Research Article

Intelligent Selection of Machining Parameters in Multipass Turnings Using Firefly Algorithm

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Determination of optimal cutting parameters is one of the most important elements in any process planning of metal parts. In this paper, a new optimization technique, firefly algorithm, is used for determining the machining parameters in a multipass turning operation model. The objective considered is minimization of production cost under a set of machining constraints. The optimization is carried out using firefly algorithm. An application example is presented and solved to illustrate the effectiveness of the presented algorithm.

1. Introduction

The selection of optimal cutting parameters, like the number of passes, depth of cut for each pass, feed, and speed, is a very important issue for every machining processes [1].

Several cutting constraints must be considered in machining operations. In turning operations, a cutting process can possibly be completed with a single pass or by multiple passes. Multipass turning is preferable over single-pass turning in the industry for economic reasons [2].

The optimization problem of machining parameters in multipass turnings becomes very complicated when plenty of practical constraints have to be considered [3].

Traditionally, mathematical programming techniques like graphical methods [4], linear programming [5], dynamic programming [6, 7], and geometric programming [8, 9] had been used to solve optimization problems of machining parameters in multipass turnings. However, these traditional methods of optimization do not fare well over a broad spectrum of problem domains. Moreover, traditional techniques may not be robust. Numerous constraints and multiple passes make machining optimization problems complicated and hence these techniques are not ideal for solving such problems as they tend to obtain a local optimal solution.

Thus, metaheuristic algorithms have been developed to solve machining economics problems because of their power in global searching. There have been some works regarding optimization of cutting parameters [2, 3, 10–14] for different situations; authors have been trying to bring out the utility and advantages of genetic algorithm, evolutionary approach, and simulated annealing. It is proposed to use the new optimization technique, firefly algorithm, for the machining optimization problems.

The firefly algorithm (FA) is a metaheuristic, nature-inspired, and optimization algorithm which is based on the social (flashing) behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions [5–18]. It was developed by Dr. Yang at Cambridge University in 2007, and it is based on the swarm behavior such as fish, insects, or bird schooling in nature. In particular, although the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization (PSO), Artificial Bee Colony optimization (ABC), and Bacterial Foraging algorithms (BFA), it is indeed much simpler both in concept and implementation [15, 16, 18, 19]. Furthermore, according to recent bibliography, the algorithm is very efficient and can outperform other conventional algorithms, such as genetic

algorithms, for solving many optimization problems, a fact that has been justified in a recent research, where the statistical performance of the firefly algorithm was measured against other well-known optimization algorithms using various standard stochastic test functions [20].

The current paper focuses on the application of a new optimization technique, firefly algorithm, to determine the optimal machining parameters that minimize the unit production cost in multipass turnings.

2. Cutting Process Model

2.1. Decision Variables. In the constructed optimization problem, six decision variables are considered: cutting speeds in rough and finish machining (V_r, V_s), feed rates in rough and finish machining (f_r, f_s), and depth of cut for each pass of rough and finish machining (a_r, a_s).

2.2. Objective Function. Based on the minimum unit production cost, UC, criterion, the objective function for a multipass turning operation can be given by the equation [10]:

$$UC = C_M + C_I + C_R + C_T,$$

$$C_M = k_0 \left[\frac{\pi DL}{1000 V_r f_r} \left(\frac{a_t - a_s}{a_r} \right) + \frac{\pi DL}{1000 V_s f_s} \right],$$

$$C_I = k_0 \left[t_c + (h_1 L + h_2) \left(\frac{a_t - a_s}{a_r} + 1 \right) \right],$$

$$C_R = k_0 \frac{t_c}{T_p} \left[\frac{\pi DL}{1000 V_r f_r} \left(\frac{a_t - a_s}{a_r} \right) + \frac{\pi DL}{1000 V_s f_s} \right],$$

$$C_T = \frac{k_t}{T_p} \left[\frac{\pi DL}{1000 V_r f_r} \left(\frac{a_t - a_s}{a_r} \right) + \frac{\pi DL}{1000 V_s f_s} \right].$$

$$(1)$$

2.3. Constraints. There are some constraints which affect the selection of the optimal cutting conditions and will be taken into account.

The constraints in rough and finish machining are as outlined below [10].

2.3.1. Rough Machining

Parameter Bounds. Due to the limitations on the machine and cutting tool and due to the safety of machining the cutting parameters are limited with the bottom and top permissible limit:

$$\text{cutting speed}: V_{rL} \leq V_r \leq V_{rU},$$

$$\text{feed rate}: f_{rL} \leq f_r \leq f_{rU}, \qquad (2)$$

$$\text{depth of cut}: a_{rL} \leq a_r \leq a_{rU}.$$

Tool-Life Constraint. The constraint on the tool life is taken as

$$T_L \leq T_r \leq T_U. \qquad (3)$$

Cutting Force Constraint. The maximum amount of cutting forces Fu should not exceed a certain value as higher forces produce shakes and vibration. This constraint is given below:

$$F_r = k_1 (f_r)^\mu (a_r)^\upsilon \leq F_u. \qquad (4)$$

Power Constraint. The nominal power of the machine P_U limits the cutting process:

$$P_r = \frac{F_r V_r}{6120 \eta} \leq P_U, \qquad (5)$$

efficiency $\eta = 0.85$.

Stable Cutting Region Constraint. This constraint is given as

$$(V_r)^\lambda f_r (a_r)^\gamma \geq \text{SC}. \qquad (6)$$

Chip-Tool Interface Temperature Constraint. This constraint is given as

$$Q_r = k_2 (V_r)^\tau (f_r)^\phi (a_r)^\delta \leq Q_u. \qquad (7)$$

2.3.2. Finish Machining. All the constraints other than the surface finish constraint are similar for rough and finish machining [21].

Surface Finish Constraint. In the finishing operations, the obtained surface roughness must be smaller than the specified value, SR_U, given by technological criteria, so that the following equation is satisfied:

$$\frac{f_s^2}{8R} \leq \text{SR}_U. \qquad (8)$$

Constraints for roughing and finishing parameter relations are

$$V_s \geq k_3 V_r,$$

$$f_r \geq k_4 f_s, \qquad (9)$$

$$a_r \geq k_5 a_s.$$

The Number of Rough Cuts. The possible number of rough cuts is restricted by

$$n = \frac{a_t - a_s}{a_r}, \qquad (10)$$

where $n_L \leq n \leq n_U$,

$$n_L = \frac{(a_t - a_{sU})}{a_{rU}},$$

$$n_U = \frac{(a_t - a_{sL})}{a_{rL}}. \qquad (11)$$

The optimization problem in multipass turnings can be divided into $m = (n_U - n_L + 1)$ subproblems, in each of which the number of rough cuts n is fixed. So the solution of the whole optimization problem is divided into searching the optimal results of m subproblems and the minimum of them is the objective of whole optimization problem [3].

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Input:
f (z), z = [z₁, z₂, …, zₙ]ᵀ (Cost function)
S = [aₖ, bₖ], ∀k = 1, …, n (Constraints)
m, β₀, γ, min uᵢ, max uᵢ (Algorithm's parameters)
Output:
x_{iᵐⁱⁿ}
begin
  repeat
    iᵐⁱⁿ ← arg minᵢ f (xᵢ), x_{iᵐⁱⁿ} ← arg min_{xᵢ} f (xᵢ)
    For i = 1 to m do
      For j = 1 to m do
        If f (xⱼ) < f (xᵢ) then
          rⱼ ← Calculate distance (xᵢ, xⱼ)
          β ← β₀e^{−γrⱼ}
          uᵢ ← Generate Random Vector (min uᵢ, max uᵢ)
          For k = 1 to n do x_{i,k} ← (1 − β) x_{i,k} + βx_{j,k} + u_{i,k}
        uᵢ min ← Generate Random Vector (min uᵢ, max uᵢ)
        For k = 1 to n do x_{iᵐⁱⁿ,k} ← x_{iᵐⁱⁿ,k} + u_{iᵐⁱⁿ,k}
  until stop condition true
end
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PSEUDOCODE 1

3. Firefly Algorithm (FA)

Firefly algorithm is inspired by biochemical and social aspects of real fireflies. Real fireflies produce a short and rhythmic flash that helps them in attracting (communicating) their mating partners and also serves as protective warning mechanism. FA formulates this flashing behavior with the objective function of the problem to be optimized. The following three rules are idealized for basic formulation of FA.

   (i) All fireflies are unisex so that fireflies will attract each other regardless of their sex.

  (ii) Attractiveness is proportional to their brightness, which decreases as distance increases between two flies. Thus the less bright one will move towards the brighter one. In case it is unable to detect brighter one it will move randomly.

 (iii) The brightness of a firefly is determined by the landscape of the objective function.

3.1. Firefly Algorithm Concept [17]. The algorithm is considered in the continuous constrained optimization problem setting where the task is to minimize cost function $f(x)$ for $x \in S \subset \mathbb{R}^n$; that is, find x^* such that:

$$f(x^*) = \min_{x \in S} f(x). \tag{12}$$

Assume that there exists a swarm of m agents (fireflies) solving optimization problem iteratively and x_i represents a solution for a firefly i in algorithm's iteration k, whereas $f(x_i)$ denotes its cost.

Each firefly has its distinctive attractiveness β which implies how strong it attracts other members of the swarm. As a firefly attractiveness one should select any monotonically decreasing function of the distance $r_j = d(x_i, x_j)$ to the chosen firefly j, for example, as Yang suggests, the exponential function:

$$\beta = \beta_0 e^{-\gamma r_j}, \tag{13}$$

where β_0 and γ are predetermined algorithm parameters: maximum attractiveness value and absorption coefficient, respectively.

Every member of the swarm is characterized by its light intensity I_i which can be directly expressed as an inverse of a cost function $f(x_i)$.

Initially all fireflies are dislocated in S (randomly or employing some deterministic strategy).

To effectively explore considered search space S it is assumed that each firefly i is changing its position iteratively taking into account two factors: attractiveness of other swarm members with higher light intensity, that is, $I_j > I_i$, for all $j = 1, \ldots, m, j \neq i$, which is varying across distance and a fixed random step vector u_i.

If no brighter firefly can be found only the randomized step is being used.

3.2. Pseudocode of the Firefly Algorithm. See Pseudocode 1.

4. Application Example

Now an application example is considered to demonstrate and validate the firefly algorithm (FA) for the optimization of process parameters of the multipass turning operation. The parameters used for the numerical application are mentioned in Table 1.

4.1. Results and Discussion. The Firefly algorithm was run with these parameters:

TABLE 1: Machining data [10].

Parameter	Values	Parameter	Values	Parameter	Values
D (mm)	50	L (mm)	300	a_t (mm)	6
V_{rU} (m/min)	500	V_{rL} (m/min)	50	f_{rU} (mm/rev)	0.9
f_{rL} (mm/rev)	0.1	a_{rU} (mm)	3.0	a_{rL} (mm)	1.0
V_{sU} (m/min)	500	V_{sL} (m/min)	50	f_{sU} (mm/rev)	0.9
f_{sL} (mm/rev)	0.1	a_{sU} (mm)	3.0	a_{sL} (mm)	1.0
P	5	q	1.75	r	0.75
k_1	108	μ	0.75	υ	0.95
η	0.85	λ	2	ν	−1
k_2	132	τ	0.4	ϕ	0.2
δ	0.105	R (mm)	1.2	k_0 ($/min)	0.5
C_0	6×10^{11}	h_1	7×10^{-4}	h_2	0.3
T_L (min)	25	t_c (min/piece)	0.75	t_e (min/edge)	1.5
P_U (kW)	5	T_U (min)	45	F_u (N)	1961.3
SC	140	SR_U (μm)	10	Q_u (°C)	1000
k_3	1.0	k_4	2.5	k_5	1.0
k_t ($/edge)	2.5				

TABLE 2: The optimized turning parameters.

n	Cutting parameters (rough machining)			Cutting parameters (finish machining)			UC ($)
	V_r (m/min)	f_r (mm/rev)	a_r (mm)	V_s (m/min)	f_s (mm/rev)	a_s (mm)	
1	98.4102	0.8200	3.0000	162.2882	0.2582	3.0000	1.9358
2	145.7281	0.6067	2.3964	207.0844	0.1519	1.2072	2.7213
3	144.1821	0.7907	1.5958	191.9014	0.1590	1.2125	3.1075
4	145.8086	0.7886	1.2429	180.1447	0.1821	1.0285	3.5428
5	166.5327	0.8998	1.0000	191.3605	0.2582	1.0000	3.4586

TABLE 3: Results of optimization using different algorithms.

Algorithms		Unit cost ($)
FEGA	[2]	2.3084
SA/SP	[3]	2.2795
PSO	[10]	2.2721
GA	[11]	2.2538
SS	[12]	2.0754
GA-based approach	[13]	2.0298
ACO	[14]	1.9680
Firefly		1.9358

nf = 40 (number of fireflies),

α = 0.25 (randomness),

β_0 = 0.20 (minimum value of beta),

γ = 1 (Absorption coefficient).

The results found by the Firefly algorithm are mentioned on Table 2.

We find that the lowest value is 1.9358$ under which the minimum number of rough cuts $n = 1$ is taken.

The performance of the Firefly algorithm and others can be seen in Table 3.

According to Table 3 one notices that the firefly algorithm yields much better results than the other algorithms. Thus the firefly algorithm can tackle the optimization of multipass turning operations problem efficiently to achieve better results in reducing the unit production cost.

5. Conclusion

This paper presents a firefly algorithm optimization for solving the multipass turning operations problem. The results obtained from comparing the Firefly algorithm with those taken from recent literature prove its effectiveness.

The results of the Firefly algorithm are compared with results of genetic algorithms, simulated annealing, particle swarm intelligence, scatter search, and ant colony approaches.

The firefly algorithm obtains near optimal solution; it can be used for machining parameter selection of complex machined parts that require many machining constraints. Also, it can be extended to solve the other metal cutting optimization problems such as milling and drilling.

Abbreviations

C_I: Machine idle cost due to loading and unloading operations and tool idle motion time ($/piece)
C_M: Cutting cost by actual time in cut ($/piece)

C_R:	Tool replacement cost (\$/piece)
C_T:	Tool cost (\$/piece)
a_r, a_s:	Depth of cut for each pass of rough and finish machining (mm)
a_{rL}, a_{rU}:	Lower and upper bound of depth of cut in rough machining (mm)
a_{sL}, a_{sU}:	Lower and upper bound of depth of cut in finish machining (mm)
a_t:	Depth of material to be removed (mm)
D, L:	Diameter and length of workpiece (mm)
f_r, f_s:	Feed rates in rough and finish machining (mm/rev)
f_{rL}, f_{rU}:	Lower and upper bound of feed rate in rough machining (mm/rev)
f_{sL}, f_{sU}:	Lower and upper bound of feed rate in finish machining (mm/rev)
F_r, F_s:	Cutting forces during rough and finish machining (N)
F_u:	Maximum allowable cutting force (N)
h_1, h_2:	Constants related to cutting tool travel and approach/departure time (min)
k_0:	Direct labor cost plus overhead (\$/min)
k_t:	Cutting edge cost (\$/edge)
$k1, \mu, v$:	Constants of cutting force equation
k_2, τ, ϕ, δ:	Constants related to chip-tool interface temperature equation
k_3, k_4, k_5:	Constants for roughing and finishing parameter relations
λ, v:	Constants related to expression of stable cutting region
n:	Number of rough cuts (an integer)
N_U, N_L:	Upper and lower bounds of n
p, q, r, C_0:	Constants of tool-life equation
P_r, P_s:	Cutting power during rough and finish machining (kW)
P_U:	Maximum allowable cutting power (kW)
Q_r, Q_s:	Chip-tool interface rough and finish machining temperatures (°C)
Q_U:	Maximum allowable chip-tool interface temperature (°C)
q:	A weight for $T_p [0, 1]$
R:	Nose radius of cutting tool (mm)
SC:	Limit of stable cutting region constraint
SR_U:	Maximum allowable surface roughness (mm)
T, T_r, T_s:	Tool life, expected tool life for rough machining, and expected tool life for finish machining (min)
T_p:	Tool life of weighted combination of T_r and T_s (min)
T_U, T_L:	Upper and lower bounds for tool life (min)
UC:	Unit production cost except material cost (\$)
V_r, V_s:	Cutting speeds in rough and finish machining (m/min)
V_{rL}, V_{rU}:	Lower and upper bound of cutting speed in rough machining (m/min)
V_{sL}, V_{sU}:	Lower and upper bound of cutting speed in finish machining (m/min).

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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