Tuning of PID Controller Based on Foraging Strategy for Pneumatic Position Control System*

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Abstract

Pneumatic servo system has been applied in many industry fields. The system has many advantages, such as high speed, high flexibility and low price. However, the application of the system is restricted because the physical parameters have strong nonlinearity, inaccuracy and uncertainty, so that it is very difficult to find an optimal controller by means of traditional control theory. Proportional integral derivative (PID) control is one of the earlier control strategies; it has a simple control structure and can be easily tuned. Optimization of PID controller parameters is one of the recent control solutions; especially when the system is of high complexity. In this paper foraging strategy has been adopted to optimize the gains of PID controller for positioning control of a pneumatic system. The foraging theory is based on the assumption that animals search for nutrients in a way that maximize their energy intake per unit time spent for foraging. The bacterial foraging algorithm is a non-gradient and stochastical optimization technique; as no need for measurement and analytical description. In the work, the optimization model of *E. coli* bacterial foraging has been used and the performance index (cost) is based on Integral Square Error (ISE) for obtaining sub-optimal values of controller parameters. The behavior of bacteria (solutions) over their lifetime has been simulated and the effect of foraging parameters on cost function has been studied.

Keywords: E. coli bacterial foraging, pneumatic actuator, PID controller, position control.

تنغيم مكونات المسيطر التناسبي التفاضلي التكاملي باستخدام طريقة التغذية لمنظومة السيطرة الهوائية

الخلاصة:

تستخدم منظومات المؤازرة الهوائية في كثير من التطبيقات الصناعية. حيث تمتاز مثل هذه المنظومات بعدة ميزات اهمها السرعة والمرونة العالية وكذلك كلفتها الواطئة. مع ذلك فان تلك المنظومات يصعب السيطرة عليها وذلك لان بعض معلماتها او العناصرالمكونة للمنظومة غير خطية ومتغيرة مع الزمن وكذلك صعوبة الحصول على انموذج دقيق يمثل المنظومة، لذلك من الصعوبة ايجاد مسيطر مثالي باستخدام طرق السيطرة التقليدية. يمتاز المسيطر (التناسبي . التفاضلي . التكاملي) ببساطة تركيبه وسهولة تنغيم مكوناته. ان تحقيق الأمثلية (optimization) لمؤشر اداء معين بتنغيم معلمات المسيطر هو احد الطرق المستخدمة حديثا" عندما تكون المنظومات معقدة وتحوي لاخطية عالية. في هذا البحث تم استخدام تقنية التغذية وذلك لتنغيم عناصر المسيطر للحصول على الاستجابة الافضل للنظومة الهوائية. تستند نظرية التغذية بأن الكائنات الحية تبحث عن المواد الغذائية بطريقة تمكنها من الحصول على اعلى طاقة في وحدة زمنية معينة. في هذا البحث تم استخدام الانموذج الخاص بتغذية البكتريا المسماة "ايكولي" لغرض تنغيم مكونات المسيطرالتقليدي.

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1. Introduction

Pneumatically actuated drives are used in widespread applications of modern automation systems mainly for pick-and-place positioning problems. They can be a cheaper alternative to electric and hydraulic systems, especially for light load applications. However, the possibility for the application of pneumatic drives is limited in practice by the problems regarding how to control these plants. The nonlinear effects of pneumatic systems caused by the phenomena associated with air compressibility, significant friction effects, wide range of air supply pressure, load variations, etc., make them difficult to control pneumatic axis [1,2,3].

Proportional integral derivative (PID) control is one of the earlier control strategies. Its early implementation was in pneumatic devices, followed by vacuum and solid state analog electronics, before arriving at today's digital implementation of microprocessors. It has a simple control structure which was understood by plant operators and which they found relatively easy to tune [4,5,6].

Industrial processes such as pneumatic systems are subjected to variation in parameters and parameter perturbations so that the control system performs poor in characteristics and even becomes unstable, if improper values of the controller tuning constants are used. Therefore, it becomes necessary to tune the controller parameters to synchronize the controller with the controlled variable, thus allowing the process to be kept at its desired operating condition and to achieve good control performance with the proper choice of tuning constants. Practically all PID controllers made today are based on microprocessors. This has given opportunities to provide additional features like automatic tuning, gain scheduling, and continuous adaptation (continuously updating the parameters of a controller) [5,6].

The foraging theory is based on the assumption that animals try to find and consume nutrients in a manner that maximize the energy obtained from nutrient sources per unit time spent for foraging, while at the same time minimizing exposure to risks from predators. If the organism has a decision-making mechanism (e.g., a brain), then one can view this mechanism as the controller and the remainder of organism and environment as the "plant" (process to be controlled) [7,8,9,10].

In foraging, animals conduct an optimization process without the use of an analytical expression for the gradient and hence, they perform nongradient optimization for "search". This is because it is impossible for most animals (e.g., bacteria) to know the mathematical expression of how the nutrient concentration will change as the bacterium makes small changes in position. This is both because it does not have the memory to store it, and also due to the high level of uncertainty about the environment it lives in (e.g., time-varying and stochastical effects).

In the present work, the optimization model of E. coli bacterial foraging has been analyzed. Then, this model has been employed for tuning the parameters of PID controller for positioning control of a pneumatic system to account for the system variation of parameters.

2. Description of E coli bacterium and its motility behavior

The E. coli bacterium is shown in Fig.(1). It has a control system that enables it to search for food and try to avoid noxious substances [7, 8].

An E. coli bacterium can move in two different ways: it can "run" (swim for a period of time) or it can "tumble", and it alternates between these two modes of operation its entire lifetime.

Locomotion is achieved via a set of relatively rigid flagella that enable it to swim. If the flagella rotate clockwise, each flagellum pulls on the cell and the net effect is that each flagellum operates relatively independent of the others and so the bacterium "tumble" about (i.e., the bacterium does not have a set direction of movement and there is little displacement) (See Figure (1-a)).

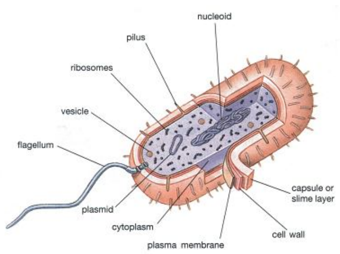


Figure (1) *E. coli bacterium [8]*

If the flagella moves counterclockwise, their effects accumulate by forming a "bundle" and hence, they essentially make a "composite propeller" and push the bacterium so that it runs (swims) in one direction (See Figure (1-a)).

If an E coli is in some substance that is neutral, in the sense that it does not have food or noxious substances, then the flagella will simultaneously alternate between moving clockwise and counterclockwise so that the bacterium will alternatively tumble and run as shown in Fig.(2.b).

Next, suppose that the bacterium happens to encounter a nutrient gradient as shown in Fig.(2.c). The change in the concentration of the nutrient triggers a reaction bacterium will spend more time swimming and the and less time tumbling. As long as it travels on a positive concentration gradient, it will tend to lengthen the time it spends swimming (i.e., it runs farther).

On the other hand, typically if the bacterium happens to swim down concentration gradient, it will return to its baseline behavior so that essentially it tries to search for a way to climb back up the gradient.

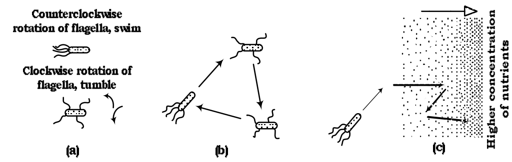


Figure (2) *Motility behavior of E. coli bacterium (a) Bundling phenomenon of flagella (b) swimming and tumbling behavior of E. coli bacterium in a neutral medium (c) there is a nutrient concentration gradient.*

Finally, if the concentration of the nutrient is constant for the region it is in, after it has been on a positive gradient for some time. In this case, the bacterium will return to the same proportion of swimming and tumbling as when it was in the neutral substance so that it returns to its standard behavior.

3. Modeling of E. coli bacterial foraging process

To define the model of E. coli bacterial foraging, one need to define a population (set) of bacteria, and then model how they execute chemotaxis, swarming, reproduction, and elimination/dispersal [7]. A path through the components of the foraging process is shown as a flowchart in Fig. (3.a).

3.1 Population and Chemotaxis

Let j, k and ℓ be the indices for the che- motactic, reproduction step and elimination /dispersal event, respectively. Then,

$$P(j,k,\ell)=\{\theta^i(j,k,\ell)\,|\,i=1,2,\ldots,S\} \qquad (1)$$

Represents the positions of each member in the population of the S bacteria at the j^{th} chemotactic step, k^{th} reproduction step, and ℓ^{th} elimination-dispersal event. Here, let $J(i,j,k,\ell)$ denotes the cost at the location of the i^{th} bacterium $\theta^i(j,k,\ell)\in\Re^p$.

Let N_c be the length of the lifetime of the bacteria as measured by the number of chemotactic steps they take during their life. Let $C(i) > 0,\ i = 1,2,\ldots,S$ denote the lengths of steps during runs. To represent a tumble, a unit length random direction, say $\phi(j)$, is generated; this will be used to define the direction of movement after a tumble.

$$\theta^i(j+1,k,\ell) = \theta^i(j,k,\ell) + C(i)\ \phi(j) \quad (2)$$

so that $C(i)$ is the size of the step taken in the random direction specified by the tumble. If at $\theta^i(j+1,k,\ell)$ the cost $J(i,j+1,k,\ell)$ is better (lower) than at $\theta^i(j,k,\ell)$, then another step of size $C(i)$ in this same direction will be taken, and again, if that step resulted in a position with a better cost value than at the previous step, another step is taken. This swim is continued as long as it continues to reduce the cost, but only up to a maximum number of steps, N_s. This represents that the cell will tend to keep moving if it is headed in the direction of increasingly favorable environments. The flow chart in Fig.(3.b) represents the steps of chemotactic event.

3.2 Swarming Mechanism

The cell secretes attractants to signal other cells that they should swarm together. To model this, let $d_{attract}$ be the depth of the attractant released by the cell (a quantification of how much attractant is released), $w_{attract}$ be a measure of the width of the attractant signal (a quantification of the diffusion rate of the chemical). If the attraction relationship between one an cell and other is represented by a Gaussian form, then the addition of such relation to the nutrient concentration (cost function) can be given by:

$$J_{cc\_attract}(\theta,\theta^i(j,k,\ell)) = \sum_{i=1}^{S}\left[-d_{attract}\ \exp\left(-w_{attract}(\theta_m-\theta_m^i)^2\right)\right] \quad (3)$$

where $m = 1,2,\ldots,p$ and $\theta = [\theta_1,\ldots,\theta_2]^T$ is a point on the search domain and θ_m^i is the m^{th} component of the i^{th} bacterium position

The cell also repels a nearby cell in the sense that it consumes nearby nutrients and it is not physically possible to have two cells at the same location. To model this, let $h_{repellent}$ be the height of the repellent effect (magnitude of its effect) and $w_{repellent}$ be a measure of the width of the repellent. Similarly, if the repelling relationship among bacteria is of Gaussian form, then the contribution of such effect to the cost function is given by

$$J_{cc\_repel}(\theta,\theta^i(j,k,\ell)) = \\ = \sum_{i}^{S}\left[h_{repellent}\ \exp\left(-w_{repellent}(\theta_m-\theta_m^i)^2\right)\right] \quad (4)$$

The cell-to-cell attraction and repelling effects can be combined in one formula

$$J_{cc}(\theta,\ P(j,k,\ell)) = \sum_{i}^{S} J_{cc}^{i}(\theta,\ \theta^i(j,k,\ell))$$

$$= \sum_{i=1}^{S}\left[-d_{attract}\ \exp\left(-w_{attract}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] + \sum_{i=1}^{S}\left[h_{repellent}\exp\left(-w_{repellent}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \quad (5)$$

The swarming effect is added to the cost function. Therefore, the i^{th} bacterium will hill-climb on

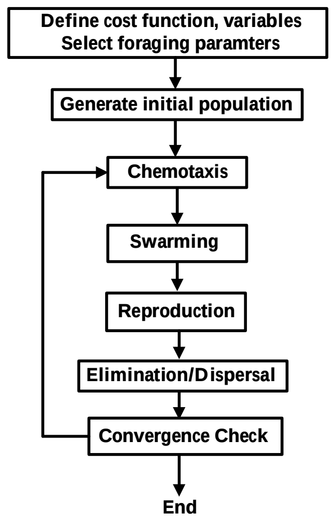
$$J(i,j,k,\ell) + J_{cc}(\theta,P) \quad (6)$$

so that the cells will try to find nutrients, avoid noxious substances, and try to move towards other cells, but not too close to them.

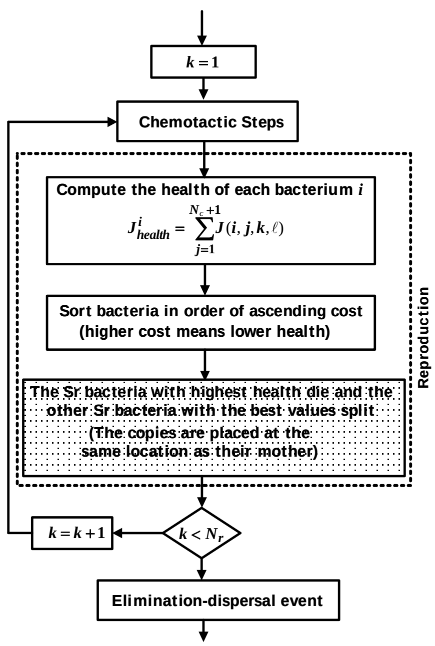
3.3 Reproduction

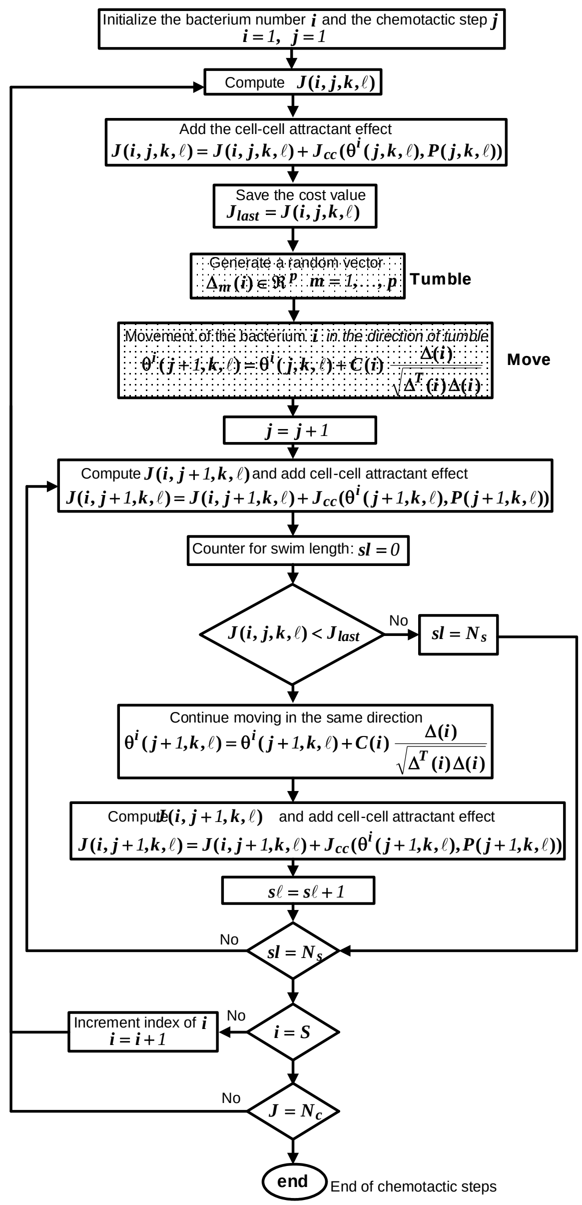
After N_c chemotactic steps a reproduction step is taken. Let N_{re} be the number of reproduction steps to be taken.

Let $S_r = S/2$ be the number of population members who had sufficient nutrients so that they will reproduce (split in two) with no mutation.



(a) Flow chart of foraging process





***(c)** Flow chart of reproduction steps* ***(b)** Flow chart of chemotactic steps*

Figure (3) *(a) Flowchart of foraging process (b) Flowchart of chemotactic steps (c) Flowchart of reproduction steps*

For reproduction, the population is sorted in the order of ascending accumulated cost (higher accumulated cost represents that it did not get as many nutrients during its lifetime of foraging and hence, is not as "healthy" and thus unlikely to reproduce); then S_r least healthy bacteria die and the other S_r healthiest bacteria each split into two bacteria, placed at the same location. This method rewards bacteria that have encountered a lot of nutrients, and allows us to keep a constant population size, which is convenient in coding the algorithm. The flowchart of Fig.(3.c) shows the steps of reproduction event .

3.4 Elimination –dispersal event

If N_{ed} is the number of elimination-dispersal events, each bacterium in the population is subjected to elimination-dispersal event with probability p_{ed} .

4. Dynamic Model of Pneumatic Actuator

Figure (4) shows the position controlled pneumatic system used in the simulations. From Fig.(4), the nonlinear mathematic model of a pneumatic system can be derived as [1,3,11].

$$M\,\ddot{x} + C\,\dot{x} + k\,x = A(P_p - P_n) \qquad (7)$$

$$\dot{m}_p = \frac{V_p}{\gamma\, R T_s}\frac{dP_p}{dt} + \frac{P_p}{R T_s}\frac{dV_p}{dt} \qquad (8)$$

$$\dot{m}_n = \frac{V_n}{\gamma\, R T_s}\frac{dP_n}{dt} + \frac{P_n}{R T_s}\frac{dV_n}{dt} \qquad (9)$$

where M is the piston and the load mass, C is the air damping constant, k is the spring constant, A is the bore area, P_p is the pressure in chamber p, P_n is the pressure in chamber n, V_p is the air volume in chamber p, V_n is the air volume in chamber n, c is the ratio of specific heat, R is the universal gas constant, T is the operating temperature, $\dot{m}_p$ is the mass flow rate into chamber p, and $\dot{m}_n$ is the mass flow rate into chamber n.

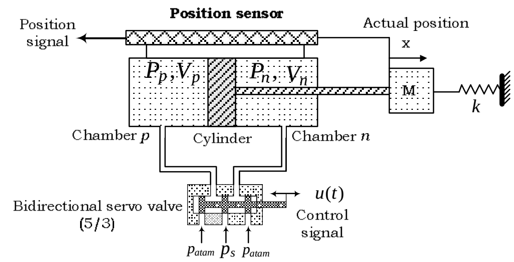


Figure (4) Position controlled pneumatic system

To linearize the system, a small deviation from an initial equilibrium point is considered. Assume that at the equilibrium point, the values of the state variables are x=0, $P_p = P_{po}$, $P_n = P_{no}$, $V_p = V_{po}$, $V_n = V_{no}$. Thus, Esq. (7)–(9) can be rewritten as [1]

$$\Delta\dot{m}_p = \frac{\Delta V_{po}}{\gamma\, R T_s}\Delta\dot{P}_p + \frac{P_{po}}{R T_s}\Delta\dot{V}_p \qquad (10)$$

$$\Delta\dot{m}_n = \frac{\Delta V_{no}}{\gamma\, R T_s}\Delta\dot{P}_n + \frac{P_{no}}{R T_s}\Delta\dot{V}_n \qquad (11)$$

$$M\,\Delta\ddot{x} + C\,\Delta\dot{x} + k\,\Delta x = A\,(\Delta P_p - \Delta P_n) \quad (12)$$

where Δ denotes the small deviation value. If the proportional flow control valve is used, the input valve voltage is proportional to the airflow rate. Assume that mass flow rate is identical in both chambers and the displacement of the spool valve is proportional to the valve voltage. Then the relation between the input voltage deviation and the flow rate deviation can be written as [1]

$$\Delta\dot{m}_p = K\,\Delta u \;\;,\;\; \Delta\dot{m}_n = -K\,\Delta u \qquad (13)$$

By simple volume equation,

$$\Delta\dot{V}_p = A\Delta\dot{x} \;\;,\;\; \Delta\dot{V}_n = -A\Delta\dot{x} \qquad (14)$$

Substituting Eqs.(13) and (14) into Eqs.(10) and (11) and rearranging the equations, the following equations are obtained:

$$\Delta\dot{P}_p = -\frac{\gamma\, A P_{po}}{V_{po}}\Delta\dot{x} + K\frac{\gamma\, R T}{V_{po}}\Delta u \qquad (15)$$

$$\Delta\dot{P}_n = \frac{\gamma\, A P_{no}}{V_{no}}\Delta\dot{x} - K\frac{\gamma\, R T}{V_{no}}\Delta u \qquad (16)$$

Rearrange Eq. (12), the motion equation then becomes

$$\Delta\ddot{x} = \frac{A}{M}\left(\Delta P_p - \Delta P_n\right) - \frac{C}{M}\Delta\dot{x} - \frac{k}{M}\Delta x \quad (17)$$

Assume the state variables vector of the form $x_s = [\Delta P_p \;\; \Delta P_n \;\; \Delta x \;\; \Delta\dot{x}]$, then Eqs.(15)–(17) are then represented in a state-space form,

$$\left.\begin{aligned} \dot{x}_s &= A_s\, x_s + B_s\, u \\ y &= C_s\, x_s \end{aligned}\right\} \quad (18)$$

where

$$A_s = \begin{bmatrix} 0 & 0 & 0 & \left(-\gamma\, A P_{po}/V_{po}\right) \\ 0 & 0 & 0 & \left(\gamma\, A P_{no}/V_{no}\right) \\ 0 & 0 & 0 & 1 \\ (A/M) & (-A/M) & (-k/M) & -C/M \end{bmatrix}$$

$$B_s = \begin{bmatrix} \left(\gamma\, KRT/V_{po}\right) \\ -\left(\gamma\, KRT/V_{no}\right) \\ 0 \\ 0 \end{bmatrix}, \; C_s = [0 \;\; 0 \;\; 1 \;\; 0].$$

5. *E.*coli Bacterial Swarm Foraging for Tuning PID controller

The structure of foraging-based PID controller is shown in Fig.(5). Each bacterium represents a solution of the problem and hence it consists of three terms: the first one is the k_p value, the second one is the k_d value and the third one is k_I. Then the Bacterium vector is given by: Bacterium= [$k_p \;\; k_d \;\; k_I$].

It must be noted here that the range of each gain must be specified, i.e., $k_{p\min} \le k_p \le k_{p\max}$, $k_{d\min} \le k_d \le k_{d\max}$, $k_{\mathrm{Im}in} \le k_I \le k_{I\max}$

The most crucial step in applying foraging is to choose the objective functions that are used to evaluate the cost of each bacterium. Some works use *performance indices* as the objective functions. Other works uses Mean of the Squared Error (MSE), Integral of Time multiplied by Absolute Error (ITAE), Integral of Absolute Magnitude of the Error (IAE), and Integral of the Squared Error (ISE). In this work, ISE is used to minimize the error signal [12].

Foraging strategy starts with an initial population containing a number of bacteria where each one represents a solution of the problem which performance is evaluated by a cost function. The cost is evaluated after setting the values of controller elements from foraging process, then determining the instantaneous error of the closed-loop behavior. The cost value for a specified solution is obtained by summing all the squared values of error over the settling time of system behavior.

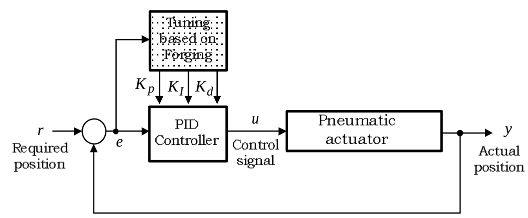


Figure (5) *Block diagram of forging-based tuning of PID controller*

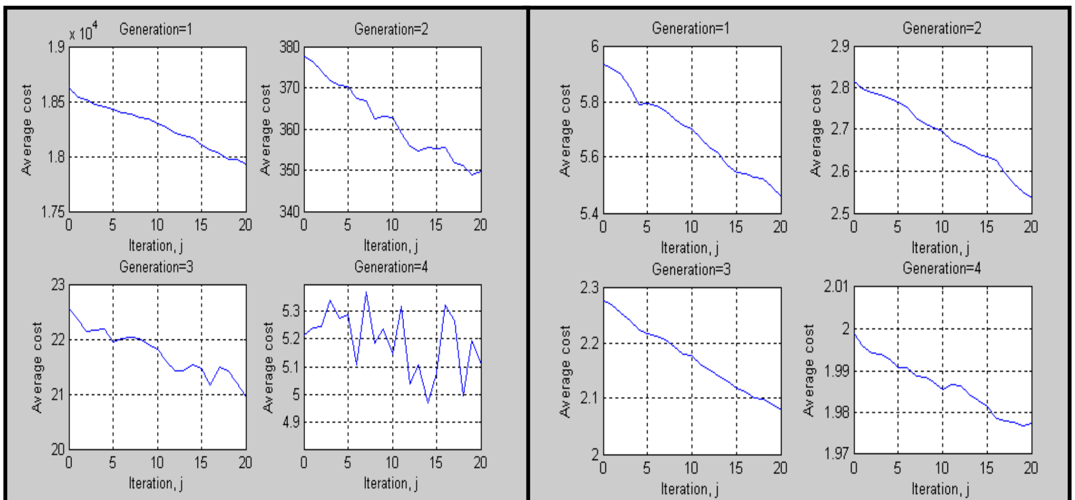
During the search process, the foraging looks for the optimal setting of the PID position controller gains which minimizes the cost function. This function is considered as the evolution criteria for the foraging process.

6. Results

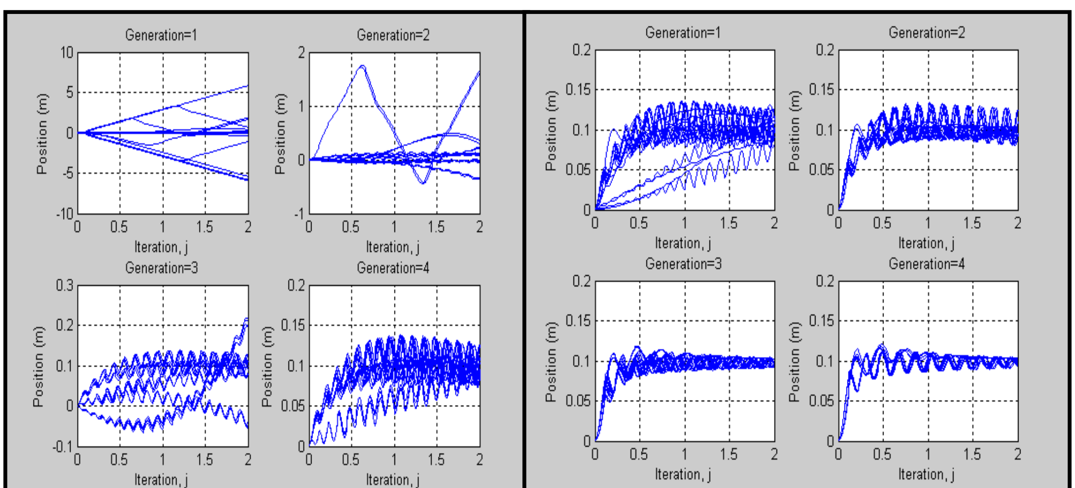
The parameters of foraging process used in the simulated results are listed in Table (2) (see the Appendix). The simulated results have been executed in Matlab package (R2008b) and the numerical solver of pneumatic system of equations is based on fourth-order Runge_Kutta with step size of 1e-4 sec.

It is worth while to note that each bacterium (at every chemotactic step) carries the solution of the three controller terms (K_p, K_d and K_I). Figure (6) shows the behaviors of bacteria solution (values of controller terms) with respect to chemotactic steps. One can see that these solutions are dispersed in the search domain at the first generation and then they converge to a specified region of values at the end of foraging events. Unfortunately, the solutions of all bacteria finally settle at two minimum regions. Actually, this could be attributed to low value of chemotactic steps (Nc=20); as the problem does not have sufficient chemotactic steps to find a global minimum. If the chemotactic steps have been increased to (Nc=50), all solutions could be reached to a region of global minimum. This is evident in Fig.(7).

Figures (6) and (7) also show the behavior of average cost with respect to chemotactic step. At each chemotactic step, the cost of each bacterium is calculated based on ISE criterion and then the average of all bacteria costs is taken. At every generation and the end of all chemotactic steps, S-solutions of controller terms are available to the controller. Therefore, one can obtain S-plots of closed-loop responses at each generation. At the end of all events, the S-final solutions would give the best values of controller parameters. Applying these final settings to controller parameters, refined S-plots of the closed-response could be obtained. One can see how well the closed-loop response could be improved over the generations of bacteria that live using this foraging process.



first elimination/dispersal event ***a*** ***second elimination/dispersal event***



first elimination/dispersal event ***b*** ***second elimination/dispersal event***

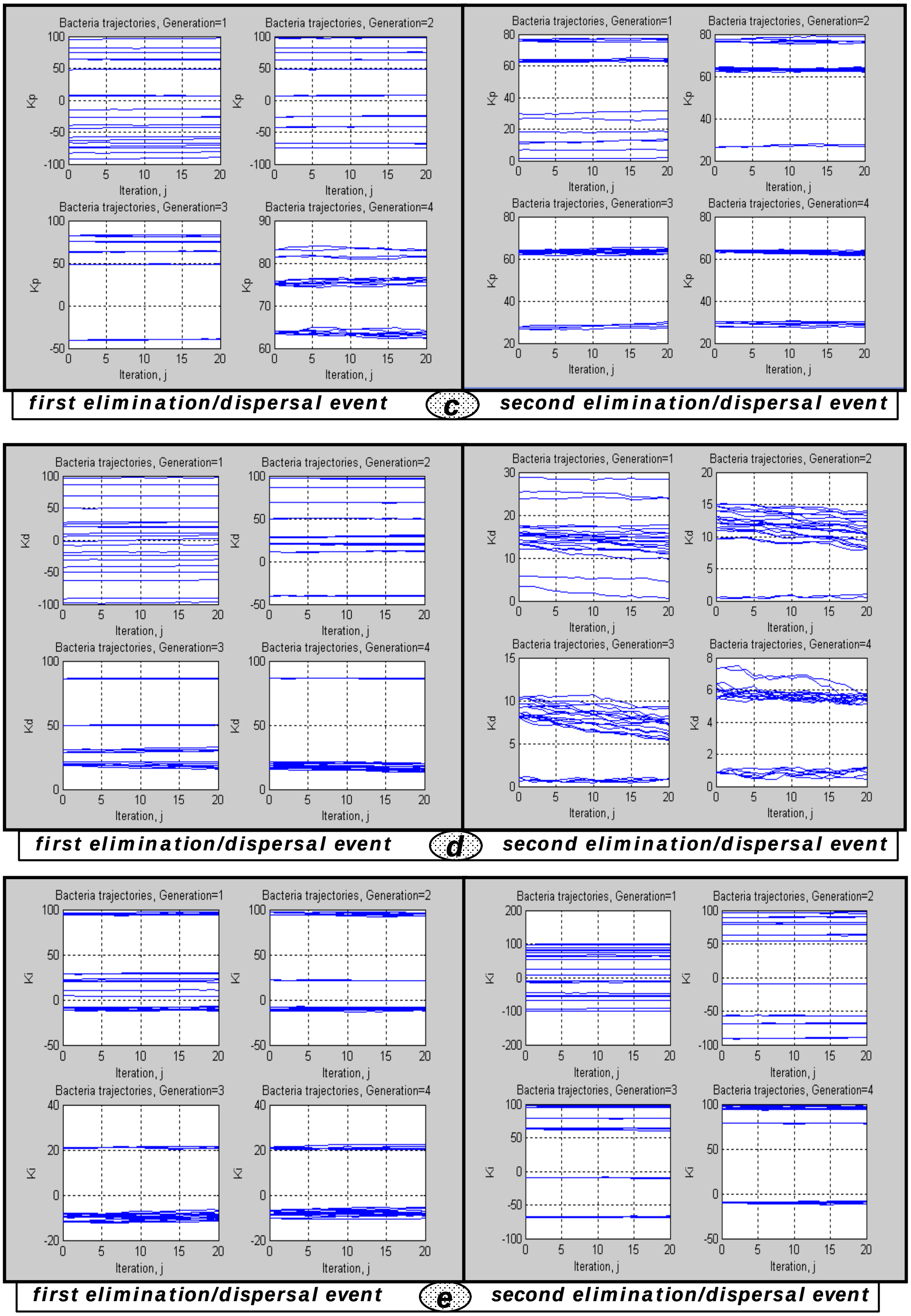
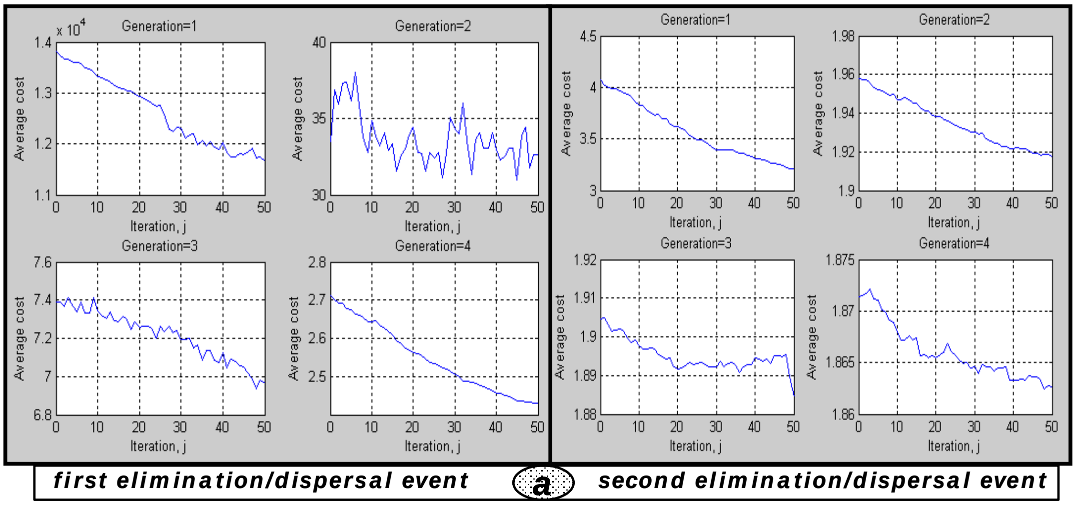
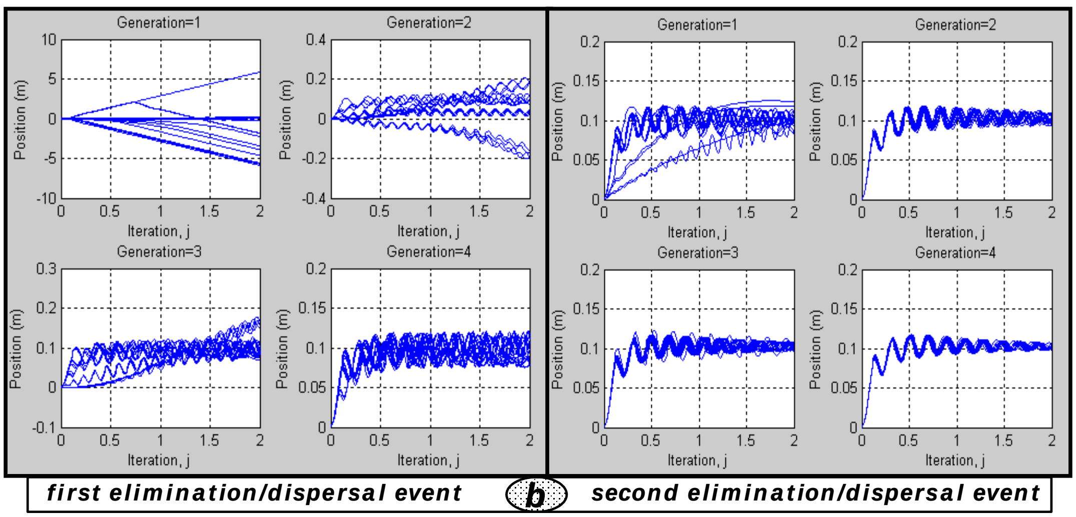
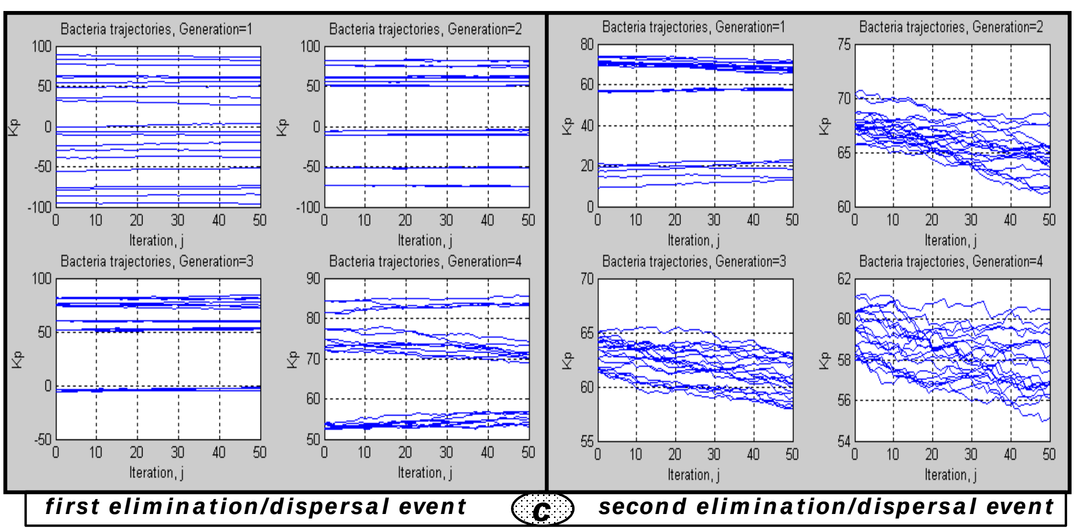


Figure (6) ***(a)*** *behavior of cost function,* ***(b)*** *position time responses,* ***(c, d, e)*** *behaviors of the PID controller elements over life time of bacteria behavior*


Generation=1
Generation=2
Generation=3
Generation=4
Average cost
Iteration, j
x 10^4
first elimination/dispersal event
a
second elimination/dispersal event


Generation=1
Generation=2
Generation=3
Generation=4
Position (m)
Iteration, j
first elimination/dispersal event
b
second elimination/dispersal event


Bacteria trajectories, Generation=1
Bacteria trajectories, Generation=2
Bacteria trajectories, Generation=3
Bacteria trajectories, Generation=4
Kp
Iteration, j
first elimination/dispersal event
c
second elimination/dispersal event

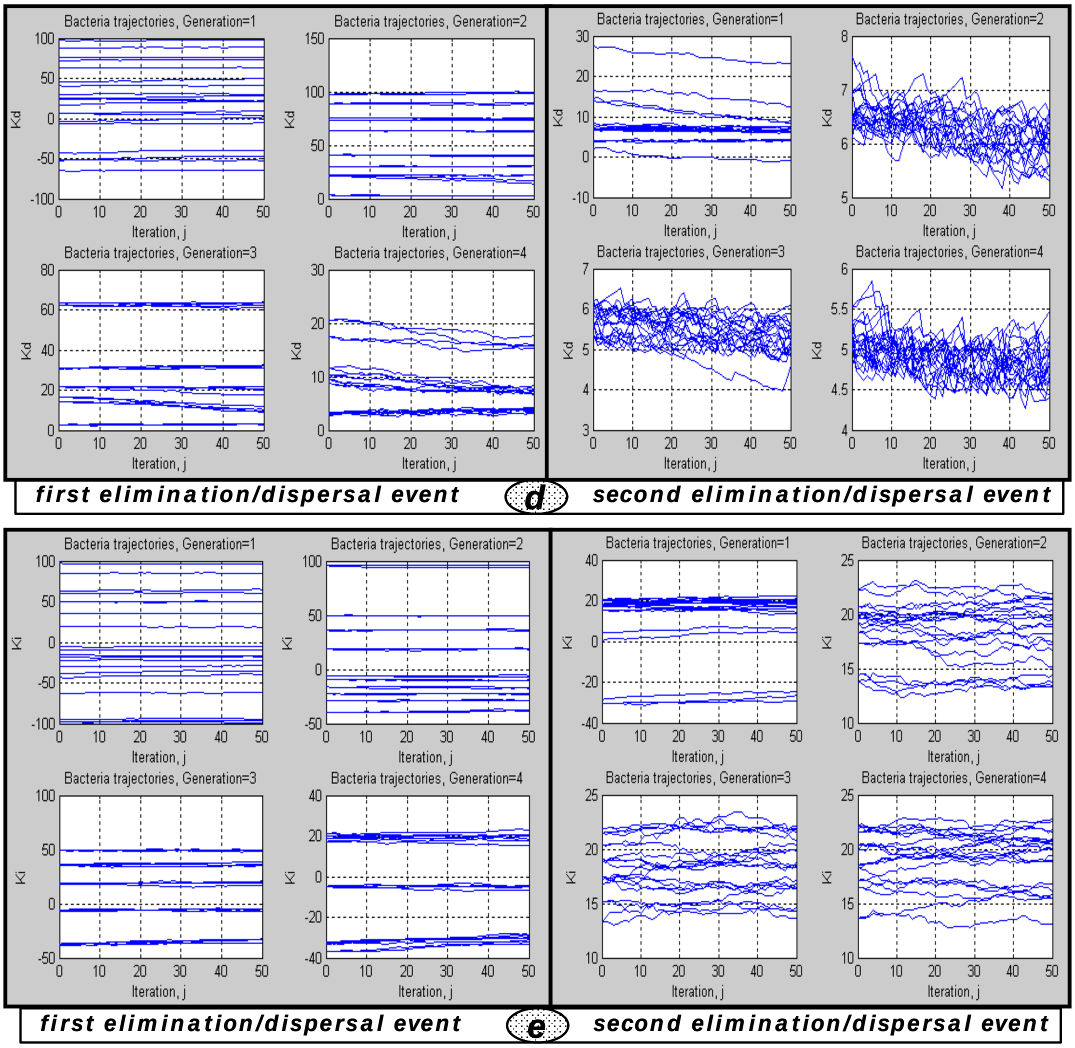


***Figure (7) (a)** behavior of cost function, **(b)** position time responses, **(c, d, e)** behaviors of the PID controller elements over life time of bacteria behavior*

Figure (8) shows the behaviors of average cost variation as changing the probability value of elimination/dispersal event occurrence (P_{ed} =0.1, 0.3, 0.4, 0.5 and 0.6). The best average cost happens with P_{ed} =0.1 and the worst one is found with P_{ed} =0.6. One can argue that increasing the probability of elimination/dispersal occurrence would increase the probability of missing the best solutions with low costs and then those with high cost might dominate.

In Fig.(9), the reproduction number has been changed in steps N_{re} =2,3 and 6. Of course, the result in figure is expected as the increasing of reproduction number occurrences would permit the population to attain newer best solutions (solutions with lower cost) and reject the worst ones. In other words, as the number of reproduction occurrences has been increased the promotion of best bacteria can be obtained.

Fixing the probability of elimination-dispersal at low value (P_{ed} =0.25) and increasing the number of such event repetitions would permit a few solutions to leave the region of swarming and try to search a new region at which the cost might be lower (regions with high concentration of nutrients). If it happens that such few solutions find a lower cost region, then the whole bacteria (solutions) would jump at this new tract.

It is seen from Fig.(10) that increasing the number of elimination/dispersal occurrence would improve the solutions toward a lower cost levels.

Figure (11) shows that lengthening the time interval of bacteria searching (when they are on the gradient) at every chemotactic step has an adverse effect on the average cost. Three values of swiming length have been chosen (N_s =8, 6 and 5). It is clear from the figure that N_s =5 won the best setting that gives the minimum cost average. One can argue that the relation between the cost function and the swim length is dependent on the considered application. In the present situation, it is expected that the valley of global minimum is of steep edges so that long swim would tend to lead the solution out of the valley minimum; i.e., swimming through its minimum without stopping.

In Fig. (12), the chemotactic steps (per bacteria life time) has been changed at N_c =25, 50 and 75. For the considered pneumatic problem, it is found that setting N_c =50 shows the lowest average cost behavior. Therefore, N_c =50 has been set for all simulations.

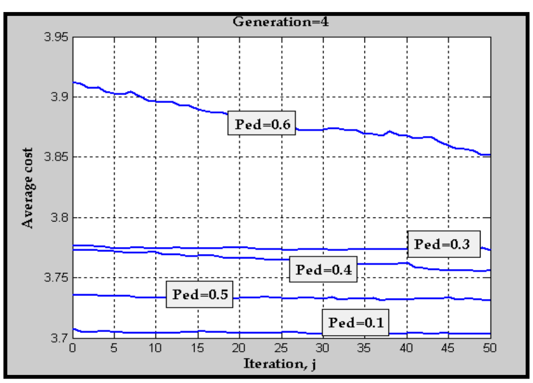


Figure (8) *Variation of probability of elimination and dispersal occurrence*

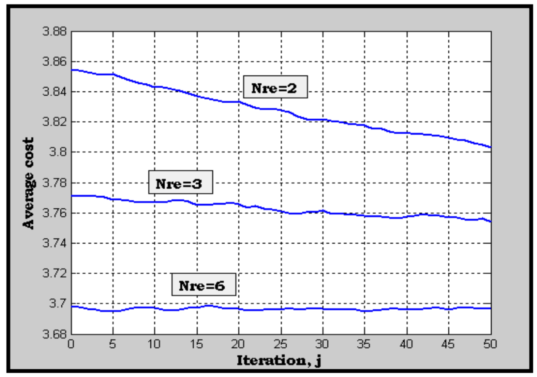


Figure (9) *Change the number of reproduction steps*

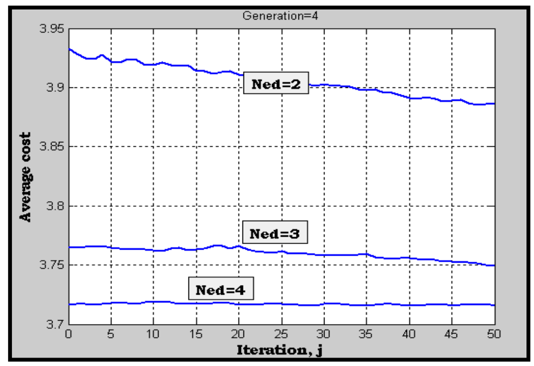


Figure (10) *Change the number occurrence of elimination/dispersal events*

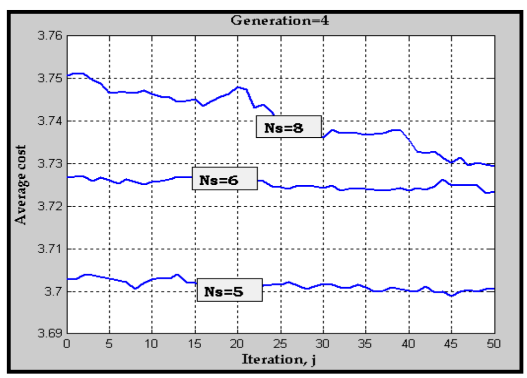


Figure (11) *Change the swim length*

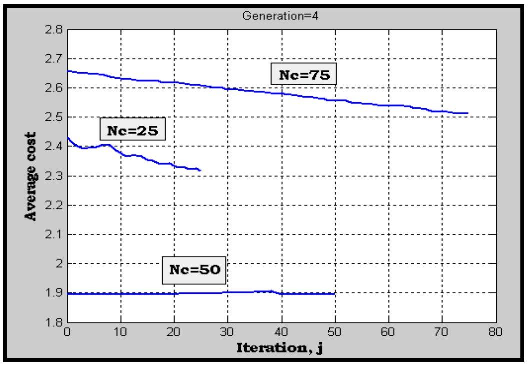


Figure (12) *Change the number of chemotactic steps (per bacteria lifetime)*

7. Conclusion

Based on the above simulated results, the following points could be highlighted:

1. The E. coli optimization model could successively find the sub-optimal values of PID controller which gives the best responses for the pneumatic position control.

2. Increasing the number of chemotactic steps would increase the time required for searching the global minimum. This of course would grant the optimization method a higher chance to lump their solutions at a global minimum.

3. The selection of the probability value of elimination/dispersal event occurrence is problem dependent. In the present pneumatic system, reaching to the global solution requires a low probability value of this event. Higher value could throw the best solutions away from global minimum and leads to instability problems. However, different systems may require different setting of this value.

4. Increasing the reproduction number would enhance the cost measure; as the foraging process could catch new best solutions and repel the worst ones.

5. Increasing the number of elimination dispersal occurrences would improve the solutions toward a lower cost level.

6. Increasing the length of chemotactic steps may have an adverse effect on finding the global solution. The lengthy time may lead the solution to a region beyond the best one and then the global minimum would be lost. Therefore, the setting of this value is problem dependent and it depends on the system complexity and behavior near a global minimum.

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Appendix

Table (1) lists the system parameters and coefficients, while Table (2) gives the values of various conditions used in the simulated results.

Table (1): *Parameters definition and values [1]*

Parameter Definition	Value
Temperature (T)	300 K
Ratio of specific heat (γ)	1.4
Air damping coefficient (C)	5 N/m^2
Universal gas constant (R)	287
Proportional valve constant (K)	0.00233 kg/s
Spring constant (k)	20 N/m
Normal pressure in chamber p (P_{po})	3×10^5 Pa
Normal pressure in chamber n (P_{no})	3×10^5 Pa
Normal pressure in chamber p (V_{po})	20×10^{-3} m^3
Normal pressure in chamber n (V_{no})	20×10^{-3} m^3
Bore area (A)	2×10^{-3} m^2
Piston mass M	0.4 kg
Supply pressure P_s	400 kPa
Atmosphere pressure (P_{atam})	100 kPa

Table (2): *Foraging parameters used in simulations*

Parameter Definition	Fig.6	Fig. 7	Fig. 8	Fig.9	Fig.10	Fig.11	Fig. 12
Number of bacteria in the population (S)	20	20	20	40	40	40	40
The length of swim (Ns)	4	4	4	4	4	**Var.**	4
Number of reproduction steps (Nre)	4	4	4	4	**Var.**	4	4
Number of chemotactic step (Nc)	20	50	**Var.**	50	50	50	50
Number of elimination / dispersal events (Ned)	2	2	2	**Var.**	2	2	2
Number of bacteria splits per generation (Sr)	10	10	10	20	20	20	20
Probability of dispersal occurrence (Ped)	0.25	0.25	0.25	0.25	0.25	0.25	**Var.**
Height of repellent effect ($h_{rep.}$)	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Width of repellent effect ($w_{rep.}$)	10	10	10	10	10	10	10
Width of attractant effect ($w_{attr.}$)	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Width of attractant effect ($d_{attr.}$)	0.1	0.1	0.1	0.1	0.1	0.1	0.1