Cultural-Based Genetic Algorithm: Design and Real World Applications

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Abstract

Due to their excellent performance in solving combinatorial optimization problems, metaheuristics algorithms such as Genetic Algorithms (GA), Simulated Annealing (SA) and Tabu Search TS make up another class of search methods that has been adopted to efficiently solve dynamic optimization problem. Most of these methods are confined to the population space and in addition the solutions of nonlinear problems become quite difficult especially when they are heavily constrained. They do not make full use of the historical information and lack prediction about the search space. Besides the knowledge that individuals inherited "genetic code" from their ancestors, there is another component called *Culture*. In this paper, a novel culture-based GA algorithm is proposed and is tested against multidimensional and highly nonlinear real world applications.

1. Introduction

The dynamic optimization of fed-batch bioreactors is a very challenging problem due to several reasons. First, the control variable (feed rate) appears linearly in the system differential equations, so the problem is singular, creating additional difficulties for its solution (especially using indirect methods). For these type of problems, the optimal operating policy will be either bang-bang, or singular, or a combination of both. Second, most bioprocesses have highly nonlinear dynamics, and constraints are also frequently present on both the state and the control variables. These characteristics introduce new challenges to the existing solution techniques; therefore, efficient and robust methods are needed in order to obtain the optimal operating policies.

The well-known numerical optimization methods [2], [37], [14], [26], [29], [30], [23], [24], of nonlinear programming do not always lead to acceptable solutions in practical problems, often becoming entrapped in local minima instead of yielding global solutions. Many stochastic methods like *Genetic Algorithm (GA)* [4], [12], [17], [27], [36], [10], [25], [19], [11], [15], [3] and *Simulated Annealing (SA)* [20], [9] can locate the vicinity of global solutions with relative efficiency , but the cost to pay is that global optimality can not be guaranteed. It has been widely confirmed [10], [25], [6], [28] that real-number encoding performs better than binary or Gray encoding for function optimizations and constrained optimizations [16]. Most of these methods are confined to the population space. They don't make full use of the historical information and lack prediction about the search space. In human societies, Culture can be viewed as a vehicle for the storage of information that is potentially accessible to all members of the society, and that can be useful in guiding their problem solving activities [39]. The Culture Algorithm (**C**A) reduces the need for immature individual to waste energy by bypassing trail and error iterations usually required to acquire information about the environment, and also enables the transmission of more information than any individual genome may feasibly contain. Rest of the paper is organized as follows. A more general investigation into the potential strength of CA in optimization problems is conducted in section 2.The new devised algorithm is presented in section 3. Section 4 covers results and computer simulations, followed by some conclusion.

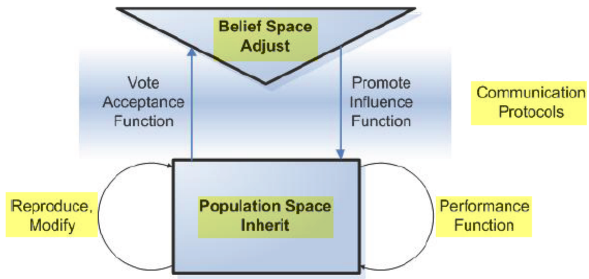

Figure 1. Culture Algorithm CA Components

Cultural Algorithms consist of a social population and a belief space [1], [31], [15], [21] as shown in Figure 1. Selected individuals from the population space contribute to cultural knowledge by means of the acceptance function. The cultural knowledge resides in the belief space where it is stored and updated based on individual experiences and their successes or failures. In turn, the cultural knowledge controls the evolution of the population by means of an influence function [7]. There are at least five basic categories of cultural knowledge that are important in the belief space of any cultural evolution model: *situational*, *normative*, *topographic*, *historical or temporal*, and *domain knowledge* [21]. The pseudo code of the general CA is as follows:

- **Begin**
- **t = 0;**
- **Initialize Belief Space** $BLF(t)$ **;**
- **Initialize Population Space** $POP(t)$ **;(in the** $BESTRANGE$ **)**
- **Repeat until termination condition achieved;**
  - o **Perform actions of the individuals in** $POP(t)$ **;**
  - o **Evaluate each individual by using the fitness function;**
  - o **Select the best individuals to become parents;**
  - o **Create new generation of offspring by mutation & crossover;**
  - o **Delete not so fit members to make room for the new ones;**
  - o $bLF(t)$ **alters the genome of the offspring - influence function;**
  - o **Best individuals can update the** $BLF(t)$ **- acceptance function;**
- **End.**

2. Related Research

In the literature, several works are available about Cultural Algorithm [32], [1], [31], [15], [21], [22]. Reynolds et al. [33] and Chung and Reynolds [7] have investigated the use of cultural algorithms for global optimization with very encouraging results. some of the works do not totally use all different sources of information in the belief space. Kobti [21] used only the topographic, domain knowledge and history knowledge. Xue [39] abstracted 4 different kinds of knowledge and succeeded in using the range of the best parameters to be one source of belief information, then followed by accepting the point or modify it to be in the proper region. Only the situational knowledge; information relating to the above-average or the best point are implemented by Yu [38] to solve the earliness / tardiness flow shop with uncertain processing time. In heavily constrained model, there is a plenty of time wasted in generating solutions in the unfeasible region and it would be great to not waste this valuable time. If there is a chance to get benefit from the history of violation and satisfaction of these constraints, it could force the algorithm to move faster and converges better. The history of violating and satisfying constraints is also used here to force the evolution process away from the region that violates the constraints at each generation. This kind of information is updated so it helps in reducing the need for immature individual to waste energy by bypassing trial and error iterations.

3. Culture Genetic Algorithm

The proposed research has employed real-coded GA integrated with culture algorithm. In the belief space there are multi sources of information that best individuals along their evolution is stored. The list of best candidates, the ranges of the best performers candidates, and the ranges of feasible regions that lead the search away from candidates that violate the constraints are the main source of information implemented in the belief space. The algorithm is detailed below

- Begin
- $t = 0$;

- Initialize Population Space $POP(t)$;
- Initialize Belief Space $BLF(t)$;($LISTBEST$, $BESTRANGE$, $FRANGE$)
  - o Repeat until termination condition achieved;
  - o Perform actions of the individuals in $POP(t)$;
  - o Evaluate each individual by using the fitness function;
  - o Penalize fitness if violation happened
  - o Select the best individuals to become parents;
  - o Create new generation of offspring by mutation & crossover;
  - o Influence function : move all individuals toward the best candidate, choose the best percent of them
  - o Generate randomly individuals in the feasible range $FRANGE$ "that satisfy the constraint"
  - o Remove from the old population an amount equal to ($FRANGE$ individuals + close individual to the $LISTBEST$)
  - o Insert these individuals into the population
  - o Best individuals can update the $BLF(t)$ - acceptance function;
- End.

The belief space consists of 3 different kinds of information sources;

1) In each generation, the best candidate LISTBEST is stored to be used later by grandsons, and in each generation, we generate random percent of individuals in the neighbor of the best candidates. in fact, we move some percent of individuals in the closest point to the best individual "like best neighbor in PSO" and this helps in leading the individuals to jump into the promising region.
2) The best range of the 20% performers in each generation is calculated $BESTRANGE$ and successive generations will be randomly generated in this promising range. This also lead to increasing convergence and not wasting time discovering the good regions.
3) The history of violating and satisfying constraints are also used here to force the evolution process away from the region that violates the constraints $FRANGE$, and at each generation this kind of information is updated so it helps in reducing the need for immature individual to waste energy by bypassing trial and error iterations and also enable the transmission for more information than any individual genome may feasibly contain.

4. Experimental Results

Three real world problems are selected to illustrate the performance of the proposed cultural genetic algorithm.

4.1. Pressure Vessel Design

A cylindrical pressure vessel with two hemispherical heads is designed for minimum cost of fabrication. Four variables are identified: thickness of pressure vessel T_s , thickness of head T_h , inner radius of the vessel R , and the length of the vessel without heads L (shown in figure 2). The variable vectors for this case are given (in inches) by $(T_s, T_h, R, L) = (x_1, x_2, x_3, x_4) = X$.

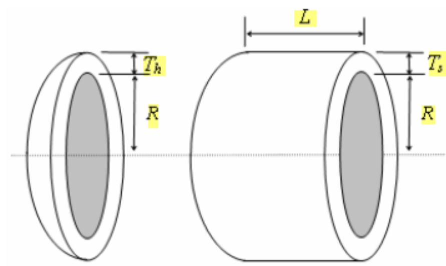

Figure 2. Pressure Vessel

The mathematical model of mixed-integer optimization problem is expressed as [8]:

$$\min f(x) = 0.6224 x_1 x_3 x_4 + 1.7781 x_2 x_3^2 + 3.1661 x_1^2 x_4 + 19.84 x_1^2 x_3 \quad (1)$$

Subject to the following constraints:

$$g_1(x) = -x_1 + 0.0193 x_3 \le 0 \quad (2)$$

$$g_2(x) = -x_2 + 0.00954 x_3 \le 0 \quad (3)$$

$$g_3(x) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1{,}296{,}000 \le 0 \quad (4)$$

$$g_4(x) = x_4 - 240 \le 0 \quad (5)$$

The following ranges of the design variables were used: $0 \le x_1 \le 99$, $0 \le x_2 \le 99$,10

$\leq x_3 \leq 200$, and $10 \leq x_4 \leq 200$. The proposed cultural-based GA was applied to the problem of pressure design vessel 50 runs, and the best objective function value obtained is 6580.8, the mean of the 50 runs is 8745.8, the worst value is 11673, and the standard deviation is 1.0658e+003.

As evident from the results, the proposed CGA method obtained a close solution to the optimal point obtained by [8] (6112.5619) even we do not implement all the information sources of the belief space in the proposed CGA method. The idea of developing the satisfaction region for constraints gives our algorithm the chance to move far away of the unfeasible region, and as the search progresses we can make sure that we are now searching in the feasible region. The optimal function value in each run is illustrated in Figure 3 and the performance of the last run (run No. 50) is depicted in Figure 4.

$$\frac{dx_2}{dt} = h_1 x_1 - u\left(\frac{x_1}{500 x_4}\right) \quad (6)$$

4.2 Optimal Control of a Fed-batch fermentor for Penicillin Production

A model of a fed-batch fermentor for the production of Penicillin [36] is illustrated in figure 5. The objective function is to maximize the amount of Penicillin produced using the feed rate as the control variable.

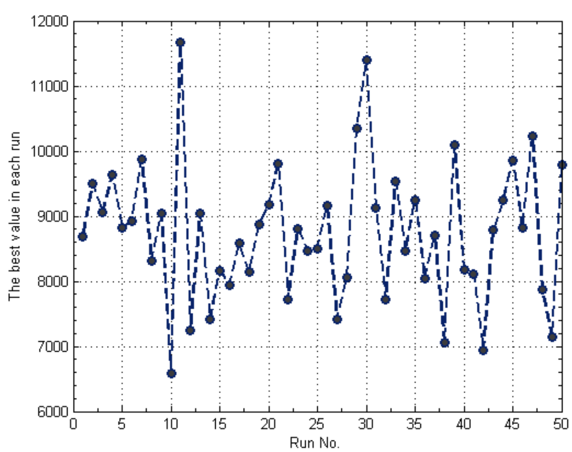

Figure 3. Best PI of each population during 50 iterations

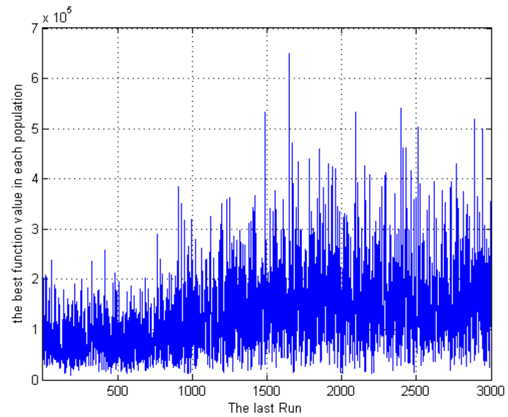

Figure 4. Best PI of each population in the last run

Find $u(t)$ and t_f over $t \in [t_0, t_f]$ to maximize $J = x_2(t) x_4(t)$ subject to

$$\frac{dx_2}{dt} = h_2 x_1 - 0.001 x_2 - u\left(\frac{x_2}{500 x_4}\right) \quad (7)$$

$$\frac{dx_3}{dt} = -\frac{h_1 x_1}{0.47} - h_2 \frac{x_1}{1.2} - x_1\left(\frac{0.029 x_3}{0.0001 + x_3}\right) + \frac{u}{x_4}\left(1 - \frac{x_3}{500}\right) \quad (8)$$

$$\frac{dx_4}{dt} = \frac{u}{500} \quad (9)$$

$$h_1 = 0.11\left(\frac{x_3}{0.006 x_1 + x_3}\right) \quad (10)$$

$$h_2 = 0.0055\left(\frac{x_3}{0.0001 + x_3(1 + 10 x_3)}\right) \quad (11)$$

Where x_1, x_2, x_3 are the biomass, penicillin and substrate concentration, and x_4 is the volume. The initial conditions are: $x(t_0) = [1.5 \quad 0 \quad 0 \quad 7]^T$.

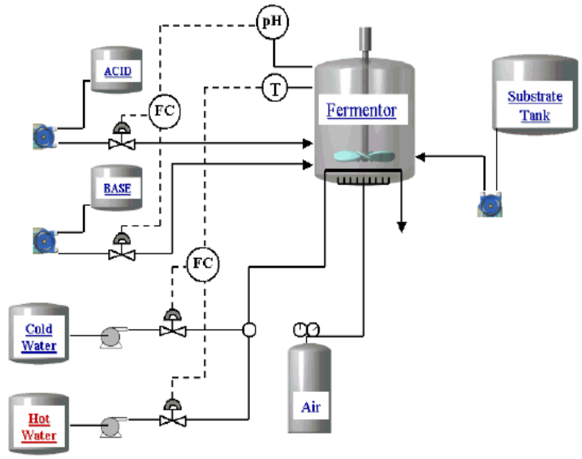

Figure 5. Fed-Batch Penicillin fermentor

The upper and lower bounds on the state variables are

$$
\begin{aligned}
0 &\leq x_1 \leq 40 \\
0 &\leq x_3 \leq 25 \qquad (12) \\
0 &\leq x_4 \leq 10
\end{aligned}
$$

The upper and lower bounds on the feed rate are

$$0 \leq u \leq 50 \qquad (13)$$

When applying the suggested technique with penalty to the fermentor problem at hand, it gives performance index equal to 83.0526, and the optimal control vector $u = 11.3901$, for $t_f = 132h$. Figure 6 illustrates the biomass, penicillin and substrate concentrations, and the volume plotted in the interval of investigation. The minimum performance index of each population is depicted in Figure 7.

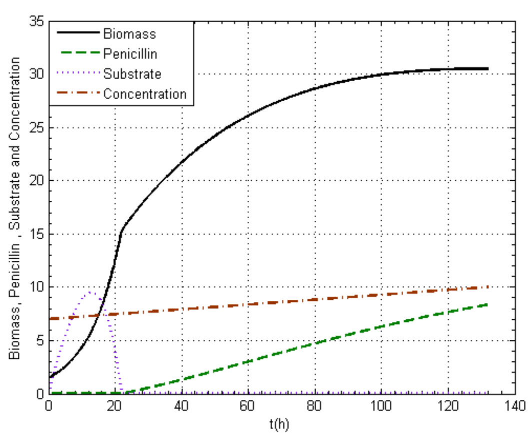

Figure 6. Penicillin production fermentor states

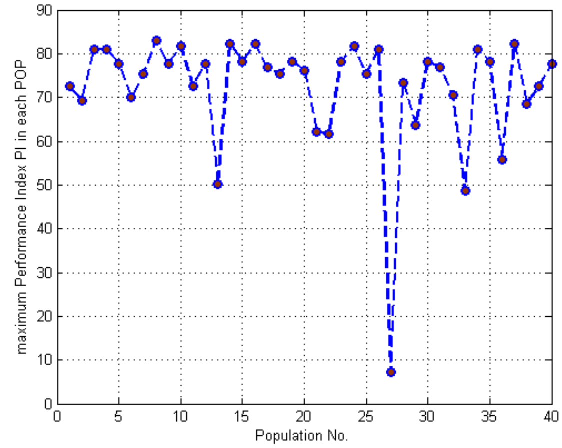

Figure 7. Optimal performance index of each population

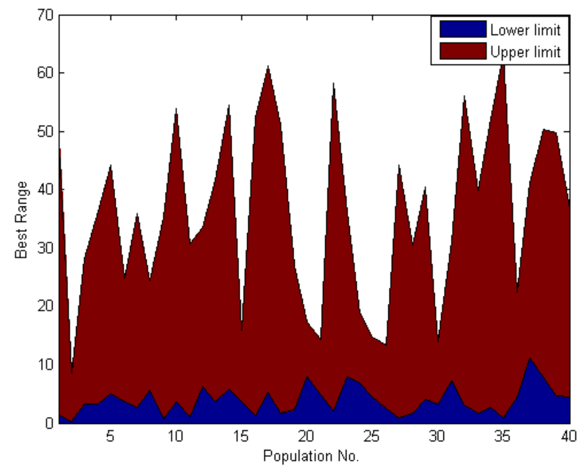

Figure 8. Best range of control vector

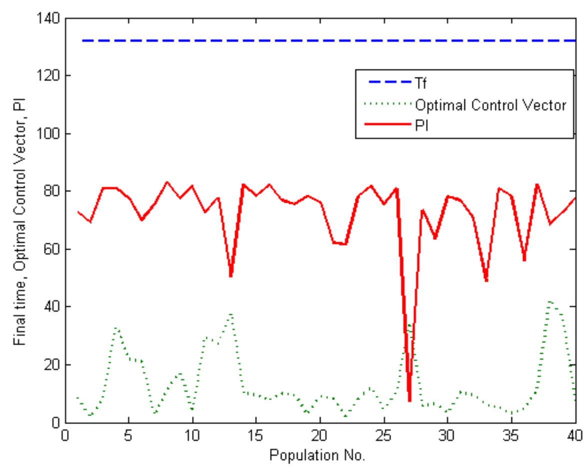

Figure 9. Final time, Control vector, and PI evolution

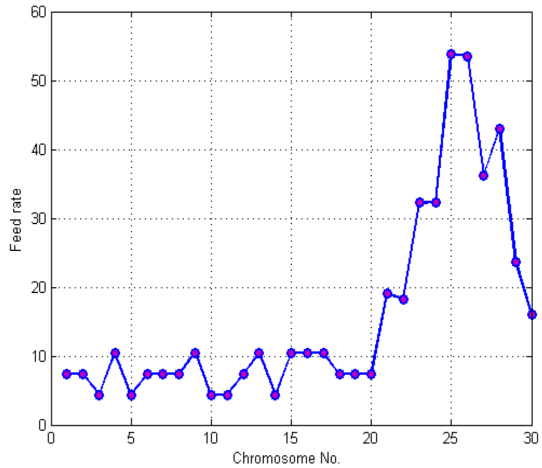

Figure 10. Last generation

The best interval range for the optimal control vector in each population is illustrated in Figure 8. The evolution of the final time, PI, and the optimal control during the 40 population are depicted in Figure 9. Last generation is illustrated in Figure 10.

5. Conclusion

The Cultural-based GA enables monitoring the search space and records important events in the search space regarding to the best individual, the best range, and the best feasible range that satisfy constraints, and this leads to reduce the effect of premature convergence to a certain extent. A real-coded GA-wise there is no encoding and decoding, low usage of memory, good precision, etc. From a computational point of view, the basic reason why cultural evolution can proceed at an increased rate is that it is able to provide selective pressure on the population by placing constraints on their performance and maintain a history of individual performance that is separate from that individual. Both of these characteristics are key factors in influencing the performance speedup associated with the specific version of cultural algorithm. The application of the proposed algorithm using the highly nonlinear and multidimensional case studies illustrates that the algorithm performs very well for the problems considered.

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