Optimization of Cutting Parameters Based on Production Time Using Colonial Competitive (CC) and Genetic (G) Algorithms

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Abstract
A properly designed machining procedure can significantly affect the efficiency of the production lines. To minimize the cost of machining process as well as increasing the quality of products, cutting parameters must permit the reduction of cutting time and cost to the lowest possible levels. To achieve this, cutting parameters must be kept in the optimal range. This is a non-linear optimization with constrains and it is difficult for the conventional optimization algorithms to solve this problem. This paper presents Colonial Competitive Algorithm (CCA) approach to determine the optimal cutting parameters required to minimize the cutting time while maintaining an acceptable quality level.CCA is inspired by competition mechanism among imperialists and colonies, in contrast to evolutionary algorithms that perform the exploration and exploitation in the solution space aiming to efficiently find near optimal solutions using a finite sequence of instructions. Therefore, a case study from literature was considered and optimized using of CCA. To validate the proposed approach, the results of CCA were finally compared with the Genetic Algorithm (GA). Based on the results, CCA has demonstrated excellent capabilities such as accuracy, faster convergence and better global optimum achievement.

Keywords
Optimization, Cutting process, Colonial Competitive Algorithm

1. Introduction

The machining processes are commonly used by manufacturers to produce near net shape, high quality and complex products in a brief period. These machining processes include different input variablesthat have conflictingeffects on the cost and quality of the products. Therefore, selection of optimum machining variables in such processes is of high importance to satisfy all the conflicting objectives of the metal cutting operations. Since the output variables of the machining process (i.e. material removal rate and surface roughness) depend on the cutting conditions, the decision concerning selection of the optimal cutting parameters is crucial. This is a nonlinear optimization problem that arises from the nonlinear dynamic nature of cutting process. To solve this problem, evolutionary algorithms such as Genetic Algorithm (GA) [1-4] , Particle Swarm Optimization Algorithm (PSO) [5], immune algorithm [6] and differential evolution algorithm [7-9] have been used instead of conventional techniques such as regression analysis or stochastic programming.

These optimization techniques are either stuck at local optimum or take a long time to converge to a reasonable result.

Colonial Competitive Algorithm [10] 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 CCA 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 as following

In Atashpaz-Gargari et al. [11], CCA 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. [12] used CCA for reverse analysis of an artificial neural network in order to characterize the properties of materials from sharp indentation test. Nazari et al. [13] solved the integrated product mix-outsourcing (which is a major problem in manufacturing enterprise) using CCA. Kaveh and Talatahari [14] utilized the CCA to optimize design of skeletal structures. Yousefi et al. [15] presented the application of Colonial Competitive Algorithm for optimization of cross-flow plate fin heat exchanger and concluded that CCA 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. [16] applied CCA to optimize intermediate epoxy adhesive layer which is bonded between two dissimilar strips of material. They compared the results of CCA with the Finite Element Method (FEM) and Genetic Algorithm; they showed the success of CCA for designing adhesive joints in composite materials.Amin Kolahdooz et al. demonstrated the potential of Colonial Competitive Algorithm (CCA) for optimization of multi pass turning process [17]. In another study, Towsyfyan et al. applied CCA to optimize the media flow speed, percentage concentration of abrasive, abrasive mesh size, number of cycles and the objective function for Abrasive Flow Machining (AFM) processes [18].

In this paper, the basic idea of Colonial Competitive Algorithm (CCA) is introduced and applied for optimization of production cutting time of end-milling operations based on the work of Jeang [19].

To validate the proposed approach, compare is made against GA method.Genetic Algorithm (GA) is an optimisation method that is non-deterministic and population-based. It was Holand [20] who brought this technique to light. What marks this method is its dependence on imitating natural evolution: only the fittest will survive. In other words, the genetic properties of the parents are changed so that new generation of individuals will be fitter than the previous ones.

For this change, mutation and crossover are used among other genetic processes to achieve the desired effect. Of course, global optimum is the utmost objective of these genetic operations, so they are modified and set for this purpose. Currently, there are four major genetic operations that create the cornerstone of genetic algorithm technique: Tournament Selection, Crossover (Single-point crossover and Multiple-point crossover), mutation and elitism [21]. Figure 1 shows the optimisation process of a GA.

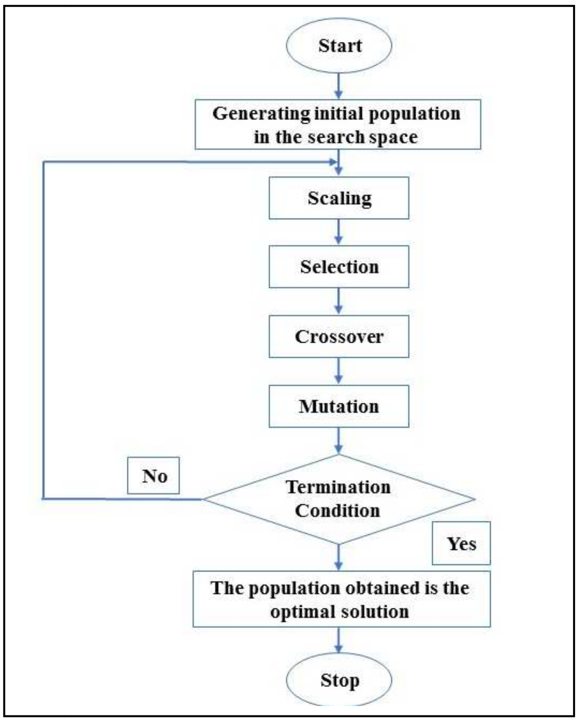

Figure1. Genetic algorithm flow chart

2.Colonial Competitive Algorithm

The proposed algorithm mimics the social–political process of imperialism and imperialistic competition. CCA 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:

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

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 2 where more powerful empires have greater number of colonies.

Figure2. 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 3.

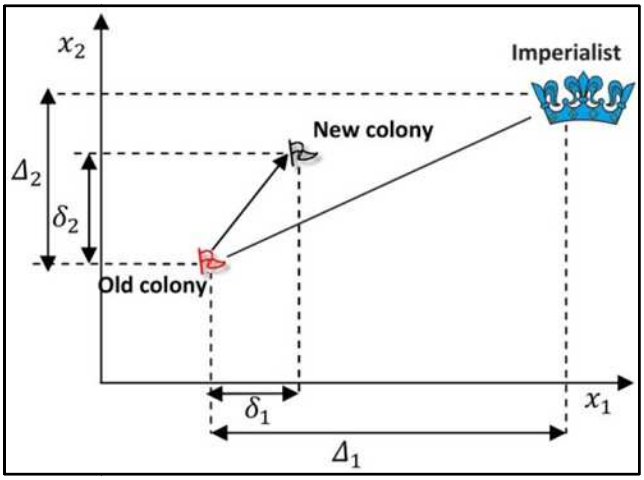

Figure3. Movement of colonies toward their relevant imperialist

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.

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

$$\theta \sim U(-\gamma, \gamma) \tag{3}$$

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 CCA 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. Figure 4 demonstrates a schematic of this process.

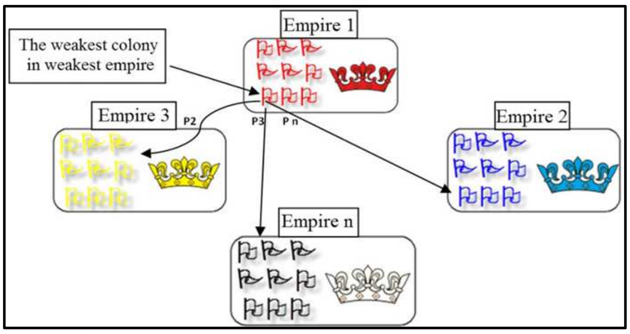

Figure4. Imperialistic competition: The more powerful an empire is, the more likely it will possess the weakest colony of the weakest empire

In this Figure empire 1 is considered as the weakest empire, where one of its colonies is under competition process. The empires 2 to *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. Figure 5 depicts a schematic view of this algorithm. Whenever the convergence criterion is not satisfied, the algorithm continues.

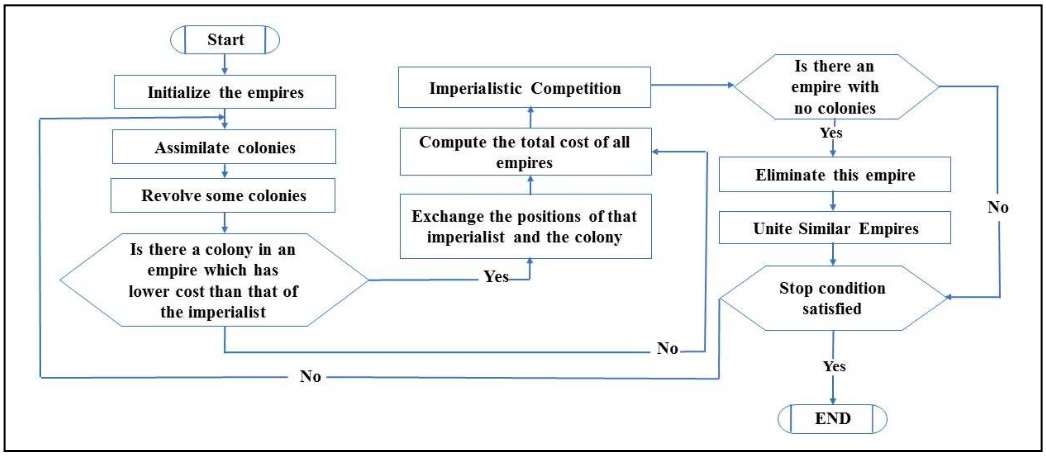

Figure5. Flowchart of the Colonial Competitive Algorithm

3. Problem Statement

Based on the work of Jeang [19] the application of proposed approach was concerned with the minimization of production time of end-milling operations for the geometrical solid part shown in Figure 6.

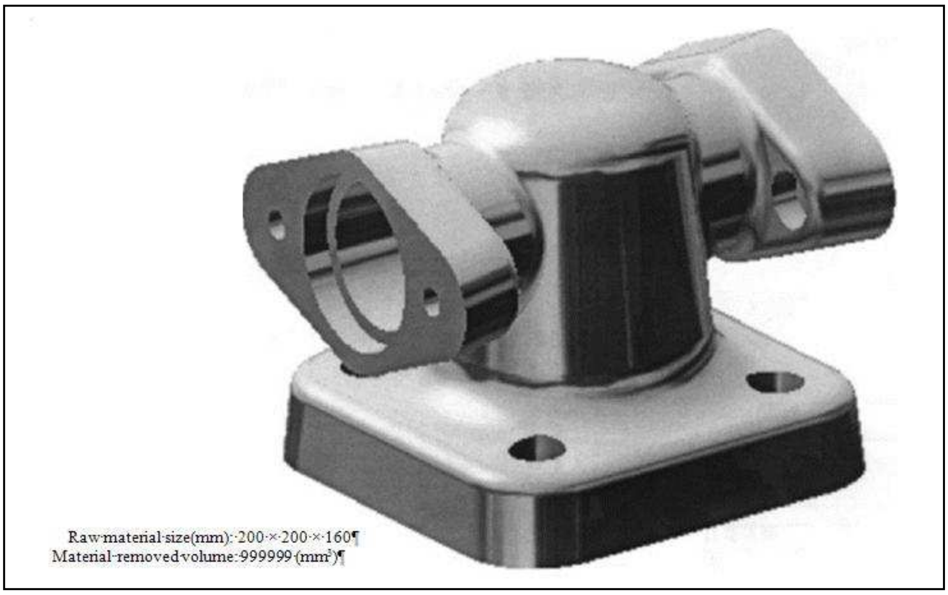

Figure6. Geometrical solid model of the part (Adopted from [19])

Jeang [19] considered the response surface methodology (RSM) for mathematical modeling of the optimization problem. Based on this method, the cutting time equation, an exact functional relationship between inputs of cutting parameters and outputs of cutting time and the importance ranking can be obtained from statistical analysis. Assume that the designer is concerned with a system involving a dependent variable Y, which depends on the independent variable X_j. It is also assumed that X_j is continuous and controllable. With RSM, the functional relationship between the response Y and the levels of n input independent variables can be written as:

$$y = f(X_1, X_2, \dots, X_n)) \tag{4}$$

A mechanistic model for such a relationship does not necessarily exist. Thus, the first step in RSM is to find a suitable approximation for $f(X_1, X_2, \dots, X_n)$using a low-order polynomial in some region of the independent variables. If the approximated function has linear variables, a first-order polynomial can be used and written in terms of the independent variables:

$$y = f(X_1, X_2, \dots, X_n) = a_0 + a_1X_1 + a_2X_2 + \cdots\ a_nX_n \tag{5}$$

Otherwise, a second-order polynomial can be used:

$$y = f(X_1, X_2, \dots, X_n) = a_0 + \sum_{i=1}^{n} a_iX_i + \sum_{i=1}^{n} a_iX_i^2 + \sum_{i=1}^{n} \sum_{j=i+1}^{n-1} C_{ij}X_1X_j \tag{6}$$

Interested readers may refer to works of [22-24] for a detailed discussion on the principle of the RMS.

With reference to response surface analysis carried out by Jeang [19], the approximate prediction function of the cutting time (CT) can be mathematically stated as follow:

$$\begin{aligned} CT = {} & 186.138164 - 818.990391U_1 - 0.175875U_2 - 45.512888U_3 - 0.207139U_4 \\ & - 1333.663147t_1 - 0.800158t_2 - 115.761923t_3 - 6.080922t_4 \\ & + 1849.178628U_1^2 + 0.581895U_1U_2 - 0.000121U_2^2 + 99.896494U_3U_1 + U_3U_2 \\ & + 3.170921U_3^2 - 2.287801U_4U_1 - 0.001648U_4U_2 - 0.037862U_4U_3 \\ & + 0.009124U_4^2 + 3181.641725t_1U_1 + 3.777632t_1U_2 + 6.503827t_1U_3 \\ & - 0.085769t_1U_4 - 11988t_1^2 - 1.243108t_2U_1 - 0.00594t_2U_2 - 0.038822t_2U_3 \\ & - 0.002115t_2U_4 + 99.383651t_2t_1 + 0.011173t_2^2 + 498.293313t_3U_1 \\ & - 0.99119t_3U_2 - 9.427224t_3U_3 + 0.029579t_3U_4 - 1708.205889t_3t_1 \\ & + 5.160582t_3t_2 + 508.680105t_3^2 - 21.518899t_4U_1 - 0.01622t_4U_2 \\ & + 0.032537t_4U_3 + 0.01218t_4U_4 + 482.84453t_4t_1 + 0.391119t_4t_2 \\ & + 37.582409t_4t_3 - 0.320419t_4^2 \end{aligned} \tag{7}$$

Equation 7 is the objective (cost) function that aims to be minimized in this Study. U_1 and t_1 are the mean and tolerance values of the feed rate (mm/rev), U_2 and t_2 are the mean and tolerance values of the cutting speed (m/min), U_3 and t_3 are the mean and tolerance values of depth of the cut (mm), and U_4 and t_4 are the mean and tolerance values of the percentage of tool diameter. According to the work of Jeang [19], Uj and tj are the controllable factor levels and represented by Equations 8 to 15:

$$0.056 \leq U_1 \leq 0.150, \tag{8}$$
$$100.0 \leq U_2 \leq 150.0, \tag{9}$$
$$1 \leq U_3 \leq 5, \tag{10}$$
$$24 \leq U_4 \leq 75, \tag{11}$$
$$0.003 \leq t_1 \leq 0.009 \tag{12}$$
$$6 \leq t_2 \leq 12, \tag{13}$$
$$0.9 \leq t_3 \leq 0.15, \tag{14}$$
$$1 \leq t_4 \leq 2 \tag{15}$$

4. Result and Discussion

CCA algorithm is used to minimize the cutting time subject to the mentioned constraints. After very careful investigation, CCA parameters were selected based on Table 1.

Table1. Parameters used in CCA

CCA Parameters	
Revolution rate	0.3
Number of Countries	200
Number Of Initial Imperialists	5
Number of decades	200
Assimilation Coefficient (β)	0.5
Assimilation Angle Coefficient (γ)	0.5
Zeta ζ	0.02
Variable min (U_1,U_2, U_3, U_4, t_1, t_2, t_3, t_4)	(0.056, 100, 1, 25, 0.003, 6, 0.09, 1)
Variable max (U_1,U_2, U_3, U_4, t_1, t_2, t_3, t_4)	(0.150, 150, 5, 75, 0.009, 12, 0.15 2)

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 cutting time can be seen in Figure 7. According to Figure7, it can be seen that in this case study the variation of the objective function is high for the number of countries less than 150. Increasing the number of countries up to 200 slightly improves the results. Although more increase in the number of initial countries yields in decrease in the objective function, the changes arenot considerable. Therefore, the number of countries for this study is set to 200 for the rest of the paper.

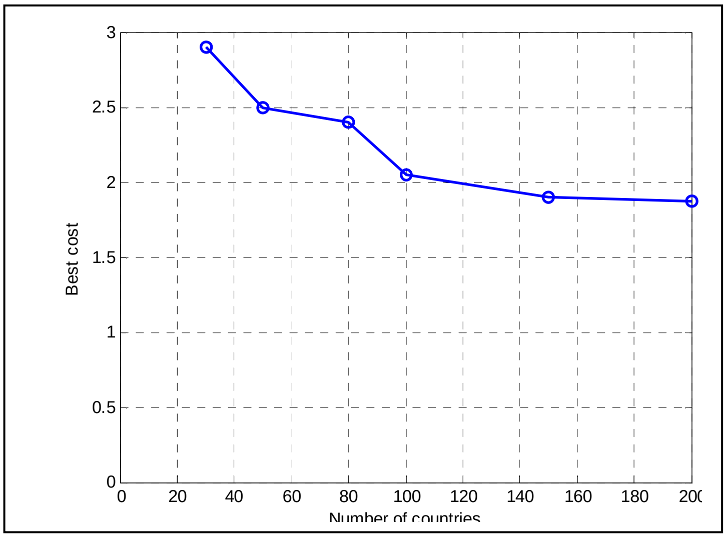

Figure7. Effect of variation of the number of countries on the minimum manufacturing cost

Figures 8 and 9 demonstrate the iteration process of CCA and GA methods respectively for minimization of cutting time. In case of CCA a significant decrease in the target function is seen in the beginningof the evolution process. Here GA shows better convergence as it gets the minimum cost only after 40 generations.

A careful investigation is carried out to compare the design efficiency of the proposed algorithm with traditional Genetic Algorithm (GA). The following GA parameters were determined to yield the best results: probability of mutation p_m=0.008; population size N= 200; maximum number of generation G = 200. To be fair in the comparison, CCA parameters were considered as Table 1 similar to GA configurations.

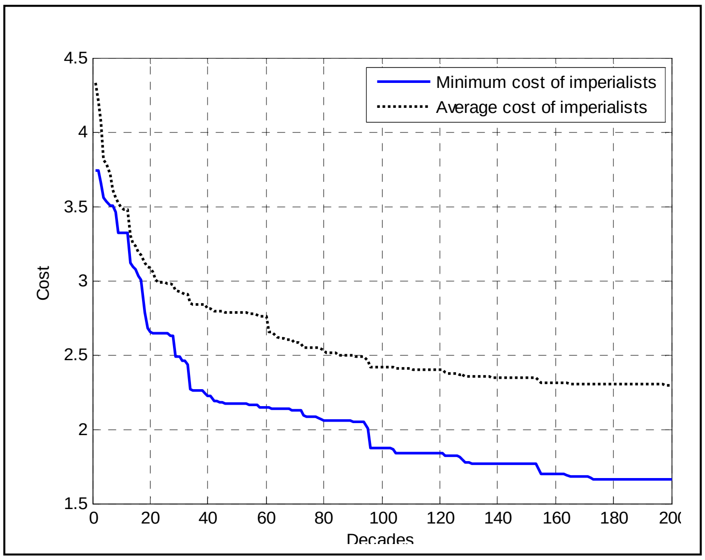

Figure8. Convergence of the objective of minimum cutting time for CCA

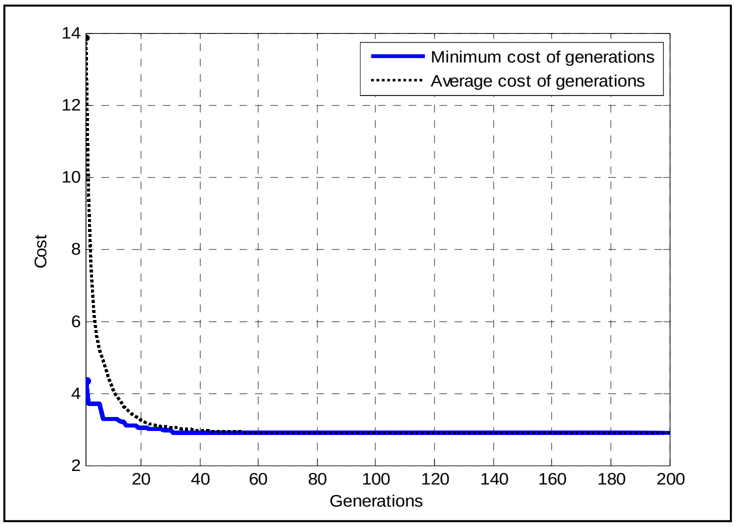

Figure9. Convergence of the objective of minimum cutting time for GA

Both CCA and GA algorithms are programmed in MATLAB, the results of simulationare presented in Table 2. As it is observed the results are completely matchedwith the work of Angus Jeang [19] for optimizing tolerances of the individual components for the minimum cost of manufacturing.

Table2. Comparison of the optimal cutting parameters for cutting operation for the CCA and GA approaches

Optimization method	CPU time (s)	$U_1(mm/rev)$	$\mathrm{U_2(m/min)}$	$\mathrm{U_3(mm)}$	$\mathrm{U_4}$ %	$\mathrm{t_1(mm/rev)}$	$\mathrm{t_2(m/min)}$	$\mathrm{t_3(mm)}$	$\mathrm{t_4}$ %	CT
ICA	8	0.1256	147.5858	3.80738	48.29988	0.00339	11.22789	0.1157	1.83535	2.08051
GA	22	0.12441	147.5428	3.80972	47.78932	0.0037	9.868983	0.11923	1.852811	2.45688

Since the minimum cost is desired, compare is made for the best cost of optimization in Figure 10. As it is illustrated in Figure 10, CCA is more successful for predicting the minimum of (CT) in comparison with GA.

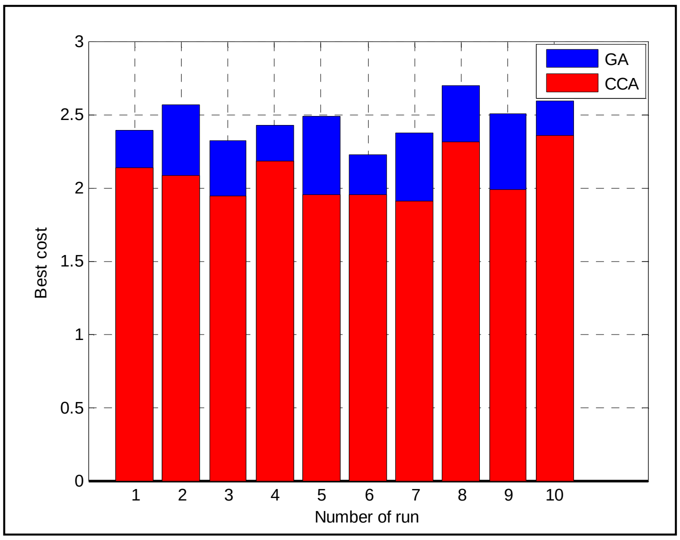

Figure10. Optimization results for Cutting Time (CT)

5. Conclusion

The optimization of cutting parameters is a nonlinear problem with multiple aspects. One property of interest related to the cost is cutting time, which is dependent on the length of cutting materials, the feed rate, the cutting speed, the depth of cut, and the percentage of tool diameter. In this study the CCA approach has been used to optimization cutting parameters and minimization the cutting time. According to the results, CCA algorithm comparing to the traditional GA 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 CCA algorithm. Moreover, considering the high complexity of the cost function going to be minimized, and it confirms the ability of CCA in dealing with difficult optimization tasks.Therefore, CCA has a promising potential to be used as a new solution approach in a variety of problems.

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