



Cutting Parameters Optimization for Minimizing Production Time in Turning Process using Imperialist Competitive Algorithm

Ahmad Esfandiari

Department of Computer Engineering,
Sama College, Islamic Azad University,
Sari Branch, Sari, Iran

Maedeh Mehdizadeh

Department of Computer Engineering,
Mazandaran University of Science and
Technology, Babol, Iran

Abstract: *Imperialist Competitive Algorithm (ICA) is one of the recent meta-heuristic algorithms proposed to solve optimization problems. The ICA has shown excellent capabilities, such as faster convergence and better global optimum achievement. In metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product. In this paper, to find optimal cutting parameters during a turning process, the ICA has been used as an optimal solution finder to optimize the production time within in some operating constraints. Finally, the results of ICA are compared with the genetic algorithm (GA). Comparison shows the success of ICA for cutting parameters selection.*

Keywords: *Cutting parameters; Minimum production time; Imperialist Competitive Algorithm; Genetic Algorithm*

I. INTRODUCTION

Turning is a widely used machining process in manufacturing. Therefore, an optimal selection of cutting parameters to satisfy an economic objective within the constraints of turning operation plays a very important role [1]. Two economic objectives have been considered, i.e., maximum production rate and minimum production cost. In the literature, several optimization studies of cutting parameters for turning operations have been documented [1]. To determine the optimal cutting parameters, reliable mathematical models have to be formulated to associate the cutting parameters with cutting performance. However, it is also well known that reliable mathematical models are not easy to obtain.

To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the machining parameters when the process parameters are selected in CNC machining. In general, machining economics involves the optimum selection of machining conditions, e.g. cutting speed, feed and depth of cut. The machining parameters directly affect the cost, productivity and quality of products.

In the past decade, the new trend in the optimization of the machining processes has been based on the use of meta-heuristic algorithms [2-10].

The aim of this paper is the construction of a mathematical model describing the objective function in terms of the cutting parameters that minimize the production time with some operating constraints, then; the mathematical model was optimized by using the Imperialist Competitive Algorithm (ICA). To validate the proposed approach, compare is made against Genetic Algorithm (GA).

II. IMPERIALIST COMPETITIVE ALGORITHM

Imperialist Competitive Algorithm (ICA) simulates the socio-political process of imperialism and imperialistic competition [11, 12]. This algorithm contains a population of agents or countries. This meta-heuristic optimization algorithm has shown excellent capabilities, such as faster convergence and better global optimum achievement [13]. Fig. 1 shows the flowchart of the ICA. The steps of the algorithm are as follows [11]:

A. Creation of initial empires

The goal of optimization is to find an optimal solution in terms of the variables of the problem. We form an array of variable values to be optimized. In the GA terminology, this array is called 'chromosome', but in ICA the term 'country' is used for this array. In an N_{var} -dimensional optimization problem, a country is a $1 \times N_{var}$ array. This array is defined as following:

$$\text{Country} = [p_1, p_2, p_3, \dots, p_{N_{var}}],$$

where p_{is} are the variables to be optimized. The variable values in the country are represented as floating point numbers. Each variable in the country can be interpreted as a socio-political characteristic of a country. The cost of a country is found by evaluation of the cost function f at variables $(p_1, p_2, p_3, \dots, p_{N_{var}})$. So we have:

$$\text{cost} = f(\text{country}) = f(p_1, p_2, p_3, \dots, p_{N_{var}}). \quad (1)$$

To start the optimization algorithm, initial countries of size $N_{Country}$ is produced. We select N_{imp} of the most powerful countries to form the empires. The remaining N_{col} of the initial countries will be the colonies each of which belongs to an empire. As a result, we will have two types of countries: imperialist and colony. Now, we divide the N_{col} colonies among N_{imp} imperialists. We define the normalized cost of an imperialist by:

$$C_n = c_n - \max_i \{c_i\}, \tag{2}$$

where c_n is the cost of the n th imperialist and C_n is its normalized cost. Having the normalized cost of all imperialists, the normalized power of each imperialist is defined by:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{3}$$

So, the initial number of colonies of the n th empire will be:

$$N.C_n = \text{round}\{p_n \cdot N_{col}\}, \tag{4}$$

where $N.C_n$ is the initial number of colonies of the n th empire and N_{col} is the total number of initial colonies. To divide the colonies, $N.C_n$ of the colonies are randomly chosen and given to the n th imperialist. These colonies along with the n th imperialist form the n th empire. Fig. 2 shows the initial empires where more powerful empires have greater number of colonies.

B. Assimilation: movement of colonies toward the imperialist

In the ICA, the assimilation policy is modeled by moving all the colonies toward the imperialist. This movement is shown in Fig. 3 in which a colony moves toward the imperialist by x units.

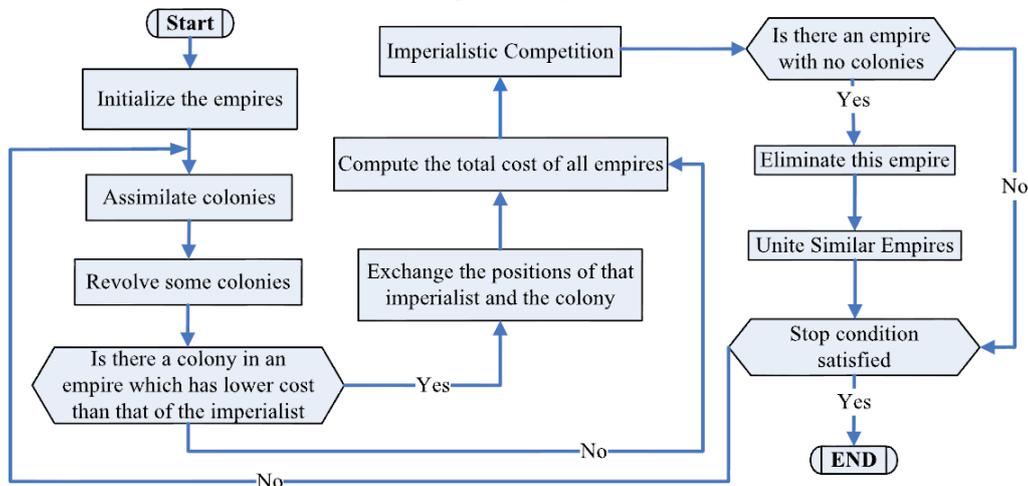


Fig. 1. Flowchart of the ICA[11].

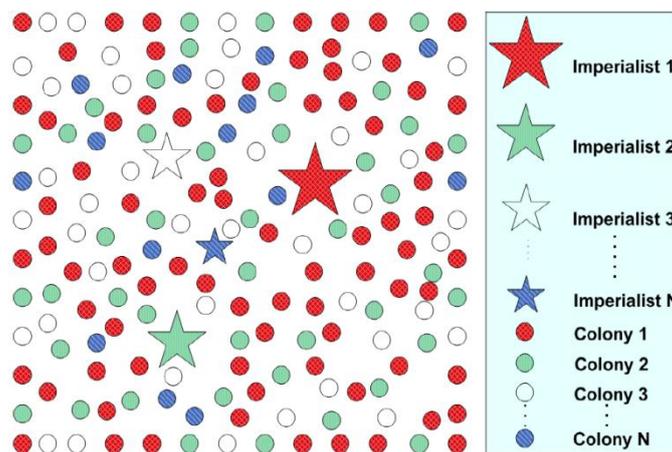


Fig. 2. Generating the initial empires: The more colonies an imperialist possess, the bigger is its relevant (★) mark.

In this figure x is a random variable with uniform distribution. Then

$$x \in U(0, \beta \times d), \beta > 1 \tag{5}$$

where d is the distance between the colony and the imperialist state. $\beta > 1$ causes the colonies to get closer to the imperialist state from both sides.

Assimilating the colonies by the imperialist states did not result in direct movement of the colonies toward the imperialist. That is, the direction of movement is not necessarily the vector from colony to the imperialist. To model this fact and to increase the ability of searching more area around the imperialist, a random amount of deviation is added to the direction of movement. Fig. 4 shows the new direction. In this figure θ is a parameter with uniform (or any proper) distribution. Then

$$\theta \in U(-\gamma, \gamma), \tag{6}$$

where γ is a parameter that adjusts the deviation from the original direction.

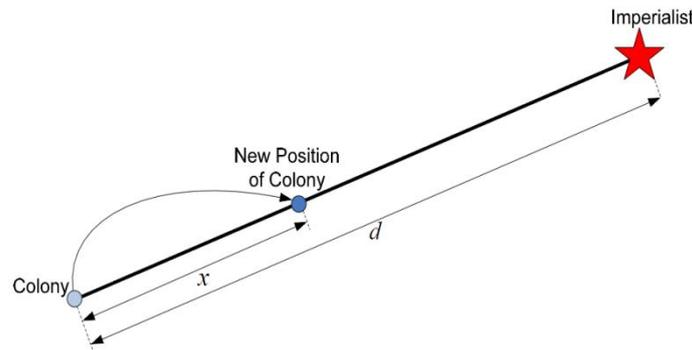


Fig. 3. Movement of colonies toward their relevant imperialist.

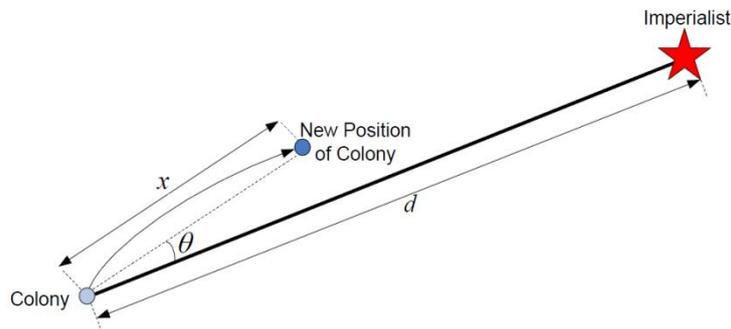


Fig. 4. Movement of colonies toward their relevant imperialist in a randomly deviated direction.

C. Revolution

In the terminology of ICA, revolution causes a country to suddenly change its socio-political characteristics. The revolution increases the exploration of the algorithm and prevents the early convergence of countries to local minima. The revolution rate in the algorithm indicates the percentage of colonies in each empire which will randomly change their position.

D. Exchanging positions of the imperialist and a colony

While moving toward the imperialist, a colony might reach to a position with lower cost than the imperialist. In this case, the imperialist and the colony change their positions. Then, the algorithm will continue by the imperialist in the new position and the colonies will be assimilated by the imperialist in its new position.

E. Total power of an empire

Total power of an empire is mainly affected by the power of imperialist country. However, the power of the colonies of an empire has an effect, albeit negligible, on the total power of that empire. This fact is modeled by defining the total cost of an empire by:

$$T.C. = Cost(imperialist_n) + \xi mean\{Cost(colonies_of_empire_n)\} \tag{7}$$

where $T.C._n$ is the total cost of the n th empire and ξ is a positive small number.

F. Imperialistic competition

All empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones. Fig.5 shows an imperialistic competition. To start the competition, first, a colony of the weakest empire is chosen and then the possession probability of each empire is found. The possession probability PP is proportionate to the total power of the empire. The normalized total cost of an empire is simply obtained by:

$$N.T.C._n = T.C._n - \max_i \{T.C._i\}, \tag{8}$$

where $T.C._n$ and $N.T.C._n$ are the total cost and the normalized total cost of n th empire, respectively. Having the normalized total cost, the possession probability of each empire is given by:

$$P_{Pn} = \left| \frac{N.T.C._n}{\sum_{i=1}^{N_{imp}} N.T.C._i} \right| \tag{9}$$

To divide the mentioned colonies among empires, vector \mathbf{P} is formed as follows:

$$P = [P_{P_1}, P_{P_2}, P_{P_3}, \dots, P_{P_{N_{imp}}}] \quad (10)$$

Then, the vector **R** with the same size as **P** whose elements are uniformly distributed random numbers is created.

$$R = [r_1, r_2, r_3, \dots, r_{N_{imp}}] \cdot U(0,1) \quad (11)$$

Finally, we have vector **D** by:

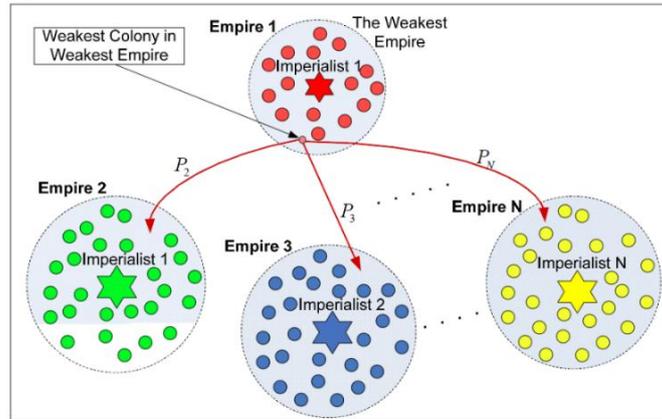


Fig. 5. Imperialistic competition: The more powerful an empire is, the more likely it will possess the weakest colony of the weakest empire.

$$D = P - R = [D_1, D_2, D_3, \dots, D_{N_{imp}}] = [P_{P_1} - r_1, P_{P_2} - r_2, P_{P_3} - r_3, \dots, P_{P_{N_{imp}}} - r_{N_{imp}}] \quad (12)$$

Referring to vector **D**, the mentioned colony (colonies) is handed to an empire whose relevant index in **D** is maximized.

G. Convergence

Different criteria can be used to stop the algorithm. One idea is to use a number of maximum iteration of the algorithm, called maximum decades, to stop the algorithm. Or the end of imperialistic competition, when there is only one empire, can be considered as the stop criterion of the ICA. On the other hand, the algorithm can be stopped when its best solution in different decades cannot be improved for some consecutive decades [13].

III. OPTIMIZATION OF CUTTING PARAMETERS

A. Production model design

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning module with other auto-mated systems such as production, transportation, assembly, etc.

Process planning involves determination of appropriate machines, tools for machining parts, cutting fluid to reduce the average temperature within the cutting zone and machining parameters under certain cutting conditions for each operation of a given machined part [14, 15].

In machining economics problem, there are a large number of factors that can be considered. In general, machining economics involves the optimum selection of machining conditions, e.g. cutting speed, feed and depth of cut. The machining parameters directly affect the cost, productivity and quality of products.

A typical optimization problem of a machining operation comprises one or multiple economic objectives with several machining constraints. The economic objectives may include: (1) maximum production rate or minimum unit production time; (2) minimum unit production cost; and (3) maximum profit rate. In general, modeling the machining optimization problem requires explicit knowledge of the machining process [16].

Several cutting constraints that should be considered in machining economics include: tool-life, cutting force, power, stable cutting region, chip-tool interface temperature, surface finish, and roughing and finishing parameter relations [14].

The purpose of this paper is to determine such a set of the cutting conditions v (cutting speed), f (feedrate), a (depth of cut), that minimize the production time without violating any imposed cutting constraints.

Several practical cutting constraints that were considered in the optimization of the production time in machining economics include: tool-life constraint, cutting force constraint, power, stable cutting region constraint, chip-tool interface temperature constraint, surface finish constraint, roughing and finishing parameter relations, and the number of passes.

Usually, the production rate is measured as the entire time necessary for the manufacture of a product (T_p). It is the function of the metal removal rate (MRR) and of the tool life (T) [17]:

$$T_p = T_s + V(1 + T_c/T)/MRR + T_i \quad (13)$$

where T_s , T_c , T_i and V are the tool set-up time, the tool change time, the time during which the tool does not cut and the volume of the removed metal. In some operations the T_s , T_c , T_i and V are constants so that T_p is the function of MRR and T .

The material removal rate MRR can be expressed by analytical derivation as the product of the cutting speed, feeding and cutting depth:

$$MRR = 1000 * v * f * a \tag{14}$$

The tool life (T), is measured as the average time between the tool changes or tool sharpening. The relation between the tool life and the parameters is expressed with the well-known Taylor's formula:

$$T = K_T / v^{\alpha_1} * f^{\alpha_2} * a^{\alpha_3} \tag{15}$$

where the k_T , a_1 , a_2 and a_3 , which are always positive constant parameters, are determined statistically[17].

The most important criterion for the assessment of the surface quality is roughness, R_a , calculated according to:

$$R_a = K * v^{x_1} * f^{x_2} * a^{x_3} \tag{16}$$

where x_1 , x_2 , x_3 and K are the constants relevant to a specific tool-workpiece combination.

There are several factors limiting the cutting parameters. Those factors originate usually from technical specifications and organizational considerations. 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 allowable limit. Allowable ranges of cutting conditions are:

$$v_{min} \leq v \leq v_{max}, f_{min} \leq f \leq f_{max}, a_{min} \leq a \leq a_{max} \tag{17}$$

There are some other constraints related to the machine features such as cutting power and force constraints. The consumption of the power, P , can be expressed as the function of the cutting force, F , and cutting speed:

$$P = \frac{F.v}{6122.45 * \eta} \tag{18}$$

where η is the mechanical efficiency of the machine and F (cutting force) is given by following formula:

$$F = k.f^{\beta_2} .a^{\beta_3} \tag{19}$$

where the k , β_2 and β_3 , which are constant parameters, are determined statistically.

The constraints of the power and cutting force are equal to:

$$P(v, f, a) \leq P_{max}, F(v, f, a) \leq F_{max} \tag{20}$$

The problem of the optimization of cutting parameters can be formulated by defining the goal function as the minimum production time, T_p :

$$\min T_p(v, f, a) \tag{21}$$

B. Illustrative example and results

On the NC lathe we want to machine a cast steel blank by means of the tool made from HSS. The task is to find optimum cutting conditions for the process of turning. The values of coefficients are statistically determined on the basis of the data measured experimentally. Values of coefficients:

$$\begin{aligned} T_s &= 0.12 \text{ min} & T_c &= 0.26 \text{ min} & T_i &= 0.04 \text{ min} & K &= 1.001 \\ K_T &= 1686145.34 & x_1 &= 0.0088 & x_2 &= 0.3232 & x_3 &= 0.3144 \\ \alpha_1 &= 1.70 & \alpha_2 &= 1.55 & \alpha_3 &= 1.22 & V &= 251378 \text{ mm}^3 \\ \beta_1 &= 0 & \beta_2 &= 1.18 & \beta_3 &= 1.26 & P &= 4420.5 \text{ W} \end{aligned}$$

The objective function is fixed as the minimum production time, T_p :

$$\min T_p = T_s + V / (1000 * v * f * a) + \left(V * T_c * \left(v^{(1/n-1)} * f^{(m/n-1)} * a^{(r/n-1)} \right) \right) / (1000 * P^{(1/n)}) + T_i \tag{22}$$

Where:

$m = 0.9117$, $n = 0.5882$, $r = 0.7176$, $v_{min} = 70$ m/min, $v_{max} = 100$ m/min, $f_{min} = 0.1$ mm/rev, $f_{max} = 1$ mm/rev, $a_{min} = 0.1$ mm, $a_{max} = 5.0$ mm, $F_{max} = 230$ N and $P_{max} = 5$ kW.

The optimization problem is determining the cutting parameters that minimize the production time using of ICA. After very careful investigation, ICA parameters were selected based on Table 1.

For the GA the following parameters were used to reach the best solution: initial population=100; probability of crossover=0.5; probability of mutation=0.4; Rank scaling function, Tournament selection function, single point crossover function and Gaussian mutation function.

Table 1: ICA parameters

ICA Parameters	
Revolution rate	0.35
Number of Countries	90
Number of initial imperialist	8
Number of decades	35
Assimilation Coefficient (β)	0.55
Assimilation Angle Coefficient (γ)	0.5
Zeta (ζ)	0.02

To choose the proper number of countries the ICA executed for different number of initial countries. Table 2 shows the Effect of variation of the number of countries on cutting parameters in ICA with eight imperialists. As seen in Table 2, increasing the number of countries up to 90-100 improves the results. Therefore, the number of countries for this study set to 90. Table 3 shows Effect of variation of the number of imperialists on cutting parameters in ICA with 90 countries. According to this Table, the best results occur when the number of empires is 8. If the number is lower or greater than 8, the algorithm loses the optimal solution. The cutting parameters and minimum of objective function for different numbers iterations in ICA and GA are shown in Table 4. GA is reached to best cost 0.6642 at iterations 51. ICA has achieved to 0.6641 at iterations 35. The results of the two algorithms show that ICA converges to the optimal solution faster than the GA. Also, the accuracy of the ICA is better than GA.

Fig. 6 shows the initial empires, empires at iteration 15, empires at iterations 25 and 40 (maximum iteration) in ICA. ICA has reached to global optima at iterations 35. Fig. 7 and 8 show the minimum and mean costs the objective function using GA and ICA, respectively. It can be observed that the objective function converges within about 51 generations in the GA. Also, according to Fig. 8 the ICA converges within about 35 generations. Comparing the convergence rate of GA and ICA can be beneficiary too. Fig. 9 compares the convergence rate of both algorithms for finding the optimal solution. The comparison results show that the convergence rate of ICA is more than of GA.

Table 2: Effect of variation of the number of countries on cutting parameters in ICA with eight imperialists

Imperialists number	v(m/min)	f(mm/rev)	a(mm)	Best Cost
3	99.5957	0.9997	4.9981	0.6665
5	97.7026	0.9997	5.0000	0.6761
8	100	1	5	0.6641
10	99.6140	1.0000	5.0000	0.6661
12	98.6516	0.9892	4.9976	0.6768
15	99.9217	0.9939	4.9998	0.6676
17	94.6391	0.9983	4.9905	0.6945
20	94.8859	0.9988	4.9955	0.6923

Table 3: Effect of variation of the number of imperialists on cutting parameters in ICA with 90 countries

Countries number	v(m/min)	f(mm/rev)	a(mm)	Best Cost
30	92.7331	0.9199	4.9937	0.7513
40	97.3702	0.9514	4.9803	0.7062
50	93.8126	1.0000	4.9998	0.6973
60	99.4872	0.9992	4.9823	0.6689
70	97.8000	1.0000	5.0000	0.6754
80	99.7978	0.9974	4.9977	0.6667
90	100	1	5	0.6641
100	100	1	5	0.6641

Table 4: Comparison of results in ICA and GA

Method	Iteration	v(m/min)	f(mm/rev)	a(mm)	Best Cost
ICA	1	93.8200	0.9638	4.7301	0.7490
	3	99.8049	0.9459	4.8212	0.7136
	5	99.6716	0.9203	4.9734	0.7123
	8	94.7191	0.9867	4.9378	0.7060
	10	95.4670	0.9955	4.9721	0.6933
	15	97.1376	1.0000	4.9975	0.6792
	20	97.2264	1.0000	5.0000	0.6785
	25	99.6269	1.0000	4.9988	0.6662
	30	99.9831	1.0000	4.9996	0.6643
	35	100	1	5	0.6641
GA	1	81.234	0.951	1.883	1.8896
	5	93.135	0.858	2.915	1.2403
	8	99.192	0.73	4.725	0.8962
	10	98.965	0.887	4.551	0.7906
	15	95.817	0.924	4.995	0.7295
	20	99.415	0.947	4.974	0.6980
	25	00.904	0.996	5	0.6668
	30	99.684	0.993	5	0.6690
	35	99.998	0.997	4.998	0.6655
	40	99.991	1	4.998	0.6645
	45	99.988	1	4.999	0.6643
	51	99.999	1	4.999	0.6642

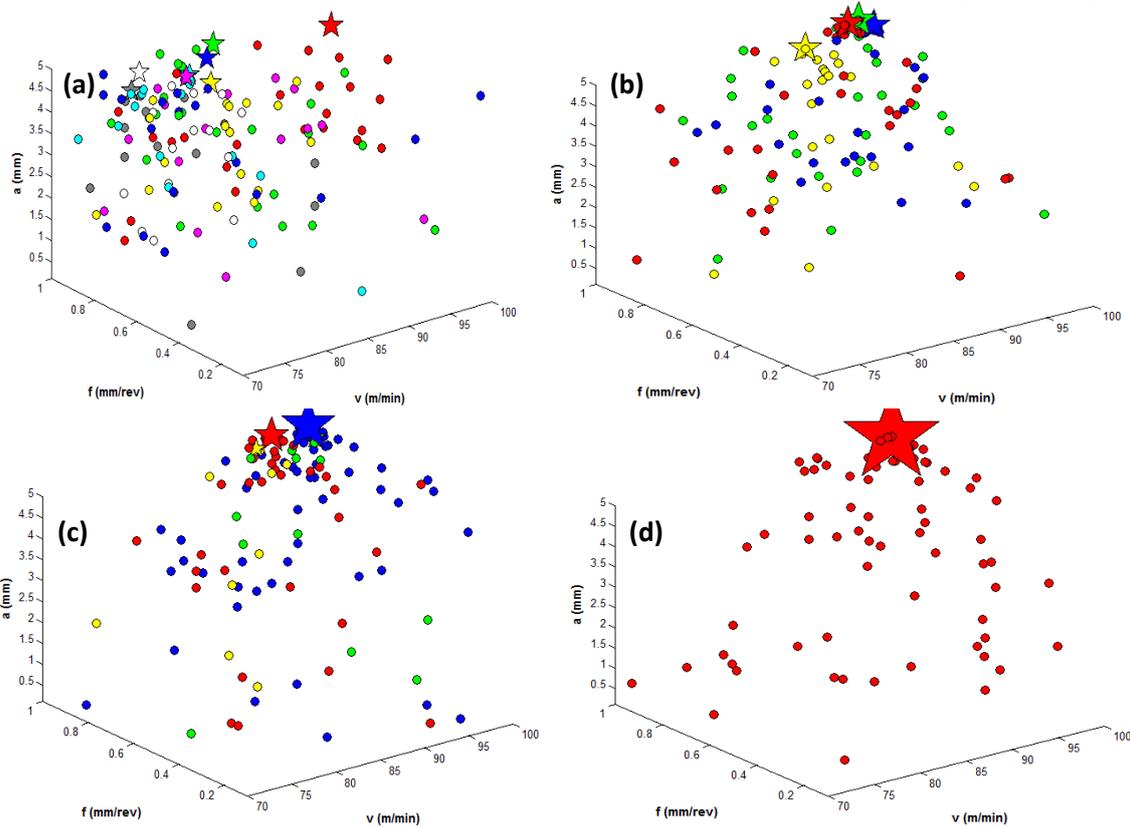


Fig. 6. ICA empires; (a) Initial empires, (b) empires at iteration 15, (c) empires at iteration 25, (d) final solution

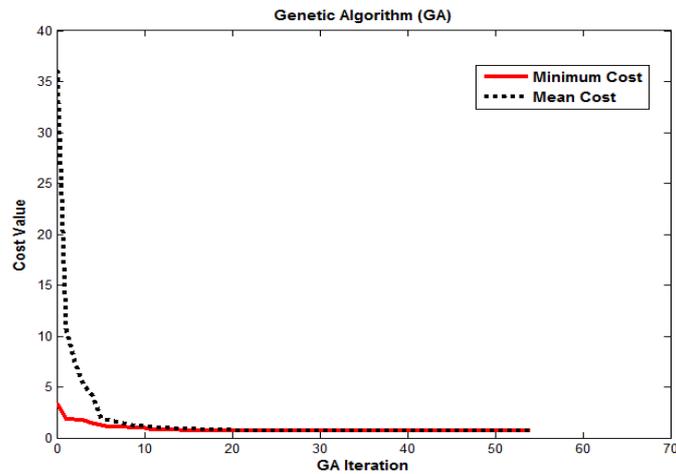


Fig. 7. Minimum and mean cost of GA versus iteration.

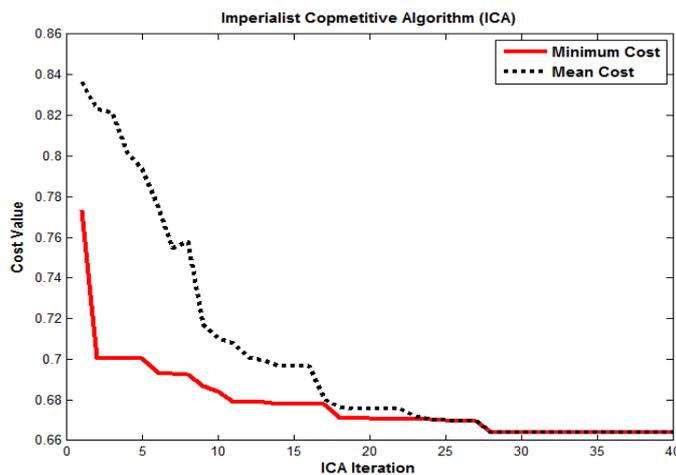


Fig. 8. Minimum and mean cost of ICA versus iteration.

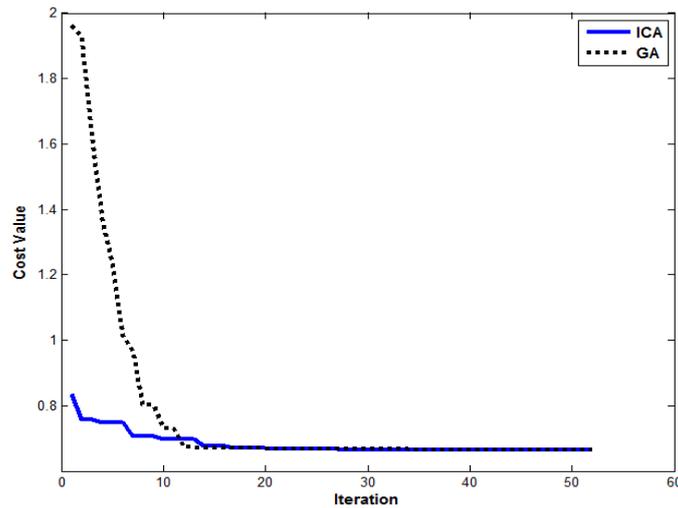


Fig. 9. Convergence of the ICA algorithm compared with GA.

IV. CONCLUSION

In metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product. In this paper, we have proposed an Imperialist Competitive Algorithm to find optimal cutting parameters during a turning process. Process optimization has to yield minimum production time, while considering technological and material constrains.

The results obtained from the ICA have presented a fast and suitable solution for automatic selection of the machining parameters. Also, the optimization results are compared with the ones of genetic algorithm. This comparison shows that the results of ICA are more optimized than genetic algorithm and the number of its iteration is less than genetic algorithm.

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