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### **Emerald Article: Colonial competitive algorithm: A novel approach for PID controller design in MIMO distillation column process**

Esmaeil Atashpaz Gargari, Farzad Hashemzadeh, Ramin Rajabioun, Caro Lucas

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# Colonial competitive algorithm

## A novel approach for PID controller design in MIMO distillation column process

Colonial  
competitive  
algorithm

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Esmail Atashpaz Gargari, Farzad Hashemzadeh,  
Ramin Rajabioun and Caro Lucas

*School of Electrical and Computer Engineering,  
Control and Intelligent Processing Centre of Excellence, University of Tehran,  
Tehran, Iran*

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### Abstract

**Purpose** – This paper aims to describe colonial competitive algorithm (CCA), a novel socio-politically inspired optimization strategy, and how it is used to solve real world engineering problems by applying it to the problem of designing a multivariable proportional-integral-derivative (PID) controller. Unlike other evolutionary optimization algorithms, CCA is inspired from a socio-political process – the competition among imperialists and colonies. In this paper, CCA is used to tune the parameters of a multivariable PID controller for a typical distillation column process.

**Design/methodology/approach** – The controller design objective was to tune the PID controller parameters so that the integral of absolute errors, overshoots and undershoots be minimized. This multi-objective optimization problem is converted to a mono-objective one by adding up all the objective functions in which the absolute integral of errors is emphasized to be reduced as long as the overshoots and undershoots remain acceptable.

**Findings** – Simulation results show that the controller tuning approach, proposed in this paper, can be easily and successfully applied to the problem of designing MIMO controller for control processes. As a result not only was the controlled process able to significantly reduce the coupling effect, but also the response speed was significantly increased. Also a genetic algorithm (GA) and an analytical method are used to design the controller parameters and are compared with CCA. The results showed that CCA had a higher convergence rate than GA, reaching to a better solution.

**Originality/value** – The proposed PID controller tuning approach is interesting for the design of controllers for industrial and chemical processes, e.g. MIMO evaporator plant. Also the proposed evolutionary algorithm, CCA, can be used in diverse areas of optimization problems including, industrial planning, resource allocation, scheduling, decision making, pattern recognition and machine learning.

**Keywords** Optimization techniques, Programming and algorithm theory

**Paper type** Research paper

### 1. Introduction

This paper describes a novel socio-politically inspired evolutionary optimization algorithm, colonial competitive algorithm (CCA). Unlike the current evolutionary algorithms, such as genetic algorithm (GA) and simulated annealing (SA), that are computer simulation of natural processes such as natural evolution and annealing process in materials, CCA uses imperialism and imperialistic competition, socio-political evolution processes, as source of inspiration.

Similar to the other evolutionary algorithms that start with an initial population, CCA begins with initial empires. Any individual of an empire is called a country. There are two types of countries; colony and imperialist state that collectively form empires.



Imperialistic competitions among these empires form the basis of the CCA. During this competition, weak empires collapse and powerful ones take possession of their colonies. Imperialistic competitions converge to a state in which there exists only one empire and its colonies are in the same position and have the same cost as the imperialist.

In this paper, we apply CCA to the real world engineering problem of designing a multivariable proportional-integral-derivative (PID) controller for a typical distillation column process. Although many advanced methodologies have been successfully developed in control engineering, PID controller has remained the most popular control loop feedback mechanism since 1950s, and has been extensively used in controlling industrial processes, especially where rapid transitional responses are not the most important design concept. In addition to its capabilities, PID can be implemented easily in industrial control processes; and the existing PID controllers can easily be retuned or upgraded. PID controller tries to correct the error between the measured outputs and desired outputs of the process so that transient and steady state responses are improved as much as possible. Although it is used widely, PID tuning is still an area of research in realm of both academic and industrial control engineering and different methods have been proposed (Bao *et al.*, 1999; Chidambaram and Sree, 2003; Lee *et al.*, 2004; Wang *et al.*, 1998). Ziegler and Nichols (1942) tuning method is the first significant and most known one.

Compared to their SISO counterparts, MIMO processes are more complicated in controller design. The main problem is the coupling between inputs and outputs (Xiong *et al.*, 2007). In last several decades, designing controllers for MIMO systems has attracted a lot of research interests and many multivariable control approaches have been proposed (Christen *et al.*, 1997). Among the methods used to control MIMO processes, PID controllers have been deployed extensively due to their less complexity, high performance and easy implementation (Xiong *et al.*, 2007; García-Alvarado *et al.*, 2005; Halevi *et al.*, 1997; Ruiz-López *et al.*, 2006). Also some numerical search strategies are proposed in the literature, to design MIMO controllers by minimizing suitable cost functions (Chang, 2007; Hsin-Chieh *et al.*, 2008; Su and Wong, 2007).

In this paper, CCA is applied to the problem of designing a multivariable PID controller for a distillation column process. The design objective is to tune the PID controller so that the integral of absolute errors, overshoots and undershoots be minimized. The coefficients of the PID controller were obtained by two evolutionary methods, CCA and GA. In the determination of the tradeoff coefficients in fitness functions, we emphasized on reduction of the integral of error as long as the overshoots/undershoots remain acceptable. The controller obtained by CCA is compared with those of GA and decentralized relay feedback (DRF) method (Wang *et al.*, 1997). The simulation results showed that the evolutionary method proposed in this paper for PID controller design has a better convergence rate than its classic counterpart, GA, and in a certain number of function calls, it reaches to better solutions.

In the following paper, Section 2 comprehensively introduces CCA. Section 3 shows that how CCA can be used to design a PID controller for a multivariable processes and in Section 4, as a case study, the approach discussed in Section 3 is applied to an industrial process, distillation column. Eventually conclusion of the paper is given in Section 5.

## 2. Colonial competitive algorithm

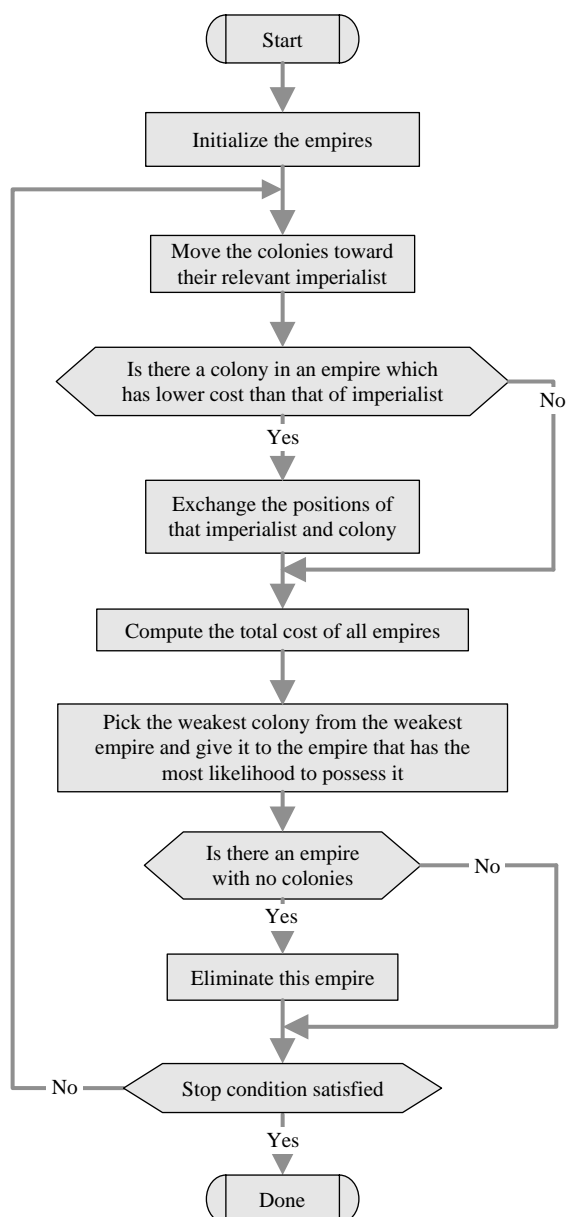
From a general point of view, optimization is the process of making something better (Haupt and Haupt, 2004). Having a function  $f(x)$  in optimization, we want to find an argument  $x$  whose relevant cost is optimum (usually minimum). Different methods have been proposed to solve an optimization problem. Some of these methods are the computer simulation of the natural processes. For example, GAs are a particular class of evolutionary algorithms that evolve a population of candidate solutions to a given problem, using operators inspired by natural genetic variation and natural selection (Melanie, 1999). SA is another example which simulates the annealing process in which a substance is heated above its melting temperature and then gradually cooled to produce the crystalline lattice, which minimizes its energy probability distribution (Haupt and Haupt, 2004). As another example, ant colony optimization is inspired by the foraging behavior of real ants (Dorigo and Blum, 2005). Also the inspiration source of PSO which was formulated by Edward and Kennedy in 1995 was the social behavior of animals, such as bird flocking or fish schooling (Haupt and Haupt, 2004).

The available optimization algorithms are extensively used to solve different optimization problems such as industrial planning, resource allocation, scheduling, decision making, pattern recognition and machine learning. Furthermore, optimization techniques are widely used in many fields such as chemistry, business, industry, engineering and computer science (Johnston and Cartwright, 2004; Darwen and Yao, 1996; Chellaboina and Ranga, 2005; Bontoux and Feillet, 2006; Varol and Bingul, 2004).

However, CCA simulates the social political process of Imperialism and imperialistic competition. Figure 1 shows the flowchart of CCA. Similar to the other evolutionary algorithms, this algorithm starts with an initial population. Each individual of the population is called a country. Some of the best countries (in optimization terminology, countries with the least cost) are selected to be the imperialist states and the rest form the colonies of these imperialists. All the colonies of initial countries are divided among the mentioned imperialists based on their power. The power of each country, the counterpart of fitness value in GAs, is inversely proportional to its cost. The imperialist states together with their colonies form some empires.

After forming initial empires, the colonies in each of them start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy which was pursued by some of the imperialist states. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. This fact is modeled by defining the total power of an empire as the power of imperialist country plus a percentage of mean power of its colonies.

Then the imperialistic competition begins among all the empires. Any empire that is not able to succeed in this competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately they will collapse. The movement of colonies toward their relevant imperialist states along with competition among empires and also the collapse mechanism will hopefully cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies have the same position and power as the imperialist.



**Figure 1.**  
Flowchart of the proposed algorithm

### 2.1 Generating 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 GA terminology, this array is called “chromosome”, but here the term “country” is used for this array. In an  $N_{\text{var}}$ -dimensional optimization problem, a country is a  $1 \times N_{\text{var}}$  array. This array

is defined by:

$$\text{country} = [p_1, p_2, p_3, \dots, p_{N_{\text{var}}}] \quad (1)$$

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

$$\text{cost} = f(\text{country}) = f(p_1, p_2, p_3, \dots, p_{N_{\text{var}}}) \quad (2)$$

To start the optimization algorithm, initial countries of size  $N_{\text{country}}$  is produced. We select  $N_{\text{imp}}$  of the most powerful countries to form the empires. The remaining  $N_{\text{col}}$  of the initial countries will be the colonies each of which belongs to an empire.

To form the initial empires, the colonies are divided among imperialists based on their power. That is, the initial number of colonies of an empire should be directly proportionate to its power. To proportionally divide the colonies among imperialists, the normalized cost of an imperialist is defined by:

$$C_n = c_n - \max_i \{c_i\} \quad (3)$$

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:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{\text{imp}}} C_i} \right| \quad (4)$$

The initial colonies are divided among empires based on their power. Then the initial number of colonies of the  $n$ th empire will be:

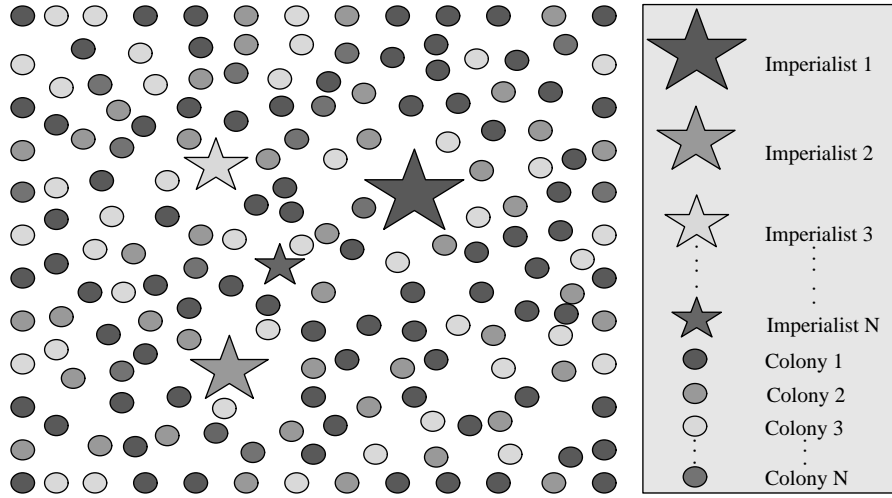
$$\text{N.C.}_n = \text{round}\{p_n \cdot N_{\text{col}}\} \quad (5)$$

where  $\text{N.C.}_n$  is the initial number of colonies of the  $n$ th empire and  $N_{\text{col}}$  is the number of initial colonies. To divide the colonies,  $\text{N.C.}_n$  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. Figure 2 shows the initial empires. As shown in this figure bigger empires have greater number of colonies while weaker ones have less. In this figure, imperialist 1 has formed the most powerful empire and consequently has the greatest number of colonies.

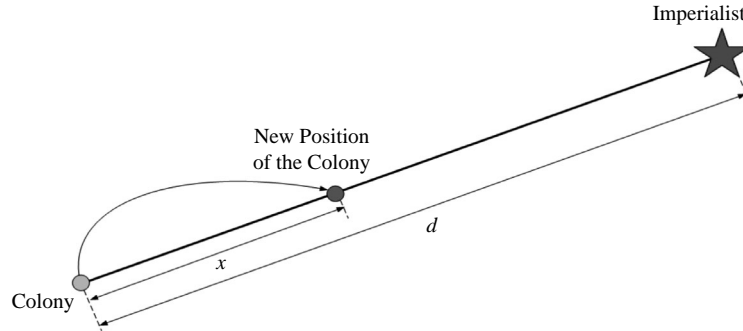
### 2.2 Movement of an empire's colonies toward the imperialist

In CCA, the assimilation policy, pursued by some of former imperialist states, is modeled by moving all the colonies toward the imperialist. This movement is shown in Figure 3 in which a colony moves toward the imperialist by  $x$  units. The new position of colony is shown in a darker color. The direction of the movement is the vector from the colony to the imperialist. In this figure,  $x$  is a random variable with uniform (or any proper) distribution. We consider  $x$  to be uniformly distributed between 0 and  $\beta \times d$ . Then:

**Figure 2.**  
Generating the initial  
empires: the more colonies  
an imperialist possess, the  
bigger is its relevant ★  
mark



**Figure 3.**  
Movement of colonies  
toward their relevant  
imperialist



$$x \sim U(0, \beta \times d) \quad (6)$$

where  $\beta$  is a number greater than 1 and  $d$  is the distance between colony and imperialist.  $\beta > 1$  causes the colonies to get closer to the imperialist state from both sides.  $\beta \gg 1$  gradually results in divergence of colonies from the imperialist state while a  $\beta$  very close to 1 reduces the search ability of the algorithm.

To search different points around the imperialist, a random amount of deviation is added to the direction of movement. Figure 4 shows the new direction. In this figure,  $\theta$  is a random number with uniform (or any proper) distribution. Then:

$$\theta \sim U(-\gamma, \gamma) \quad (7)$$

where  $\gamma$  is a parameter that adjusts the deviation from the original direction. Nevertheless, the values of  $\beta$  and  $\gamma$  are arbitrary, in most of implementations a value of about 2 for  $\beta$  and about  $\pi/4$  (Rad) for  $\gamma$  results in good convergence of countries to the global minimum.

### 2.3 Exchanging positions of the imperialist and a colony

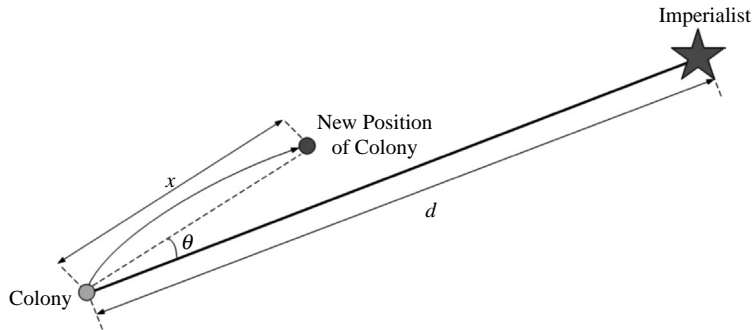
While moving toward the imperialist, a colony might reach to a position with lower cost than that of imperialist. In this case, the imperialist and the colony change their positions. Then the algorithm will continue by the imperialist in the new position and then colonies start moving toward this position. Figure 5(a) shows the position exchange between a colony and the imperialist. In this figure the best colony of the empire is shown in a darker color. This colony has a lower cost than that of imperialist. Figure 5(b) shows the whole empire after exchanging the position of the imperialist and that colony.

### 2.4 Total power of an empire

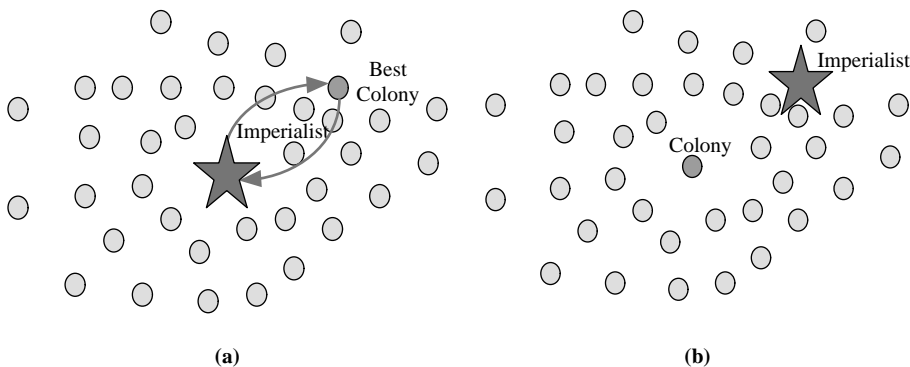
Total power of an empire is mainly affected by the power of imperialist country. But the power of the colonies of an empire has an effect, albeit negligible, on the total power of that empire. This fact is modeled by defining the total cost by:

$$T.C._n = \text{Cost}(\text{imperialist}_n) + \xi \text{ mean}\{\text{cost}(\text{colonies of empire}_n)\} \quad (8)$$

where  $T.C._n$  is the total cost of the  $n$ th empire and  $\xi$  is a positive number which is considered to be less than 1. A little value for  $\xi$  causes the total power of the empire to be determined by just the imperialist and increasing it will add to the role of the colonies in determining the total power of an empire. The value of 0.1 for  $\xi$  is a good value in most of the implementations.



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



**Figure 5.**  
(a) Exchanging the  
positions of a colony and  
the imperialist; (b) the  
entire empire after  
position exchange



### 2.5 Imperialistic competition

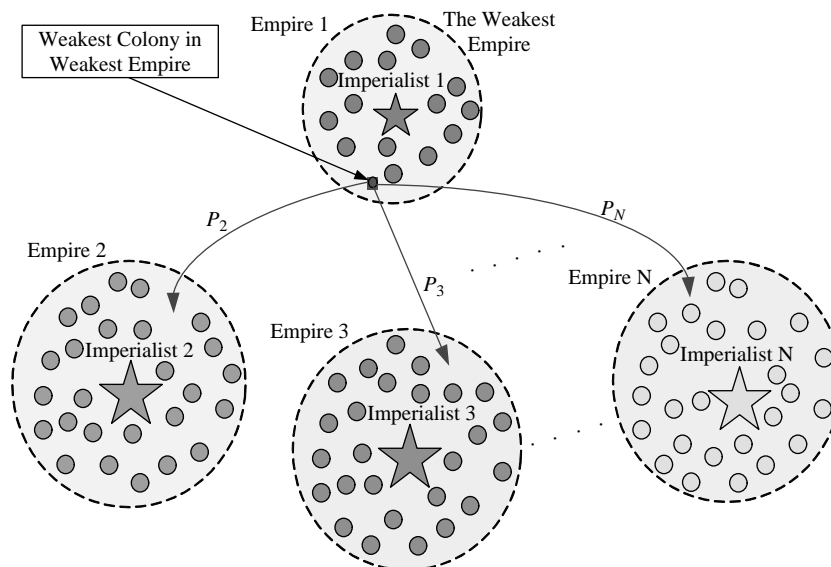
All empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones. The imperialistic competition is modeled by just picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess these (this) colonies. Figure 6 shows a big picture of the modeled imperialistic competition. Based on their total power, in this competition, each of empires will have a likelihood of taking possession of the mentioned colonies. In other words these colonies will not be possessed by the most powerful empires, but these empires will be more likely to possess them.

To start the competition, first, the possession probability of each empire which is based on its total power is found. The normalized total cost is simply obtained by:

$$N.T.C._n = T.C._n - \max_i \{T.C._i\} \quad (9)$$

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:

$$p_{p_n} = \left| \frac{N.T.C._n}{\sum_{i=1}^{N_{imp}} N.T.C._i} \right| \quad (10)$$



**Figure 6.**  
Imperialistic competition:  
the more powerful an  
empire is, the more likely  
it will possess the weakest  
colony of the weakest  
empire

To divide the mentioned colonies among empires based on the possession probability of them, vector  $\mathbf{P}$  is formed as:

$$\mathbf{P} = [p_{p_1}, p_{p_2}, p_{p_3}, \dots, p_{p_{N_{\text{imp}}}}] \quad (11)$$

Then a vector with the same size as  $\mathbf{P}$  whose elements are uniformly distributed random numbers is created:

$$\mathbf{R} = [r_1, r_2, r_3, \dots, r_{N_{\text{imp}}}] \quad (12)$$

$$r_1, r_2, r_3, \dots, r_{N_{\text{imp}}} : U(0, 1) \quad (13)$$

Then vector  $\mathbf{D}$  is formed by subtracting  $\mathbf{R}$  from  $\mathbf{P}$ :

$$\begin{aligned} \mathbf{D} = \mathbf{P} - \mathbf{R} &= [D_1, D_2, D_3, \dots, D_{N_{\text{imp}}}] \\ &= [p_{p_1} - r_1, p_{p_2} - r_2, p_{p_3} - r_3, \dots, p_{p_{N_{\text{imp}}}} - r_{N_{\text{imp}}}] \end{aligned} \quad (14)$$

Referring to vector  $\mathbf{D}$  the mentioned colony (colonies) is handled to an empire whose relevant index in  $\mathbf{D}$  is maximum.

### 2.6 Eliminating the powerless empires

Powerless empires will collapse in the imperialistic competition and their colonies will be divided among other empires. To model the collapse mechanism different criteria can be defined to consider an empire powerless. In implementations of this paper, an empire is assumed to be collapsed when it loses all of its colonies.

### 2.7 Convergence

After a while all the empires except the most powerful one will collapse and all the colonies will be under the control of this unique empire. In this ideal new world all the colonies have the same positions and same costs and they are controlled by an imperialist with the same position and cost as themselves. In this ideal world, there is no difference not only among colonies but also between the colonies and imperialist. In this condition the imperialistic competition ends and the algorithm stops.

The main steps of CCA are summarized in the pseudo-code shown in below:

- (1) Define the cost function,  $f$ , to be minimized.
- (2) Select some random points on the function and using equations (2-5) initialize the empires.
- (3) Move the colonies toward their relevant imperialist referring to equations (6 and 7) (Assimilating).
- (4) If there is a colony in an empire which has lower cost than that of imperialist, exchange the positions of that colony and the imperialist.
- (5) Using (8) compute the total cost of all empires (Related to the power of both imperialist and its colonies).
- (6) Pick the weakest colony (colonies) from the weakest empire and give it (them) to the empire that has the most likelihood to possess it (Imperialistic competition). Use equations (9-14).

- (7) Eliminate the powerless empires.
- (8) If there is just one empire, stop, if not go to 2.

Theoretical proofs for convergence to asymptotic probability laws in all stochastic optimization algorithms, considering the Markovian nature of the underlying processes, require some sort of detailed balance or reversibility condition which means the algorithm loses much of its efficiency. Furthermore, if one insists on eventual convergence to the global optima in the strong or even weak sense, very slow annealing is also called for. The strength of stochastic algorithms stem from the fact that their very probabilistic nature ensures that the algorithms will not necessarily get stuck at local optima, and there is no need for using any information on objective gradients, further requiring differentiability conditions.

### 3. Controller design using CCA

#### 3.1 PID controller for MIMO processes

Consider the multivariable PID control loop in Figure 7.

In Figure 1, multi variable process  $\mathbf{P}(s)$  could be demonstrated as following:

$$\mathbf{P}(s) = \begin{bmatrix} p_{11}(s) & K & p_{1n}(s) \\ M & O & M \\ p_{n1}(s) & K & p_{nn}(s) \end{bmatrix} \quad (15)$$

where  $g_{ij}(s)$  is the transfer function between  $y_i$  and  $u_j$ .

In Figure 1, vectors  $\mathbf{Y}_d$ ,  $\mathbf{Y}$ ,  $\mathbf{U}$  and  $\mathbf{E}$  are in following form:

$$\mathbf{Y}_d = [y_{d1} \ y_{d2} \ L \ y_{dn}]^T \quad (16)$$

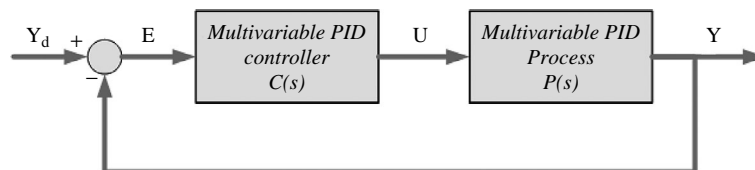
$$\mathbf{Y} = [y_1 \ y_2 \ L \ y_n]^T \quad (17)$$

$$\mathbf{U} = [u_1 \ u_2 \ L \ u_n]^T \quad (18)$$

$$\mathbf{E} = \mathbf{Y}_d - \mathbf{Y} = [e_{11} \ e_{22} \ L \ e_{nn}]^T \quad (19)$$

Multi variable PID controller  $\mathbf{C}(s)$  in Figure 1, is as following form:

$$\mathbf{C}(s) = \begin{bmatrix} c_{11}(s) & K & c_{1n}(s) \\ M & O & M \\ c_{n1}(s) & K & c_{nn}(s) \end{bmatrix} \quad (20)$$



**Figure 7.**  
Block diagram  
of a multivariable  
controlled process

where  $c_{ij}(s)$  that  $i, j \in \{1, 2, K \dots, n\}$  is in following form:

$$c_{ij}(s) = K_{Pij} + K_{Iij} \frac{1}{s} + K_{Dij}s \quad (21)$$

where  $K_{Pij}$  is the proportional,  $K_{Iij}$  is the integral and  $K_{Dij}$  is the derivative gains of the PID controller  $c_{ij}(s)$ .

### 3.2 Evolutionary PID design

In designing PID controllers, the goal is to tune proper coefficients  $K_P$ ,  $K_I$  and  $K_D$  so that the output has some desired characteristics. Usually, in time domain, these characteristics are given in terms of overshoot, rise time, settling time and steady state error. Two kinds of performance criteria in output tracking, usually considered in the controller designing, are the integral squared error and integral absolute error (IAE) of the desired output.

In multivariable controller design, one of the major aims is that each output  $y_i(t)$  track the desired input  $y_{di}(t)$  and reduce the effect of other inputs  $y_{dj}(t)$ , for  $i, j \in \{1, 2, \dots, n | i \neq j\}$ .

Considering the decoupling aim, IAE is defined in the following form:

$$IAE @ \sum_{i=1}^n \sum_{j=1}^n IAE_{ij} @ \sum_{i=1}^n \sum_{j=1}^n \int_0^\infty (|e_{ij}(t)|) dt \quad (22)$$

where  $IAE_{ij}$  is the integral of absolute error  $e_{ij}(t)$  over time,  $|e_{ii}(t)|$  is absolute error of the output  $y_i(t)$  when tracking input  $y_{di}(t)$  and  $|e_{ij}(t)|$  is the absolute error caused by the effect of the input  $y_{dj}(t)$  on the output  $y_i(t)$ , ( $i \neq j$ ). The source of  $|e_{ij}(t)|$  is the coupling problem.

Another performance criteria used in controller design is the percent overshoot (PO) and percent undershoot (PU) which is defined as follows:

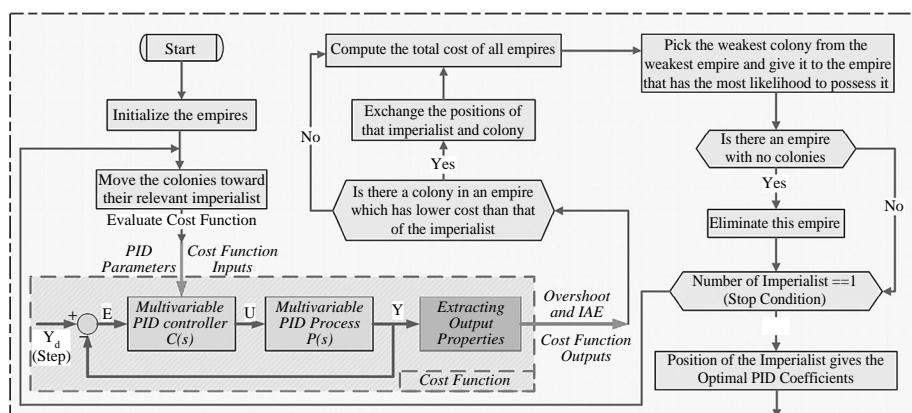
$$POU @ \sum_{i=1}^n \sum_{j=1}^n POU_{ij} @ \sum_{i=1}^n \sum_{j=1}^n \text{Max}\{PO_{ij}, PU_{ij}\} \quad (23)$$

where  $PO_{ij}$ ,  $PU_{ij}$  are the PO and PU of the output  $y_{ij}(t)$  and  $POU_{ij}$  is their maximum value. The aim is to design a controller to track the desired outputs by minimizing both the integral of absolute error and maximum of overshoot and undershoot. Since POU usually has smaller values compared with IAE and also to put emphasis on minimizing POU, the total objective function is defined as IAE plus ten times of POU:

$$\text{Cost} = IAE + 10 \times POU \quad (24)$$

In the next section, CCA is used to tune the PID controller parameters for a typical distillation column process and the results are compared with those of GA and the method introduced in (Wang *et al.*, 1997). Figure 8 shows how CCA is used to find optimal PID parameters for a MIMO process. Each country in CCA is a set of controller parameters that is evaluated by obtaining the step response of the MIMO system by means of the mentioned controller parameters. After step responses are found, two features of the output, namely, overshoots/undershoots and IAE are calculated and are used to form the final cost function for the controller parameters set in the country. Then CCA is used to find the best country that is the best set of controller parameters for the MIMO system.

**Figure 8.**  
Flowchart of CCA to find  
the controller parameters

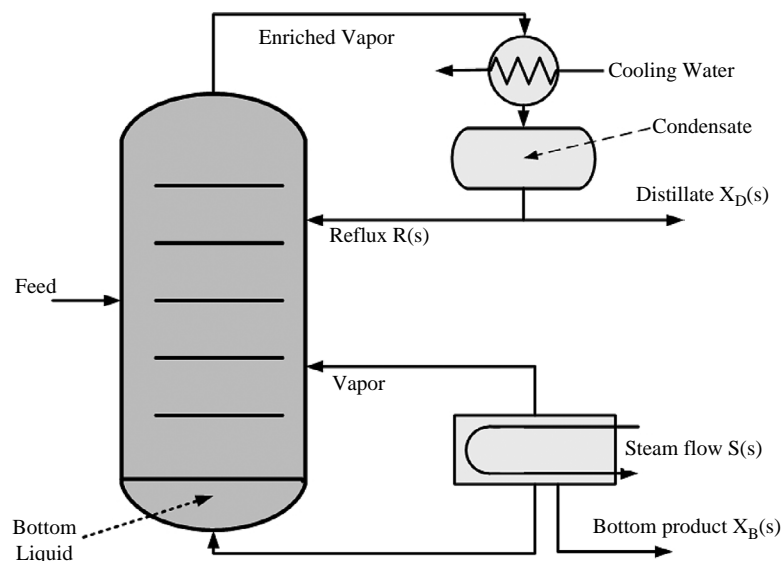


#### 4. Case study

In this section, a multivariable PID controller is designed for a MIMO model of a chemical process. This system is a typical  $2 \times 2$  model of distillation column taken from Luyben (1986). The controller is designed using two evolutionary algorithms, CCA and GA. Both of the controllers, obtained by evolutionary algorithms CCA and GA, are compared to one obtained by delayed relay feedback (DRF) method by simulating the entire control process. A simple schematic of distillation column system (DCS) is shown in Figure 9.

The matrix transfer function of DCS is defined as:

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{1+16.7s} & \frac{-18.9e^{-3s}}{1+21s} \\ \frac{6.6e^{-7s}}{1+10.9s} & \frac{-19.4e^{-3s}}{1+14.4s} \end{bmatrix} \cdot \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} a \quad (25)$$



**Figure 9.**  
A simple schematic of DCS

where  $X_D(s)$  and  $X_B(s)$  are percentage of methanol in the distillate and percentage of methanol in the bottom products, respectively. Also  $R(s)$  and  $S(s)$  are reflux flow rate and steam flow rate in the reboiler, respectively, (Luyben, 1986).

DCS is a  $2 \times 2$  MIMO system with strong interactions between inputs and outputs. The four transfer functions in multivariable process have first-order dynamics and significant time delays. In Wang *et al.* (1997) a multivariable PID controller for DCS is designed using decentralized relay feedback (DRF) method. The diagonal and off-diagonal elements of this controller are designed in PI and PID forms, respectively. This controller is as follows:

$$\mathbf{C}(s) = \begin{bmatrix} 0.184 + 0.0469 \frac{1}{s} & -0.0102 - 0.0229 \frac{1}{s} + 0.0082s \\ -0.0674 + 0.0159 \frac{1}{s} - 0.0536s & -0.066 - 0.0155 \frac{1}{s} \end{bmatrix} \quad (26)$$

To compare the results of CCA and GA with DRF method, in tuning parameters of the PID controller for the plant defined by (25), controller  $\mathbf{C}(s)$  is considered in the following form:

$$\mathbf{C}(s) = \begin{bmatrix} K_{P11} + K_{I11} \frac{1}{s} & K_{P12} + K_{I12} \frac{1}{s} + K_{D12}s \\ K_{P21} + K_{I21} \frac{1}{s} + K_{D21}s & K_{P22} + K_{I22} \frac{1}{s} \end{bmatrix} \quad (27)$$

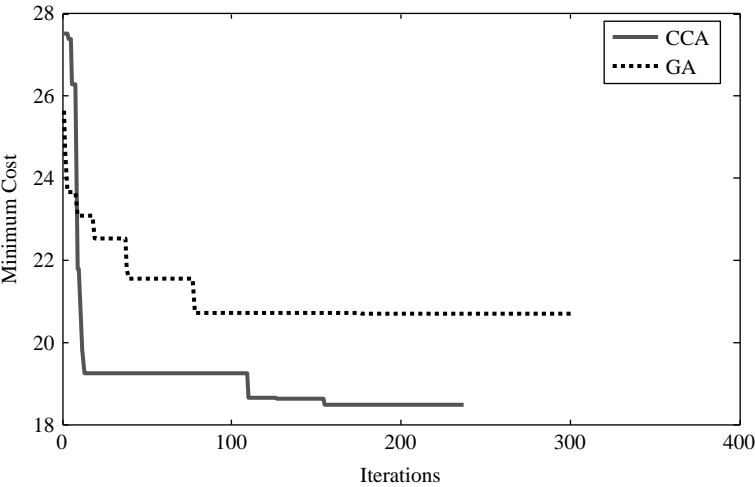
The design objective will be a ten dimensional optimization problem of determining the optimal coefficients  $[K_{P11} \ K_{I11} \ K_{P12} \ K_{I12} \ K_{D12} \ K_{P21} \ K_{I21} \ K_{D21} \ K_{P22} \ K_{I22}]$  to minimize the cost function (24). Both CCA and GA are applied to this problem for 20 times and the best result of each is given and studied in this section.

A CCA with 100 initial countries, 12 of which are chosen as the initial imperialists is used to tune controller parameters. In this algorithm  $\beta$  and  $\gamma$  are set to 2 and 0.5 (rad), respectively. The maximum number of iterations of the CCA is set to 500 but it reached to the total cost of 18.34 in 237 iterations. This is because of the fact that, at iteration 237, imperialistic competition concluded to the state in which only one imperialist is alive, when the imperialistic competition stops and the algorithm hopefully converges to the optimal point.

A GA with 100 initial population, tournament selection, Gaussian mutation and scattered crossover was used to tune the parameters of the multivariable PID controller for the simulated process. To fully exploit GAs potential in cost minimization it was equipped with a hybrid function. Figure 10 shows the minimum costs for the best results of 20 different runs of CCA and GA. As shown in this figure, the steady state convergence value of CCA is 18.34, which is smaller than that of GA, 20.63. Being randomly initialized at a bad start point, CCA converges quickly and reaches to a better cost value in less iteration, compared with GA.

Parameters of PID controller and their relevant cost values obtained by CCA, GA and DRF methods are demonstrated in Tables I and II. According to Table II, the controller obtained by GA has resulted in the least  $IAE_{21}$ ,  $POU_{21}$  for the simulated process. That is, comparing to CCA and DRF, using controller obtained by GA, the second output is decoupled from the first input, in the best way. But for the first output, the controller obtained by CCA is the best one. In spite of the least  $POU_{12}$  value

**Figure 10.**  
Minimum cost of CCA  
and GA versus iteration



**Table I.**  
Parameters of PID  
controller obtained  
by CCA, GA and DRF

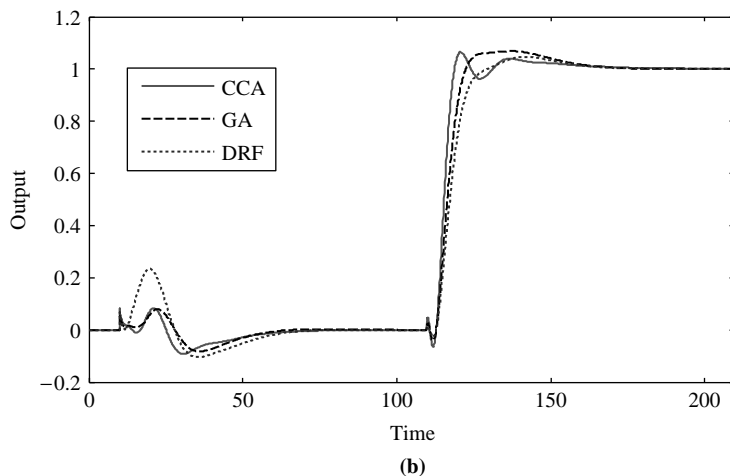
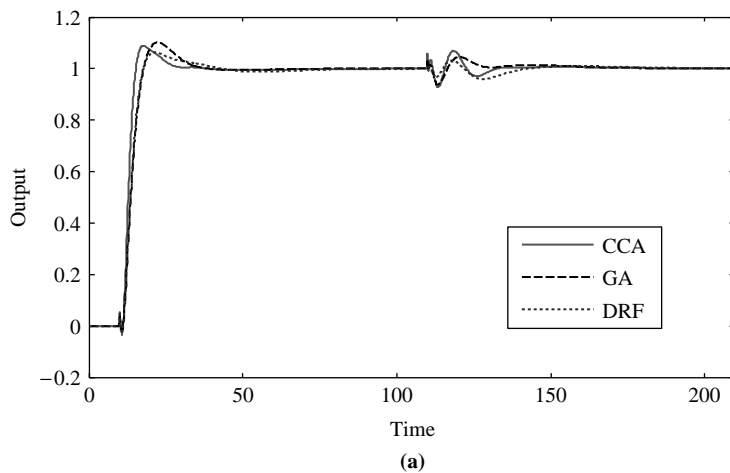
PID parameters	CCA	Method GA	DRF
$K_{P11}$	0.275	0.1763	0.184
$K_{I11}$	0.0803	0.0592	0.0469
$K_{P12}$	-0.0657	-0.0418	-0.0102
$K_{I12}$	-0.029	-0.0246	-0.0229
$K_{D12}$	0.0835	0.037	0.0082
$K_{P21}$	-0.0522	-0.0404	-0.0674
$K_{I21}$	0.033	0.0227	0.0159
$K_{D21}$	-0.068	-0.0425	-0.0536
$K_{P22}$	-0.1243	-0.0827	-0.066
$K_{I22}$	-0.021	-0.019	-0.0155

**Table II.**  
Different parts of cost  
function that are  
optimized by methods,  
CCA, GA and DRF

Criteria	CCA	Method GA	DRF
$IAE_{11}$	3.8537	4.9824	4.9278
$IAE_{12}$	1.0148	1.0351	1.0625
$IAE_{21}$	2.6570	2.2904	4.4716
$IAE_{22}$	7.1589	8.8043	9.0288
$IAE$	14.6844	17.1121	19.4907
$POU_{11}$ (percent)	9.18	10.09	9.91
$POU_{12}$ (percent)	7.23	6.40	4.07
$POU_{21}$ (percent)	10.97	8.88	22.05
$POU_{22}$ (percent)	9.33	9.82	9.86
$POU$ (percent)	37.07	35.19	45.89
Cost	18.3549	20.6313	24.0791

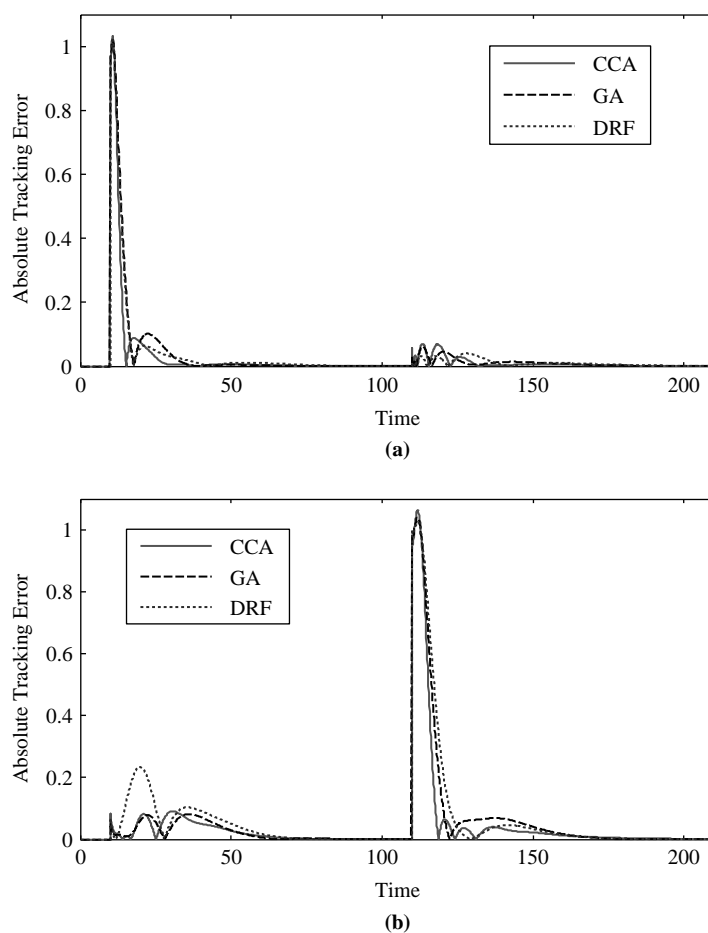
obtained by DRF, CCA's relevant  $IAE_{11}$ ,  $IAE_{12}$ ,  $IAE_{22}$ ,  $POU_{11}$ ,  $POU_{22}$  are the least, resulting in the best tracking and the least coupling. In general, regarding Table II, the controller obtained by GA has the best performance in minimizing overshoot and undershoot in the responses while CCA has resulted in a controller which performs well in tracking the inputs by outputs of the system. However, considering the total cost, the controller obtained by CCA has generally the best performance. The results in Table II show the ability of CCA in dealing with challenging optimization problems.

Figure 11 shows the response of controlled distillation column process to step inputs using different controllers obtained by CCA, GA and DRF. To have a better view of tracking ability of different controllers, the absolute tracking and coupling errors for both outputs are shown in Figure 12. In these two figures step inputs are applied with 10 and 110 s delays, respectively.



**Figure 11.**  
The response  
of distillation column  
process to different delays  
in step inputs: (a) first  
output; (b) second output





**Figure 12.**  
Absolute error of the  
response of distillation  
column process to  
different delays in step  
inputs: (a) absolute error of  
first output; (b) absolute  
error of second output

Similar to other evolutionary algorithms such as GA and PSO, the discussed method in this paper, CCA, does not necessarily guarantee the real-time requirements in exact applications. But as shown in this paper, CCA has better convergence rate than GA. Hence, in applications with cost functions of high computational complexity, the use of CCA will be more preferable. In the problem of designing a MIMO PID controller, studied in this paper, each function call requires about 1.5 s on a PC with a CPU of 1.7 GHz, 80 GB HDD and 1 GB of RAM to run. Therefore, a GA with 100 initial populations that runs for 300 iterations requires 30,000 function calls. The approximate time used to run GA will be  $30,000 \times 1.5 \text{ s} = 12.5 \text{ h}$ . On the other hand, by having more convergence rate than GA, CCA can save the time required to find the global optimum. This fact can be clearly seen in Figure 11 where CCA not only has reached to the final value of GA in about 15 iterations but also has continued to reach a more optimal point. So in spite of the fact that CCA, like GA and PSO, hardly guarantee the requirements of exact applications in real-time mode it can be useful in off-line designs in which global optimum value needs to be calculated exactly.

## 5. Conclusion

In this paper, a novel evolutionary algorithm, inspired from a socio political process, was discussed and its application to a real world industrial problem was demonstrated. Unlike the existing evolutionary algorithms that are inspired by natural processes such as natural evolution or annealing process in materials; CCA, uses imperialism and imperialistic competition, socio-political evolution processes, as source of inspiration. The discussed algorithm consists of countries that are initially divided into some empires. Competition among the empires and the movement of the colonies toward the imperialist states hopefully lead to the convergence of countries to the global minimum of the cost function. As a case study, using CCA, a multivariable controller was designed for an industrial distillation column process. The design objective was to optimally tune the PID controller so that the integral of absolute errors, overshoots and undershoots be minimized. The coefficients of PID controller were obtained by two evolutionary methods, CCA and GA. In the determination of the tradeoff coefficients in fitness functions, we emphasized on reduction of the error integral as long as the overshoots/undershoots remain acceptable. Simulation results showed that not only was the system able to significantly reduce the coupling effect, but also the response speed was significantly increased. The results of controlling the simulated process with different controllers showed that the proposed method for evolutionary optimization, CCA, had a higher convergence rate than GA, reaching to a better solution.

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#### Further reading

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#### About the authors

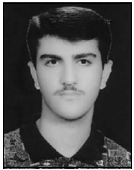


Esmail Atashpaz Gargari was born in Gargar, Iran September 21, 1983. He received his BS degree in Electrical Engineering from Tabriz University, Tabriz, Iran, 2001. He is now pursuing the Control Systems Engineering at Control and Intelligent Processing Center of Excellence at University of Tehran. His research interests are computer vision and image processing, machine learning, evolutionary computation and control of industrial processes. Esmail Atashpaz Gargari is the corresponding author and can be contacted at:

e.atashpaz@ece.ut.ac.ir



Farzad Hashemzadeh received the BSc degree in Biomedical Engineering from Amirkabir University of Technology, Tehran, Iran in 2003, and the MS degree in Control engineering from University of Tehran, Iran, in 2006. He is also a Research Assistant in Control and Intelligent Processing Center of Excellence in University of Tehran. His research interests include machine vision, pattern recognition, nonlinear control and digital control.



Ramin Rajabioun was born in Tabriz, Iran February 15, 1982. He received his BS degree in Biomedical Engineering from Sahand University of Technology, Tabriz, Iran, 2001. He is now pursuing the Control Systems Engineering at Control and Intelligent Processing Center of Excellence at University of Tehran. His research interests are image processing, system identification, computer vision, computer programming, game theory and stochastic control.



Caro Lucas received the MS degree from the University of Tehran, Iran, in 1973, and the PhD degree from the University of California, Berkeley, in 1976. He is a Professor at the Department of Electrical and Computer Engineering, University of Tehran, Iran, as well as a Researcher at the School of Cognitive Science, Institute for Studies in Theoretical Physics and Mathematics (IPM), Tehran, Iran. He has served as the Director of Research Faculty of Intelligent Systems (RFIS), IPM (1993-1997), Chairman of the ECE Department at the University of Tehran (1986-1988), Managing Editor of the Memories of the Engineering Faculty, University of Tehran (1979-1991), Associate Editor of Journal of Intelligent and Fuzzy systems (1992-1999), and Chairman of the IEEE, Iran section (1990-1992). His research interests include biological computing, computational intelligence, uncertain systems, intelligent control, neural networks, multi-agent systems, data mining, business intelligence, financial modeling and knowledge management. He has served as the Chairman of several International Conferences. He was the founder of the RFIS, Center of Excellence on Control and Intelligent Processing, and has assisted in founding several new research organizations and engineering disciplines in Iran.