A Novel Optimization Approach Applied to Multi-Pass Turning Process

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Abstract
Optimization of turning process is a non-linear optimization with constrains and it is difficult for the conventional optimization algorithms to solve this problem. The purpose of present study is to demonstrate the potential of Imperialist Competitive Algorithm (ICA) for optimization of multi-pass turning process. This algorithm is inspired by competition mechanism among imperialists and colonies, in contrast to evolutionary algorithmsthat perform the exploration and exploitation in the solution space aiming to efficiently find near optimal solutions using a finite sequence of instructions. To validate the proposed approach, the results of ICA were finally compared with Genetic Algorithm (GA).Based on the results; ICA has demonstrated excellent capabilities such as simplicity, accuracy, faster convergence and better global optimum achievement. The outcome shows the success of ICA in optimizing the machining process indicating that data analysis method developed in this work can be effectively applied to optimize machining processes.

Keywords
Imperialist Competitive Algorithm, Machining process, Optimization

1. Introduction

The machining processes are commonly used by manufacturing industries to produce high quality and complex products in a short time. These machining processes include large number of input variables which may affect the cost and quality of the products. Selection of optimum machining variables in such processes is very important to satisfy all the conflicting objectives of the metal cutting operations. As the output variables of the machining process depend on the cutting conditions, the decision concerning selection of the optimal cutting parameters has a remarkable influence on the production costs and quality. In last decades, several trials were made by various researchers to analyze machining processes using different methods such as the differential calculus [1], regression analysis [2], linear programming [3], geometric and stochastic programming [4-6], dynamic programming [7-9] and sequential unconstrained minimization technique [10] .These optimization techniques are either stuck at local optimum or take a long time to converge to a reasonable result [11].Evolutionary algorithms such as Genetic Algorithm (GA) [12-15], particle swarm optimization algorithm (PSO) [16,17], immune algorithm [18] and differential evolution algorithm [19-21] have been used in many applications instead of conventional techniques.

In 2007, Atashpaz-Gargari and Lucas [22] introduced the basic idea of Imperialist Competitive Algorithm (ICA) to solve the real world engineering and optimization problems. Imperialist Competitive Algorithm is a new meta-heuristic optimization developed based on a socio-politically motivated strategy and contains two main steps: the movement of the colonies and the imperialistic competition. From the basis of the ICA the powerful imperialists are reinforced and the weak ones are weakened and gradually collapsed, directing that algorithm towards optimum points. This algorithm has been successfully applied to solve some engineering problems in recent years, some of those are mentioned below. In Atashpaz-Gargari et al. [23], ICA is used to design an optimal controller which not only decentralizes but also optimally controls an industrial Multi Input Multi Output (MIMO) distillation column process. Biabangard-Oskouyi et al. [24] used ICA for reverse analysis of an artificial neural network in order to characterize the properties of materials from sharp indentation test. Nazari et al. [25] solved the integrated product mix-outsourcing (which is a major problem in manufacturing enterprise) using ICA. Kaveh and Talatahari [26] utilized the ICA to optimize design of skeletal structures. Yousefi et al. [27] presented the application of Imperialist Competitive Algorithm for optimization of cross-flow plate fin heat exchanger and concluded that ICA comparing to the traditional GA shows considerable improvements in finding the optimum designs in less computational time under the same population size and iterations. Mozafari et al. [28] applied ICA to optimize intermediate epoxy adhesive layer which is bonded between two dissimilar strips of material. They compared the results of ICA with the Finite Element Method (FEM) and Genetic Algorithm; they showed the success of ICA for designing adhesive joints in composite materials. Towsyfyan and Salehi compared the effectiveness of ICA and GA in optimization of submerged arc welding process [29].

In this paper, the basic idea of ICA is introduced and applied for optimization of multi-pass turning process. To validate the proposed approach, compare is made against GA method. Interested readers may refer to works of Deb [30, 31] for a detailed discussion on the principle of the GA.

2. Imperialist competitive algorithm

The proposed algorithm mimics the social–political process of imperialism and imperialistic competition. ICA contains a population of agents or countries. The pseudo-code of the algorithm is as follows.

2.1. Step1: Initial empires creation

Comparable to other evolutionary algorithms, the proposed algorithm starts by an initial population. An array of the problem variables is formed which is called Chromosome in GA and country in this algorithm. In a $N_{var}-$dimensional optimization problem a country is a $1\times N_{var}$ array which is defined as follows:

$$Country = [P_1, P_2, P_3, ..., P_{N_{var}}] \tag{1}$$

A specified number of the most powerful countries, N_{imp}, are chosen as the imperialists and the remaining countries, N_{col}, would be the colonies which are distributed among the imperialists depending on their powers which is calculated using fitness function. The initial empires are demonstrated in Figure 1 where more powerful empires have greater number of colonies.

Figure1. Generating the initial empires: The more colonies an imperialist possess, the bigger is its relevant mark

2.2. Step 2: Assimilation policy

To increase their powers, imperialists try to develop their colonies through assimilation policy where countries are forced to move towards them. A schematic description of this process is demonstrated in Figure 2.

The colony is drawn by imperialist in the culture and language axes (analogous to any dimension of problem). After applying this policy, the colony will get closer to the imperialist in the mentioned axes (dimensions). In assimilation, each colony moves with a deviation of θ from the connecting line between the colony and its imperialist by x units to increase the search area, where θ and x are random numbers with uniform distribution and β is a number greater than one and d is the distance between the colony and the imperialist state. β>1 causes the colonies to get closer to the imperialist state from both sides.

$x \sim U\,(0, \beta \times d)$ (2)

$\theta \sim U\,(-\gamma\,, \gamma)$ (3)

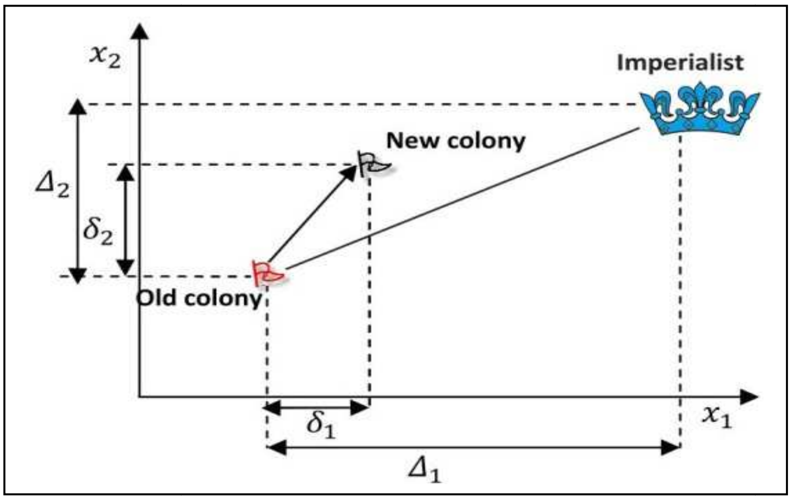


Figure2. Movement of colonies toward their relevant imperialist

2.3. Step 3: Revolution

In each decade (generation) certain numbers of countries go through a sudden change which is called revolution. This process is similar to mutation process in GA which helps the optimization process escaping local optima traps.

2.4. Step 4: Exchanging the position of imperialist and colony

As the colonies are moving towards the imperialist and revolution happens in some countries, there is a possibility that some of these colonies reach a better position than their respective imperialists. In this case, the colony and its relevant imperialist change their positions. The algorithms will be continued using this new country as the imperialist.

2.5. Step 5: Imperialistic competition

The most important process in ICA is imperialistic competition in which all empires try to take over the colonies of other empires. Gradually, weaker empires lose their colonies to the stronger ones. This process is modelled by choosing the weakest colony of the weakest empire and giving it to the appropriate empire which is chosen based on a competition among all empires. Fig.3. demonstrates a schematic of this process.

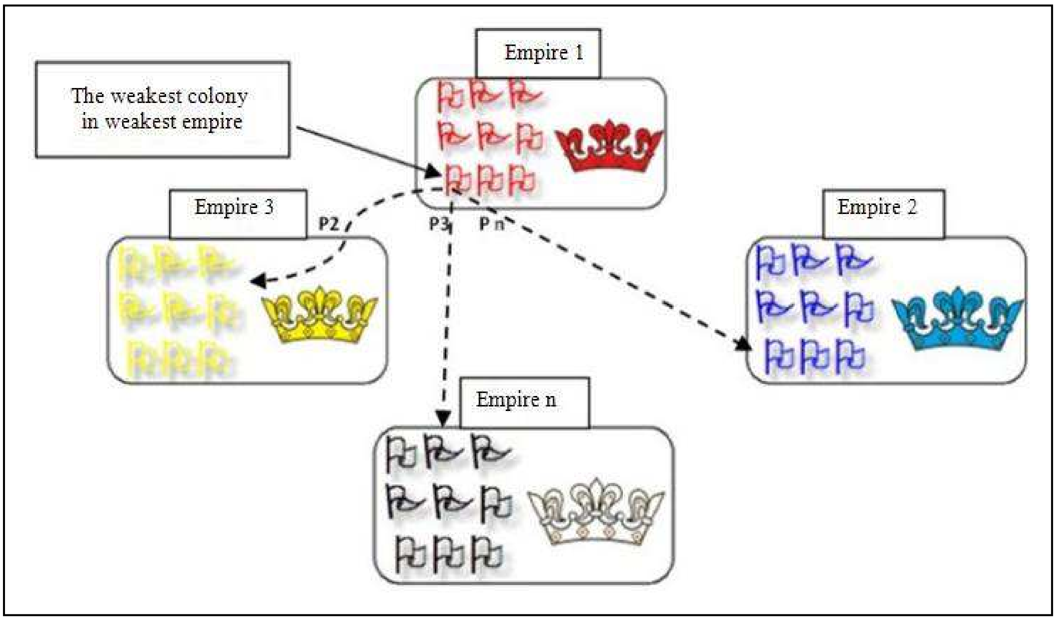


Figure3.Imperialistic competition: The more powerful an empire is, the more likely it will possess the weakest colony of the weakest empire

In this Figure Empire 1 is considered as the weakest empire, where one of its colonies is under competition process. The empires 2to *n* are competing for taking its possession. In order to begin the competition, firstly, the possession probability calculated considering the total power of the empire which is the sum of imperialist power and an arbitrary percentage of the mean power of its colonies. Having the possession probability of each empire, a mechanism similar to Roulette Wheel is used to give the selected colony to one of the empires considering a proportional probability.

2.6. Step 6: Convergence

basically the competition can be continued until there would be only one imperialist in the search space, However, different conditions may be selected as termination criteria including reaching a maximum number of iterations or having negligible improvement in objective function. Fig.4. depicts a schematic view of this algorithm. Whenever the convergence criterion is not satisfied, the algorithm continues.

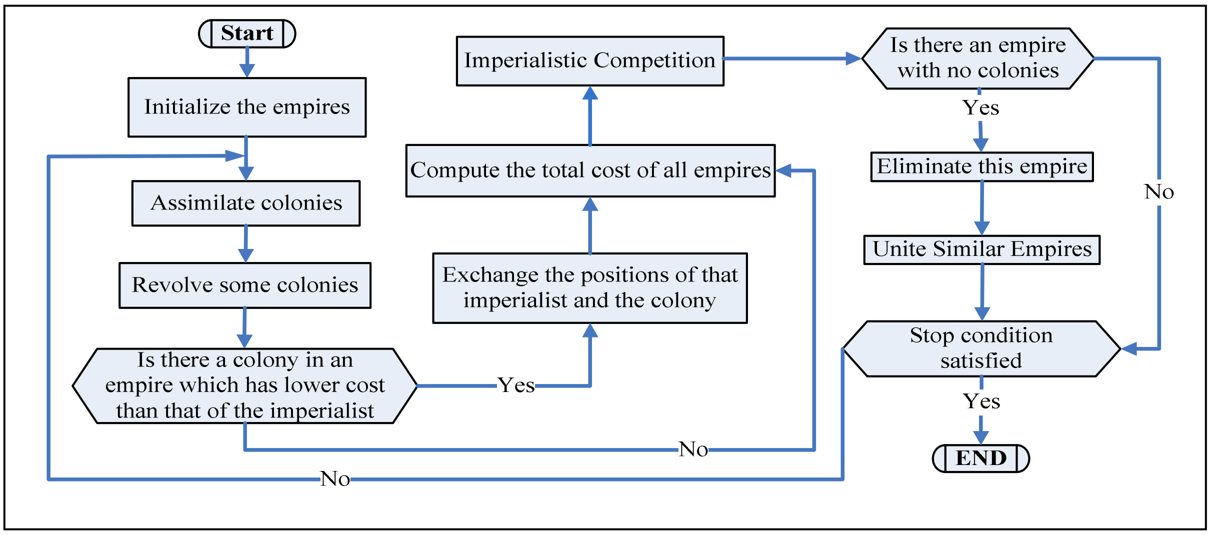


Figure4. Flowchart of the Imperialist Competitive Algorithm

The main steps of ICA summarized in the pseudo-code are given in Fig.5. The continuation of the mentioned steps will hopefully cause the countries to converge to the global minimum of the cost function. Different criteria can be used to stop the algorithm.

1-Initialization
    1-1-Set Parameters (PopSize, Number of imperialist,ξ,P-Revolution, % Assimilate)
    1-2-Generating initial Countries (Randomly)
2-Evaluate fitness of each country
3-Form initial empires
    3-1-Choice power countries as imperialists
    3-2-Assigne other countries (colonies) to imperialists based on their power
4-Move the colonies of an empire toward the imperialist (assimilation)
5-Revolution among colonies and imperialist
6- If the cost of colony is lower than own imperialist
    6-1-Exchanging positions of the imperialist and a colony
7- Calculate Total power of the empires.
8-Imperialistic competition
    8-1- Select the weakest colony of the weakest empire and assign this to one of the strange empires
9-Eliminate the powerless empires (the imperialist with no colony)
10-Stop if stopping criteria is met, otherwise go to step 4.

Figure5. Pseudo code of the Imperialistic Competitive Algorithm

3. Problem Statement

The goal of the multi-pass turning operations is to minimize unit production cost (C_U). The unit production cost is the sum of the cutting cost (C_M), machine idle cost (C_I), tool replacement cost (C_R) and tool cost (C_T). In this study, the ICA approach is used to optimize multi-pass turning operations 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 [7], Chen and Tsai [11], and Chen [33]. According to the work of A.R. Yildiz [32] the objective (cost) function for multi-pass turning process can be mathematically stated as follows:

$$C_U = C_M + C_I + C_R + C_T \quad (4)$$

$$\begin{aligned} C_U = {} & k_0\left[\frac{\pi.D.L}{1000.V_r f_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi.D.L}{1000.V_s f_s}\right]+k_0\left[t_c+(h_1L+h_2)\left(\frac{d_t-d_s}{d_r}+1\right)\right] \\ & +k_0\frac{t_e}{T_p}\left[\frac{\pi.D.L}{1000.V_r f_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi.D.L}{1000.V_s f_s}\right] \\ & +\frac{k_t}{T_p}\left[\frac{\pi.D.L}{1000.V_r f_r}\left(\frac{d_t-d_s}{d_r}\right)+\frac{\pi.D.L}{1000.V_s f_s}\right] \end{aligned} \quad (5)$$

Where the machining variables (factors) $x_1(Vr)$, $x_2(fr)$, $x_3(Vs)$, $x_4(fs)$ and $x_5(ds)$ are selected as feed, cutting speed and depth of cut in rough and finish turning respectively.

In multi-pass turning operations, the unit production cost (C_U) is imposed by different constraints which are (i) parameter bounds cover depth of cut, cutting speed and feed; (ii) tool-life constraint; (iii) cutting force constraint; (iv) power constraint; (v) stable cutting region constraint; (vi) chip-tool interface temperature constraint; (vii) surface finish constraint (only for finish machining); and (viii) parameter relations. These constraints are taken from the work of Shin and Joo [7] as follow:

3.1. Rough machining

Depth of cut:

$$d_{rL} \le d_r \le d_{ru} \quad (6)$$

Cutting speed:

$$V_{rL} \le V_r \le V_{ru} \quad (7)$$

Feed:

$$f_{rL} \le f_r \le f_{ru} \quad (8)$$

Tool-life constraint:

$$T_{rL} \le T_r \le T_{ru} \quad (9)$$

Cutting force constraint:

$$k_1 f_r^u d_r^v \le F_U \quad (10)$$

Power constraint:

$$\frac{k_1 f_r^u d_r^v V_r}{6120\eta} \le P_U \quad (11)$$

Stable cutting region constraint:

$$V_r^\lambda f_r d_r^v \ge S_C \quad (12)$$

Chip-tool interface temperature constraint:

$$Q_r = k_q V_R^{\tau} f_r^{\emptyset} d_r^{\delta} \leq Q_U \tag{13}$$

3.2. Finish machining

Depth of cut:

$$d_{sL} \leq d_s \leq d_{su} \tag{14}$$

Feed:

$$f_{sL} \leq f_s \leq f_{su} \tag{15}$$

Cutting speed:

$$V_{sL} \leq V_s \leq V_{su} \tag{16}$$

Tool-life constraint:

$$T_{sL} \leq T_s \leq T_{su} \tag{17}$$

Cutting force constraint:

$$k_1 f_s^u d_s^v \leq F_U \tag{18}$$

Power constraint:

$$\frac{k_1 f_s^u d_s^v V_s}{6120\eta} \leq P_U \tag{19}$$

Stable cutting region constraint:

$$V_s^{\lambda} f_s d_s^v \geq S_C \tag{20}$$

Chip-tool interface temperature constraint:

$$Q_r = k_2 V_S^{\tau} f_s^{\emptyset} d_s^{\delta} \leq Q_U \tag{21}$$

Surface finish constraint:

$$\frac{f_s^2}{8R} SR_U \tag{22}$$

3.3. Parameter relations

$$V_s \geq k_3 V_r \tag{23}$$

$$f_r \geq k_4 f_s \tag{24}$$

$$d_r \geq k_5 d_5 \tag{25}$$

$$d_r = \frac{(d_t - d_s)}{n} \tag{26}$$

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 Equation (27). Therefore, one can eliminate the equality constraint (Equation (26)) and the decision variable (d_r) in the optimization procedure [34].

$$d_s = d_t - nd_r \tag{27}$$

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. Brief description of parameters of multi-pass turning is shown in Table 1. Further details about the turning mathematical model and data with respect to machining can be obtained from Shin and Joo [7], Chen and Tsai [34], Chen [33], Towsyfyan [35, 36] and Yildiz [37,38,39].

Table1. Description of Parameters

C_0	constant pertaining to tool-life equation	Q_r, Q_s	temperatures during roughing and finishing (◦C)
C_I	machine idle cost ($/piece)	Q_U	maximum allowable temperature (◦C)
C_M	cutting cost by actual time in cut ($/piece)	R_a	maximum allowable surface roughness (mm)
C_R	tool replacement cost ($/piece)	R_n	nose radius of cutting tool (mm)
C_T	tool cost ($/piece)	S_c	limit of stable cutting region
d_r , d_s	depths of cut for each pass of rough and finish machining (mm)	t	tool life (min)
d_{rL}, d_{rU}	lower and upper bounds of depth of rough cut (mm)	t_c	constant term of machine idling time (min)
d_{sL}, d_{sU}	lower and upper bounds of depth of finish cut (mm)	t_e	tool exchange time (min)
d_t	total depth of metal to be removed (mm)	t_p	tool life (min) considering roughing and finishing
D	diameter of work piece (mm)	t_r, t_s	tool lives (min) for roughing and finishing
f_r, f_s	feeds in rough and finish machining (mm/rev)	t_v	variable term of machine idling time (min)
f_{rL}, f_{rU}	lower and upper bounds of feed in rough machining (mm/rev)	T_I	machine idling time (min)
f_{sL}, f_{sU}	lower and upper bounds of feed in finish machining (mm/rev)	T_L, T_U	lower and upper bounds of tool life
F_s, F_s	cutting forces during rough and finish machining (kg f)	T_M	cutting time by actual machining (min)
F_U	maximum allowable cutting force (kg f)	T_{Mr}, T_{Ms}	cutting time by actual machining for roughing and finishing (min)
h_1, h_2	constants pertaining to tool travel and approach/depart time (min)	T_R	tool replacement time (min)
$k_1, k_2,$	constants for roughing and finishing parameter relations	U_c	unit production cost except material cost ($/piece)
k_f	coefficient pertaining to specific tool-work piece combination	V_r	cutting speeds in rough machining (m/min)
k_o	direct labor cost overhead ($/min)	V_s	cutting speeds in finish machining (m/min)
k_q	coefficient pertaining to equation of chip-tool interface temperature	V_{rL}, V_{rU}	lower and upper bounds of cutting speed in rough machining (m/min)
k_t	cutting edge cost ($/edge)	V_{sL}, V_{sU}	lower and upper bounds of cutting speed in finish machining (m/min)
L	length of work piece (mm)	X	vector of machining parameters

n	number of rough passes	τ, φ, δ	constants pertaining to expression of chip-tool interface temperature
p, q, r	constants pertaining to the tool-life equation	η	power efficiency
P_r, P_s	cutting power during roughing and finishing (kW)	λ, υ	constants pertaining to expression of stable cutting region
P_U	maximum allowable cutting power (kW)	λ, υ	constants of cutting force equation

Machining data for this example of multi-pass turning are shown in Table 2.

Table 2; machine data for the example of multi-pass turning.

D = 50 mm	dr = 3.0 mm	dt = 6.0 mm	dt=8.0 mm
L = 300 mm	VrU = 500 m/min	VrL =50 m/min	VsU = 500 m/min
frL= 0.1 mm/rev	frU = 0.9 mm/rev	fsU = 0.9 mm/rev	fsL = 0.1 mm/rev
VsL = 50 m/min	dsU = 3.0 mm	dsL = 1.0 mm	ko = 0.5 $/min
kt =2.5 $/edge	$h1$ = 7 × 10−4	$h2$ = 0.3	tc = 0.75 min/piece
te = 1.5 min/edge	p = 5	q = 1.75	r = 0.75
TU = 45 min	TL = 25 min	kf = 108	μ= 0.75
υ= 0.95	η= 0.85	FU = 200 kg	fPU = 5 kW
λ= 2	ν= −1	Sc = 140	kq = 132
τ= 0.4	ϕ = 0.2	δ= 0.105	QU = 1000 ∘C
Rn = 1.2 mm	Ra = 10	$k1$= 1.0	$k2$ = 2.5
$k3$ = 1.0	C_0 = 6 × 1011		

4. Results and Discussion

4.1. Minimum Cost Function

ICA algorithm is used to optimize the production cost subject to the mentioned constraints. After very careful investigation, ICA parameters were selected based on table 3.

Table3. Parameters Used in ICA

ICA Parameters	
Revolution rate	0. 75
Number of countries	100
Number Of Initial Imperialists	8
Number of decades	200
Assimilation Coefficient (β)	0.5
Assimilation Angle Coefficient (γ)	0.5
Zeta ζ	0.02
Variable min (I, V, S)	(50, 0.1, 50, 0.1, 1)
Variable max (I, V, S)	(500, 0.9, 500, 0.9, 3)

To choose the proper number of countries for the optimization, the algorithm is executed for different number of initial countries and the respected results for the minimum total production cost can be seen in Fig.6. Due to the stochastic nature of the algorithm, each execution of the algorithm results in a different result, therefore in the entire study the best solution out of 10 executions is presented as the optimization result. According to Fig.6, it can be concluded that increasing the number of countries up to 200 slightly improves the results in both dt=6 mm and dt=8 mm cases. Although more increase in the number of initial countries yields in decrease in the objective function, the changes are not considerable. Therefore, the number of countries for this study is set to 200 for the rest of the paper.

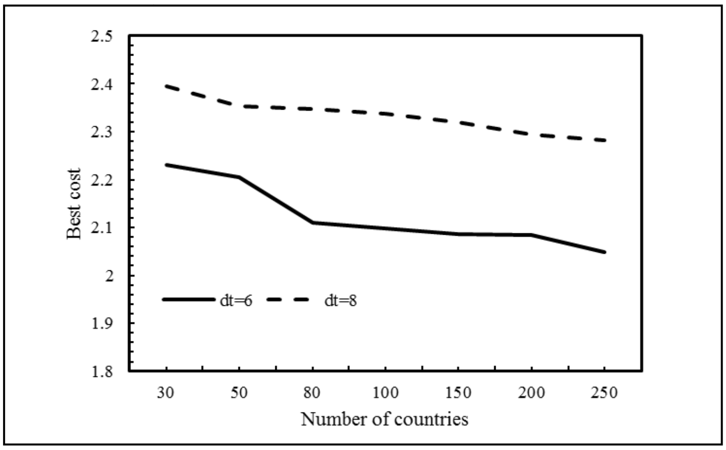


Figure6. Effect of variation of the number of countries on the minimum production cost by different dt=6 mm and dt=8 mm

Figure 7 demonstrates the iteration process of ICA method for optimization of multi-pass turning process. A significant decrease in the target function is seen in the beginning of the evolution process. After certain decades, the changes in the fitness function become relatively minute. The minimum of production cost for dt=6 mm and dt=8 mm after 200 decades was found to 2.0482 and 2.2969 respectively.

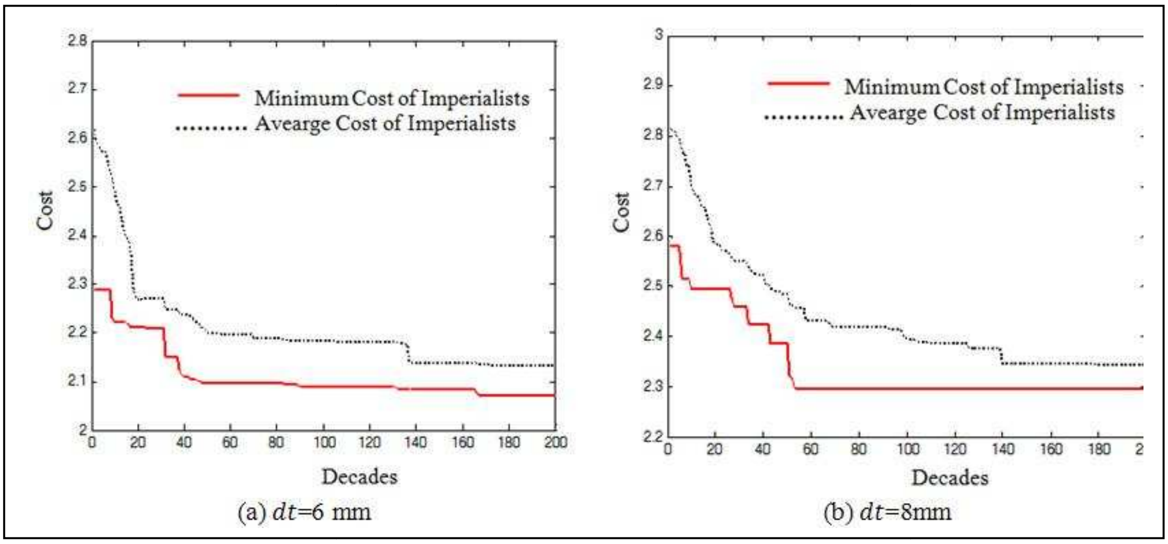


Figure7. Convergence of the Minimum Production Cost Objective; (a) dt=6 mm, (b) dt=8 mm

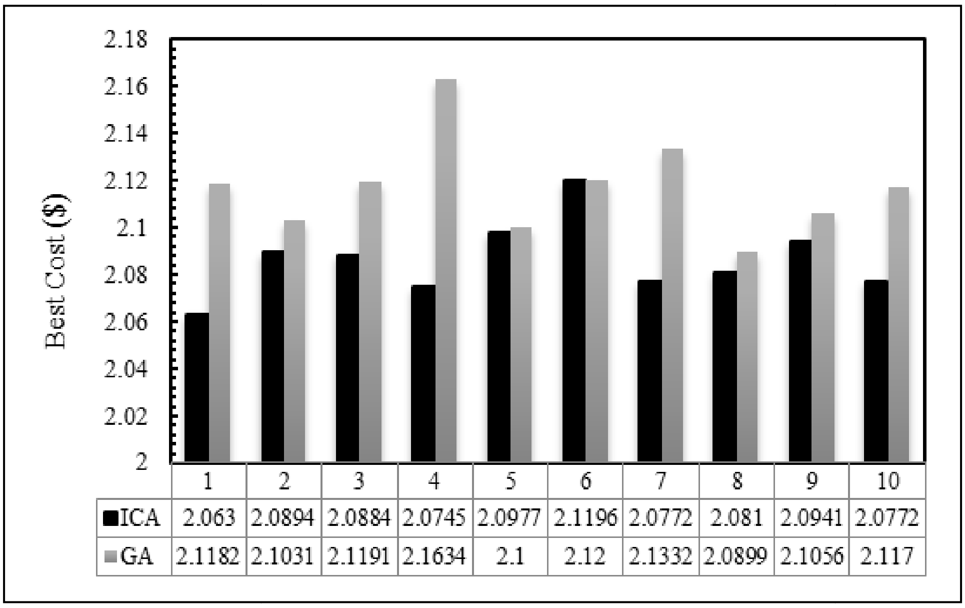
4.2. A Comparison between ICA and GA

A careful investigation is carried out to compare the design efficiency of the proposed algorithm with traditional genetic algorithm (GA). An attempt was initially made to determine the minimum values of C_M, C_I, C_R and C_T for different parameters of dt=6 mm and dt=8 mm. The following GA parameters were determined to yield the best results: probability of mutation p_m=0.45; population size N= 200; maximum number of generation G = 100. To be fair in the comparison, ICA parameters were considered as Table 3, similar to GA configurations. Both ICA and GA algorithms are programmed in MATLAB R2010b and run on an INTEL laptop, CPU Core-i3 2310M, 2.1GHz, RAM 3GB. From the comparison of best results given in Table 4, it can be concluded that the minimization of the unit production cost in multi-pass turning operation is achieved by proposed ICA.

Table4. Comparison of the best computed optimum results for turning problem of ICA and GA

	Algorithm method	Best Cost	$X_1(Vr)$	$X_2(fr)$	$X_3(Vs)$	$X_4(fs)$	$X_5(ds)$	CPU Time (s)
dt=6 mm	ICA	2.0482	460.2441	0.8365	494.7070	0.8909	2.9099	4.5
	GA	2.1079	444.7746	0.8123	498.5915	0.8747	2.5887	19.6
dt=8 mm	ICA	2.2969	440.1702	0.8419	491.5710	0.8939	2.8032	4.4
	GA	2.3259	447.0350	0.7992	491.2865	0.8721	2.8373	19.5

Since the minimum values of cost function is desired, we compare the obtained results in Figure 8. As it is illustrated in Figure 8.a and 8.b, it can be concluded that ICA is more successful for predicting the Minimum production cost (C_U) in less computation time.



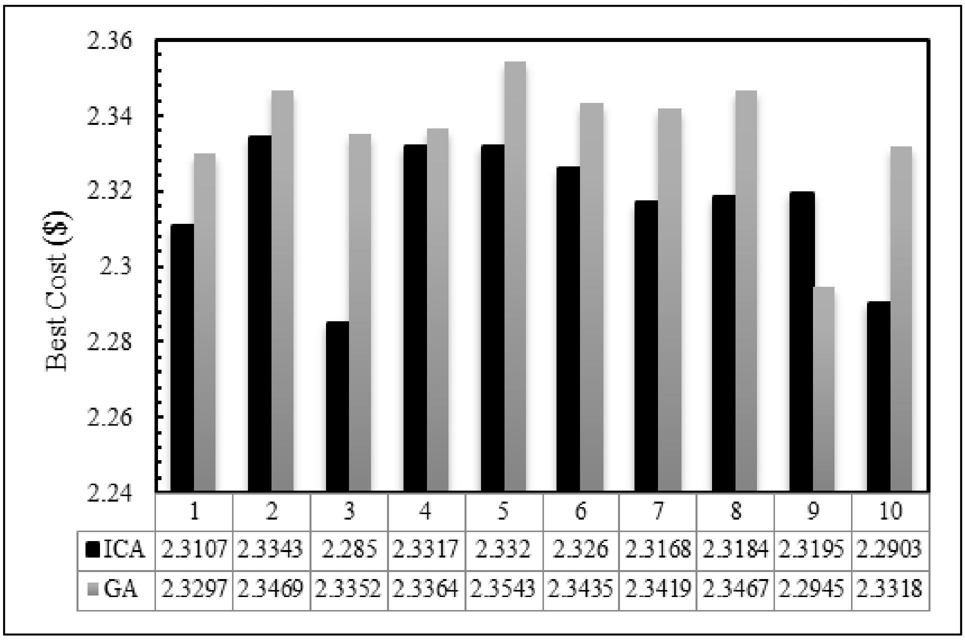


Figure8. Optimization Results for Production Cost; (a), dt=6 mm, (b), dt=8 mm

5. Conclusions

In this paper, the ICA approach has been used to optimize the objective function related to multi-pass turning process. According to the obtained results, the proposed approach comparing to the traditional genetic algorithm shows considerable improvements in finding the optimum results in less computational time under the same population size and iterations. Simplicity, accuracy, and time saving are some of advantages of the ICA algorithm. Moreover, considering the high complexity and non-linear nature of the cost function going to be minimized through analysis and unique and exact solutions obtained from algorithm confirms the ability of ICA in dealing with difficult optimization tasks. In general, ICA has a promising potential to be used as a new solution approach in a variety of problems.

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