/min) | SC ($F_s - F_c \geq 0$) | DC ($F_d - F_c \geq 0$) | PC ($P_c - \frac{F_c V_i}{6120} \geq 0$) | $T_1$ (min) | $T_2$ (min) | $T_{pr}$ ($T_1$+ $T_2$) (min) | NFE |
|---|---|---|---|---|---|---|---|---|---|
| ICA [7] | (0.342, 0.342, 0.342, 0.436) | (46.554, 46.554, 46.554, 64.164) | – | – | – | 2.0 | 1.239 | 3.239 | 40,000 |
| PSO [5] | (0.341, 0.341, 0.341, 0.435) | (54.027, 51.713, 49.041, 65.054) | – | – | – | 2.0 | 1.234 | 3.234 | 1500 |
| CPSO [5] | (0.341, 0.341, 0.341, 0.435) | (50.864, 50.864, 50.864, 64.191) | (0.3842, 0.3842, 0.3842, 271.5372) | (430.7589, 430.7589, 430.7589, −*0.0309*) | (3845.8015, 3845.8015, 3845.8015, 3847.5455) | 2.0 | 1.233 | 3.2330[a] | 1500 |
| SA [6] | (0.336, 0.336, 0.336, 0.429) | (44.633, 44.633, 44.633, 57.23) | (5.779, 5.779, 5.779, 273.91) | (436.09, 436.09, 436.09, 2.296) | (0.204, 0.204, 0.204, 1.683) | 2.0 | 1.263 | 3.263 | – |
| PSO [6] | (0.34, 0.34, 0.34, 0.434) | (46.61, 46.61, 46.61, 63.58) | (1.5, 1.5, 1.5, 271.9) | (431.9, 431.9, 431.9, 0.35) | (0.01, 0.01, 0.01, 1.422) | 2.0 | 1.240 | 3.240 | 120 |
| ABC [6] | (0.337, 0.337, 0.337, 0.432) | (46.982, 46.982, 46.982, 64.41) | (4.708, 4.708, 4.708, 271.97) | (435.02, 435.02, 435.02, 1.131) | (0.0047, 0.0047, 0.0047, 1.400) | 2.0 | 1.240 | 3.240 | 2400 |
| TLBO [8] | (0.341, 0.341, 0.341, 0.434) | (46.641, 46.641, 46.641, 66.8576) | (0.435, 0.435, 0.435, 271.975) | (430.755, 430.755, 430.755, 0.355) | (0.0001, 0.0001, 0.0001, 1.297) | 2.0 | 1.237 | 3.237 | – |
| CS [9] | (0.3413, 0.3413, 0.3414, 0.4349) | (50.471, 50.7762, 50.8559, 64.6164) | (0, 0, 0, 271.59) | (430.417, 430.422, 430.381, 0) | (3845.81, 3845.81, 3845.8, 3847.53) | 2.0 | 1.233 | 3.233 | 2000 |
| TLCS [9] | (0.3414, 0.3414, 0.3414, 0.4349) | (50.8643, 50.8643, 50.8643, 64.1905) | (−*0.0423*[b], −*0.0423*[b], −*0.0423*[b], 271.5759) | (430.3323, 430.3323, 430.3323, 0.0077) | (3845.7979, 3845.7979, 3845.7979, 3847.5459) | 2.0 | 1.2323 | 3.2323[c] | 2000 |
| COA (Present work) | (0.3413, 0.3413, 0.3413, 0.4349) | (51.0425, 50.8967, 50.6023, 63.4896) | (0.0643, 0.0643, 0.0643, 271.5759) | (430.4389, 430.4389, 430.4389, 0.0077) | (3845.7841, 3845.7961, 3845.8204, 3847.5727) | 2.0 | 1.2325 | *3.2325* | 200 |

[a] In [5], it was reported 3.232

[b] In [9], it was reported 0

[c] In [9], it was reported 3.232

learning-based optimization algorithm and the cuckoo search (TLCS). Four passes have been considered, three depths of roughness and one depth of finishing. The strength constraint limit has been exceeded. In all the previous works, the goal was to minimize the total production time using a stable approach requiring a small number of function evaluations.

The present work investigates the multi-pass milling process with an objective of minimizing the total production time based on the single objective mathematical model of Sonmez et al. [2]. The above model is considered the most important benchmark mathematical model. An approach based on the implementation of cuckoo optimization algorithm is presented in this paper for finding the optimal cutting parameters leading to minimum total production time within the constraint limits.

The remainder of the paper is organized as follows: in Section 2, the mathematical model of minimizing the total production time in the multi-pass milling process is presented; Section 3 describes the implemented cuckoo optimization algorithm with handled constraint functions and robust reproduction procedure; Section 4 highlights the obtained results with discussion; and conclusions of the whole paper and some suggestions for future work are given in Section 5.

## 2 Mathematical model of multi-pass milling process

The optimization problem of the multi-pass milling process investigated in this paper is based on the mathematical model of Sonmez et al. [2]. The objective is to minimize the total production time ($T_{pr}$) by controlling the feed per tooth ($f_{z_i}$), cutting speed ($V_i$), and the depth of cut ($a_i$), under the constraints of arbor strength, arbor deflection, power, and the bounds. The number of machining parameters (input variables) depends on the number of passes $N_p$, $i=1,\ldots, N_p$. The parameters are reported in Table 1.

### 2.1 Objective function (total production time)

The objective function is defined as follows:

$$\mathrm{T}_{pr}\left(f_{z_i}, V_i, a_i\right) = \frac{T_s}{N_b} + T_L + N_p T_a + \sum_{i=1}^{N_p}\left(\frac{\pi DL}{f_{z_i} z 1000 V_i} + \frac{T_d \pi L V_i^{\left(\frac{1}{m}-1\right)} a_i^{\left(\frac{e_v}{m}\right)} f_{z_i}^{\left(\frac{u_v}{m}-1\right)} a_r^{\left(\frac{r_v}{m}\right)} z^{\left(\frac{n_v}{m}-1\right)} \lambda_s^{\left(\frac{q_v}{m}\right)}}{1000 C_v^{\left(\frac{1}{m}\right)} D^{\left(\frac{b_v}{m}-1\right)} \left(B_m B_h B_p B_t\right)^{\left(\frac{1}{m}\right)}}\right) \tag{1}$$

### 2.2 Constraints

The total production time is subject to the following experimental limits:

(a) Arbor strength (arbor rigidity)

$$F_c \leq F_s \tag{2}$$

where $F_c$ and $F_s$ are the mean peripheral cutting force and permissible force with regard to arbor strength, respectively:

$$F_c = C_{zp} a_r z D^{b_z} a_i^{e_z} f_{z_i}^{u_z} \tag{3}$$

$$F_s = \frac{0.1 k_b d_a^3}{0.08 L_a + 0.65\sqrt{(0.25 L_a)^2 + \left(0.5 \frac{k_b}{1.3 k_t} D\right)^2}} \tag{4}$$

(b) Arbor deflection

$$F_c \leq F_d \tag{5}$$

where $F_d$ is the permissible force with regard to arbor deflection:

$$F_d = \frac{4 E e d_a^4}{L_a^3} \tag{6}$$

(c) Power

$$P_c - \frac{F_c V_i}{6120} \geq 0 \tag{7}$$

where $P_c$ is the cutting power:

$$P_c = P_m \eta \tag{8}$$

## 3 Implementation of cuckoo optimization algorithm

The cuckoo optimization algorithm (COA) is an evolutionary computation inspired by the reproductive cycle of the cuckoo bird, initially developed by Rajabioun [10]. It has been successfully implemented for solving

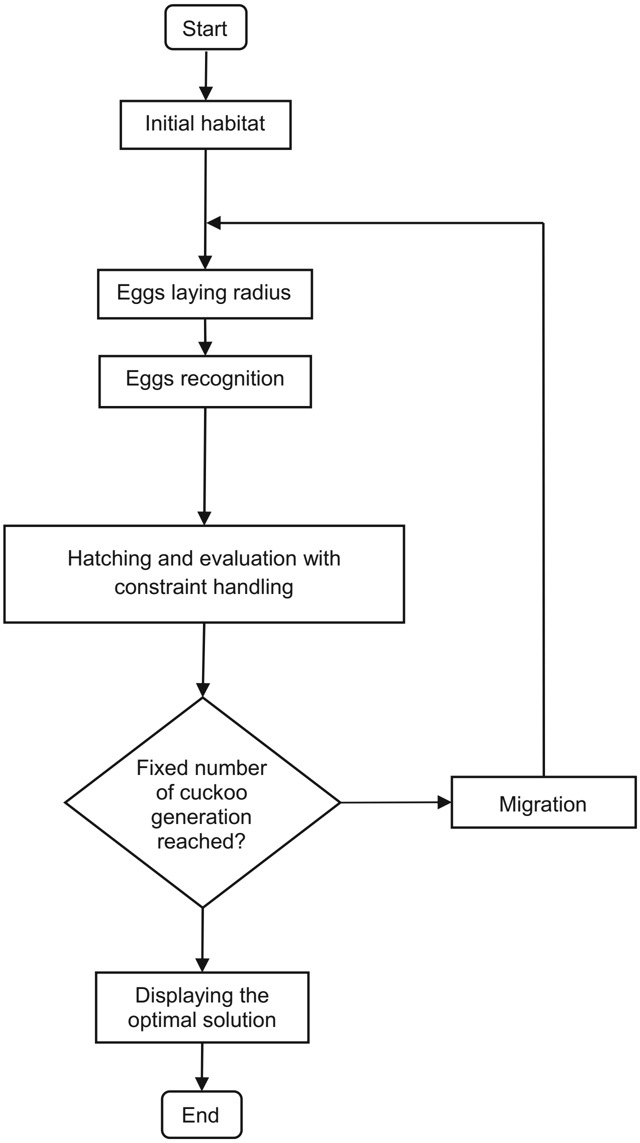


**Fig. 1** General flowchart of the implemented cuckoo optimization algorithm for the multi-pass milling process

several strong optimization problems, such as job scheduling [11], unconventional machining processes [12], multi-pass turning process [13], optimal warranty period [14], selection of optimal obsolete industrial components [15, 16], statistical process control [17], combined heat and power economic dispatch [18], and multivariable controller design [10]. It is considered one of the most robust optimization techniques in the literature.

In this paper, the pseudo-code of the implemented cuckoo optimization algorithm for solving the multi-pass milling process is given as follows:

Step 1: Initialization

Random mature cuckoos are generated within the habitat:

$$Habitat = \left(f_{z_i}, V_i, a_i\right), i = 1, \ldots, N_p \tag{9}$$

Step 2: Egg laying radius

A fixed number of eggs is fixed for each cuckoo of the population and are laid within:

$$\mathrm{ELR} = \alpha \times \frac{Number\ of\ current\ cuckoo's\ eggs}{Total\ number\ of\ eggs} \times \left[\left(f_{z_iU}, V_{iU}, a_{iU}\right) - \left(f_{z_iL}, V_{iL}, a_{iL}\right)\right] \tag{10}$$

where $\alpha$ is an integer chosen based on the stability of the algorithm.

Step 3: Egg recognition

Some eggs are considered dissimilar and destroyed.

Step 4: Hatching and evaluation

The non destroyed eggs hatch and the cuckoos mature. In order to provide solutions within the search space, the following penalty function is used [19, 20]:

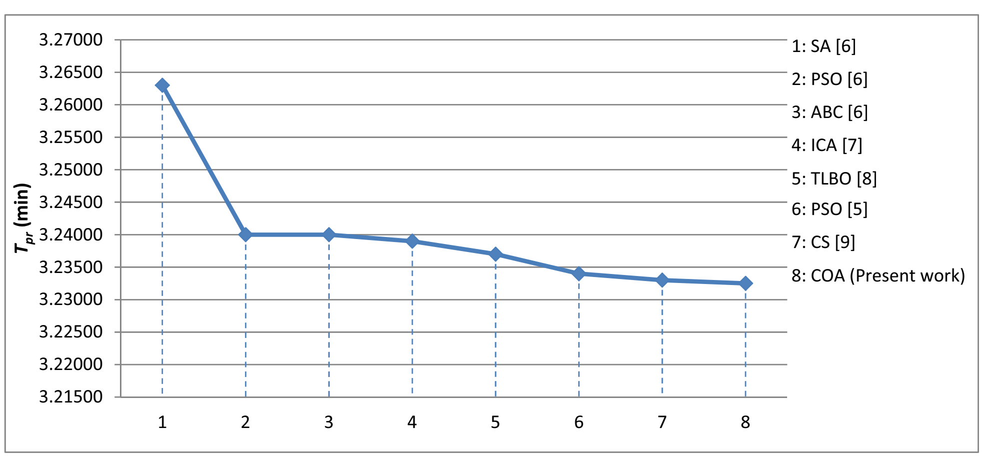


**Fig. 2** Optimal values for strategy 1

**Table 3** Comparison results for strategy 2 ($a_{\text{rough}_1} = 2,\ a_{\text{rough}_2} = 1,\ a_{\text{rough}_3} = 1,\ a_{\text{finish}} = 1$)

| Method | $f_z$ (mm/tooth) | $V$ (m/min) | SC ($F_s - F_c \geq 0$) | DC ($F_d - F_c \geq 0$) | PC ($P_c - \frac{F_c V_i}{6120} \geq 0$) | $T_1$ (min) | $T_2$ (min) | $T_{pr} = T_1 + T_2$ (min) | NFE |
|---|---|---|---|---|---|---|---|---|---|
| ICA [7] | (0.242, 0.555, 0.555, 0.190) | (46.554, 46.554, 46.554, 72.547) | – | – | – | 2.0 | 1.342 | 3.342 | 40,000 |
| PSO [6] | (0.240, 0.553, 0.553, 0.19) | (46.53, 46.42, 46.42, 70.84) | – | – | – | 2.0 | 1.342 | 3.342 | 120 |
| ABC [6] | (0.231, 0.552, 0.552, 0.189) | (48.117, 47.519, 47.519, 74.090) | – | – | – | 2.0 | 1.355 | 3.355 | 2400 |
| PSO [5] | (0.242, 0.554, 0.553, 0.190) | (52.282, 48.321, 54.230, 66.788) | – | – | – | 2.0 | 1.343 | 3.343 | 1500 |
| CPSO [5] | (0.242, 0.554, 0.554, 0.190) | (53.533, 47.327, 47.327, 72.608) | – | – | – | 2.0 | 1.335 | 3.335 | 1500 |
| COA (Present work) | (0.2420, 0.5540, 0.5540, 0.1900) | (53.5553, 47.2775, 47.1194, 72.6187) | (0.1385, 0.0289, 0.0289, 271.6039) | (430.5131, 430.4035, 430.4035, 0.0357) | (3845.5772, 3846.0948, 3846.1078, 3847.2240) | 2.0 | 1.3348 | *3.3348* | 200 |

**Table 4** Comparison results for strategy 3 ($a_{\text{rough}} = 3,\ a_{\text{finish}} = 2$)

| Method | $f_z$ (mm/tooth) | $V$ (m/min) | SC ($F_s - F_c \geq 0$) | DC ($F_d - F_c \geq 0$) | PC ($P_c - \frac{F_c V_i}{6120} \geq 0$) | $T_1$ (min) | $T_2$ (min) | $T_{pr} = T_1 + T_2$ (min) | NFE |
|---|---|---|---|---|---|---|---|---|---|
| GP [2] | (0.338, 0.570) | (26.40, 25.16) | (*−405*, *−430*) | (24.92, *−702*) | (*−0.08*, 0) | 1.801 | 0.813 | 2.614 | – |
| GA [3] | (0.366, 0.5667) | (24.69, 25.16) | (*−459*, *−427*) | (*−28.81*, *−698*) | (*−0.04*, 0) | 1.7998 | 0.8102 | 2.61 | 18,000 |
| PGSA [3] | (0.3693, 0.5886) | (24.25, 24.58) | (*−465*, *−452*) | (*−35*, *−74*) | (0.2, 0) | 1.80 | 0.80 | 2.60 | 15,000 |
| Tribes [4] | (0.587, 0.902) | (36.27, 30.16) | (*−8.50*, *−797*) | (*−420*, *−1069*) | (*−4.18*, *−2.57*) | 1.7005 | 0.512 | 2.2125 | – |
| COA (Present work) | (0.14915, 0.08303) | (57.63565, 82.10743) | (0.0219, 2.7158) | (430.3965, 0.0183) | (3845.2391, 3846.8610) | 1.80 | 1.55480 | *3.35480* | *200* |

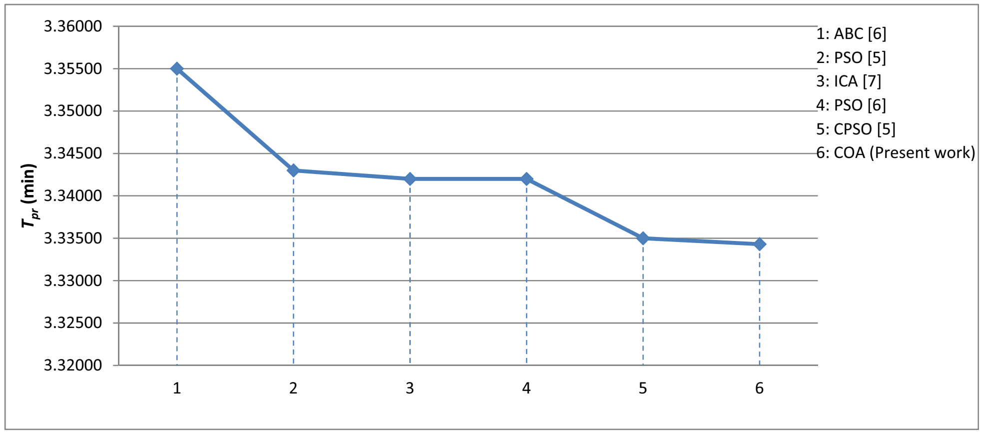


**Fig. 3** Optimal values for strategy 2

$$\mathrm{F}_{T_{pr}}\left(\vec{x}\right) = f_{T_{pr}}\left(\vec{x}\right) + \sum_{i=1}^{N_P} \Phi_i \cdot \max\left(0, h_i\left(\vec{x}\right)\right)^2 + \sum_{i=1}^{N_P} \Omega_i \cdot \max\left(0, w_i\left(\vec{x}\right)\right)^2 + \sum_{i=1}^{N_P} \Psi_i \cdot \max\left(0, y_i\left(\vec{x}\right)\right)^2 \quad (11)$$

where $\mathrm{F}_{T_{pr}}\left(\vec{x}\right)$ is the penalized objective function and $\vec{x}$ is the vector of solutions (input machining parameters). $h_i\left(\vec{x}\right)$, $w_i\left(\vec{x}\right)$, and $y_i\left(\vec{x}\right)$ are the normalized arbor strength constraint, arbor deflection constraint, and power constraint, respectively. $\Phi_i$, $\Omega_i$, and $\Psi_i$ are the penalty factors (positive constants fixed after various trials and based on the experience). It should be noted that the total number of constraints including the roughing and finishing is $3 \times N_p$.

Step 5: Migration

Move the population of cuckoos toward a new habitat and a new reproduction period begins.

Step 6: If the number of cuckoo generations is reached, stop; otherwise, go to step 2.

Figure 1 shows the general flowchart of the implemented cuckoo optimization algorithm for solving the multi-pass milling process.

## 4 Results and discussion

As reported in the literature, three main cutting strategies can be adopted according to the fixed value of $a_i$.

Strategy 1 (four passes) $a_{\mathrm{rough}_1} = 1.5, \; a_{\mathrm{rough}_2} = 1.5, \; a_{\mathrm{rough}_3} = 1.5, \; a_{\mathrm{finish}} = 0.5$

Strategy 2 (four passes) $a_{\mathrm{rough}_1} = 2, \; a_{\mathrm{rough}_2} = 1, \; a_{\mathrm{rough}_3} = 1, \; a_{\mathrm{finish}} = 1$

Strategy 3 (two passes) $a_{\mathrm{rough}} = 3, \; a_{\mathrm{finish}} = 2$

The number of function evaluations used in the whole paper is 200. Table 2 summarizes the results of the implemented cuckoo optimization algorithm and those of the literature for the first strategy. The minimum total production time obtained by the COA is 3.2325 min with respect to constraints. In [5], the provided $T_{pr}$ by the CPSO is 3.232 min. However, if one replace the values of the input parameters in Eqs. (1)–(8), then we find $T_{pr}$=3.2330 min and the power constraint in finishing is violated. Also, the implemented TLCS [9] has violated some constraints. The best solution and the constraint violation are highlighted in italic type. From Fig. 2 and Table 2, it can be observed that the optimal $T_{pr}$ obtained by the implemented COA is better. Furthermore, the number of function evaluations is small.

Tables 3 and 4 summarize the results for strategies 2 and 3, respectively. The minimum $T_{pr}$ is 3.3348 min for strategy 1 and is better than the other works available in the literature, as shown in Table 3 and Fig. 3. For strategy 3, all the optimization techniques previously applied, namely the GP [2], GA [3], PGSA [3], and Tribes [4], violated the constraints, whereas the implemented COA minimized the $T_{pr}$ to 3.3348 with respect to the constraints limits.

## 5 Conclusions and future research

This paper dealt with the minimizing of the total production time in the multi-pass milling process. An efficient approach based upon the implementation of the cuckoo optimization algorithm has been applied and the results were compared to those available in the literature. Three strategies were considered according to the adopted numerical values of the depth of cut. It has been shown that the present approach outperformed the other works in terms of minimum $T_{pr}$ and constraints limits. Future development may include the hybridization of the present approach in order to further improve the results and solving the multiobjective multi-pass milling process.

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