# PID controller parameters enhanced founded on Artificial Fish Swarm Algorithm

**B A KOUASSI[1,3,5], Yiming ZHANG[1,3], M J MBYAMM KIKI[2,3] and S OUATTARA[1,3]**

[1]College of Electronic Information and Control Engineering;
[2]College of Computer Science and Technology
[3]Beijing University of Technology,100124, Beijing, China

corresponding author's e-mail: kabonzad@yahoo.fr

**Abstract.** Optimization issues are of great importance to both the industrial and scientific worlds. Artificial Fish Swarm Algorithm (AFSA) is a clever optimization algorithm founded on a behaviour inspired by the nature. The enhanced artificial fish swarm algorithm (EAFSA), settled on chaotic model, is applied to optimize the Proportional Integral Derivatives PID parameters, which increases the dynamic of the tuning mechanism and improves its fundamental behaviour. The simulation results show that this optimization algorithm gives faster response, shorter adjustment time and smaller overshoot.

## 1. Introduction

Despite all the advances in control, the Proportional-Integral-Derivative PID controller remains the most used controllers for decades. And notwithstanding that advanced control rules are used; it is familiar to have a hierarchical design of the PID control at the lowest rank [1]. Performances of PID are mostly evaluated to control the frequency and the power of the system [2][3][4]. To enhance PID performances, various theories and algorithms have been proposed [5].

Artificial Fish Swarm AFSA algorithm founded on the behavior of the swarm. This algorithm has a strong prevention capability and overall extremity[6][7]. It is adjustable and the speed of convergence is quick [8]. It requires no characteristics such as the fitness value, so it has the particular easy-going ability to test space, belongs in principle to a Swarm with its sophisticated algorithm. In many areas of computing and optimization, this algorithm has been implemented [9] [10][11][12].

In this paper, the AFSA is applied to optimize the PID parameters, and an EAFSA were adopted, which adds the dynamic adjustment mechanism of parameters and improves its basic behaviors. Simulation results prove that it has good optimization outcomes on PID parameters, and the achievement of the EAFSA is better.

The paper is arranged as follows: the second section explains shortly the PID tuning approach. The third section is about the Artificial Fish Swarm Algorithm. Section four provides some results of simulations on Matlab/Simulink to show the performance of AFSA. Finally, section five gives the conclusion of the research.

## 2. Mathematical model of PID controller

Inherently, the PID controller depends on past and actual error values as well as an augury of the future control errors. In fact, the integral part acts on the average of past errors; the proportional part takes effect on the present error value; and the derived part acts as a forecast of future errors founded on a linear extrapolation. PID computes continually the error value $err(t)$ as the difference between the needed process variable (output) and the required input (reference) as shown below.

$$err(t) = reference - output \qquad (1)$$

By adjusting the control variable u(t), the control attempts to minimize the failure over time. In general, the theoretical time description of a PID is as follows:

$$u(t) = K_p.err(t) + K_I \int_0^t err(t).dt + K_D.\frac{d.err(t)}{dt} \qquad (2)$$

With $K_p$ proportional parameter, $K_I$ integral parameter and $K_D$ derivative parameter of the PID controller.

Commonly, the performance of the controller is described by the objective function. That typical criteria for PID tuning, can be such as the integral of absolute error (ITAE ), the integral of time-weighted absolute error (ITAE ), the integral of time-weighted squared error (ITSE ) and the integral of squared error (ISE ). However, these criteria don't have an essential repercussion on the designing of robust PID.

In the continuation of the works, the model of the PID is that represented in the following fig.1.
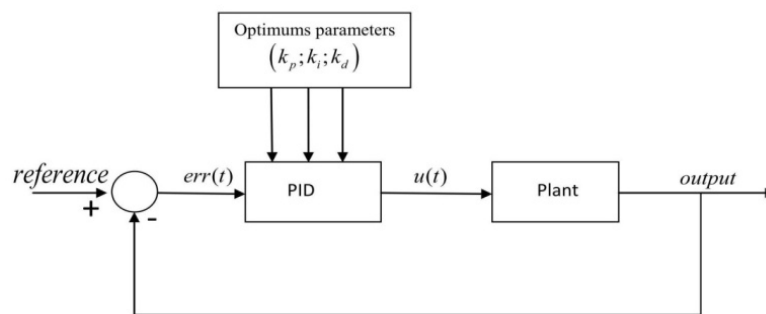


**Figure.1.** PID controller block diagram based on intelligent control

## 3. Artificial fish swarm algorithm AFSA

The swarm of artificial fish is a clever optimization algorithm simulating the basic behavior of natural fish stocks by the creation of artificial fish. It builds on a simple bottom comportment of artificial fish [13]. Furthermore, it constructs on the global optimum obtained by individuals' local probing behaviors. This algorithm is able to prevent local extremities and reach global limits. It is flexible in use and rapidly converging [14] .

### 3.1. The fundamental of AFSA

The consistency of an artificial fish food $Y$ is described as the reverse of the objective function $J$ [15]:

$$Y = \frac{1}{J} \qquad (3)$$

The fundamental of Artificial Fish Swarm Algorithm (AFSA) is founded on the following steps: searching, swarming, following and bulletin [16]. Consider a space in which, the fish are free to move as shown in fig.2. Detecting the presence of food in this given area causes the quick moving of fish nearest the food position .

Assuming the current position of a selecting fish is $x_i$ and let denote TN a trial number that help to improve the convergence efficiency. The AFSA is described as below, with $\delta$ the crowd factor :

- Select the next position $x_j$ within its field of view, and move one step towards it.

- In its field of view, randomly produced a state $x_j$ , if $Y_j > Y_i$ ( $x_j$ state when the food concentration is large), then move one step towards $x_j$. Otherwise, produce new position $x_j$, then judge. If you try TN and the move condition is still not met, thus random behavior is performed.

- In the range of individual field of view of artificial fish, the center location and number of fish are respectively $x_c$ and $n_f$ . Thereby; if $\dfrac{Y_C}{n_f} > \delta.Y_i$ (the central location of food is many and not crowded) , then move one step to the central position $x_c$ . Otherwise, the foraging behavior is performed.
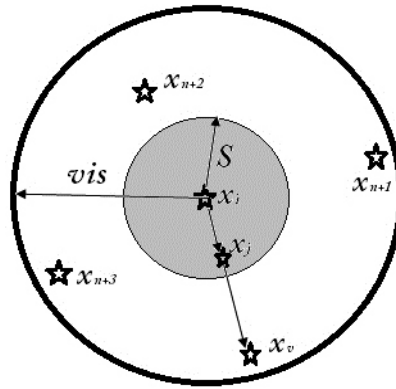


**Figure. 2.** Field of view and movement of an artificial fish

- $x_j$ is the optimal individual state of the objective function value in the field of view of the artificial fish. If $\dfrac{Y_j}{n_f} > \delta.Y_i$ (large food and not crowded), then move one step towards $x_j$. Otherwise, the foraging behavior is performed .

### 3.2. Enhancing performance of the AFSA
In this section, the descriptions of the improvements of the AFSA are given.

*3.2.1 Vision and Step improvement.* The field of view and step length have an important effect on the search of ability, precision and convergence speed of AFSA [17][18]. Thereby, the field of view *Vis* and step length $S$ are dynamically settled according to the goal.

$$\begin{cases} \alpha = \exp[-30.\beta^{\mu}] \\ Vis = Vis \times \alpha + Vis_{\min} \\ S = S \times \alpha + S_{\min} \end{cases} \qquad (4)$$

with $\beta = \dfrac{gen}{Mgen}$ , $gen$ and $Mgen$ denote respectivelly the current and the maximum iteration, $\alpha$ denote the improvement convergence coefficient, $S_{min}$ is the minimum steps lenght, $Vis_{min}$ is the minimum field of view, and $\mu$ is the rate change.

Fig.3 shows the curves of the convergence of $\alpha$ according to $\mu$ . Thus, the curves keep the highest value at the commencement of the operation, then progressively becomes larger and smaller, and finally keep the minimum. That leads quickly $Vis$ and $S$ to their maximum values. Thereby, the algorithm searches finely around the optimal value to improve the solution precision.
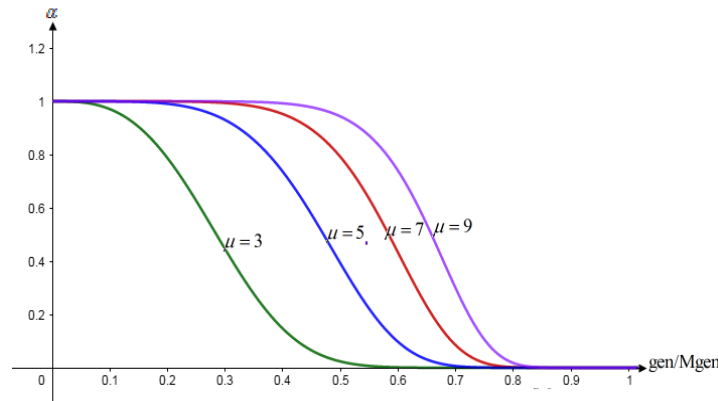


**Figure .3.** $\alpha$ curve of convergence

*3.2.2.Basic Behavior Improvement.* Foraging behavior improvement: In the field of view given by the eq.4, choose a position $x_j$. If $Y_i < Y_j$ then swim directly to $x_j$, otherwise, choose new position $x_j$ and judge. Repeat until the moving condition met, then move randomly according to the following eq.5.

$$x_j = x_i + Vis \times |2 \times rand(.) - 1| \tag{5}$$

Swarming behavior improvement: The standard AFSA is transformed into the central position of the whole fish in the center position $x_c$ of the individual neighborhood. If $Y_c.F > \delta.Y_i$ then move one step to $x_c$ ; otherwise, the foraging behavior is performed.  $F$ denotes the fish size.

$$x_i(t+1) = x_i(t) + \frac{x_C - x_i(t)}{\|x_C - x_i(t)\|} \times rand(.) \times S \tag{6}$$

Foraging behavior improvement: the appropiate position, of AFSA in the individual neighborhood, becomes the global optimal position $x_{best}$ of the whole fish group, and the optimal value is $Y_{best}$. If $Y_{best}.F > \delta.Y_i$ then move one step to $x_{best}$ ; otherwise, execute the foraging behavior.

$$x_i(t+1) = x_i(t) + \frac{x_{best} - x_i(t)}{\|x_{best} - x_i(t)\|} \times rand(.) \times S \tag{7}$$

*3.2.3. Enhanced PID parameters based on AFSA.* Tuning model: the state of an individual artificial fish is setting as $x_i = (K_P^i, K_I^i, K_D^i)$ and the distance  between individuals is $\lambda_{ij}$, described by eq.8.

$$\lambda_{i,j} = \sqrt{(K_P^i - K_P^j)^2 + (K_I^i - K_I^j)^2 + (K_D^i - K_D^j)^2} \tag{8}$$

Fitness function : The fish swarm algorithm solves the problem of large food concentration, so is taken down and converted to the maximum value. Then the food consistence is given by:

$$Y = J^{-1} = \left( \sum_{i=1}^{F} (k.T^2.\left|err(i)\right| + \left[u(i) - u(i-1)\right]^2.T) \right)^{-1} \tag{9}$$

Improvement of PID parameters: centered on the parameters $(K_P^{ZN}, K_I^{ZN}, K_D^{ZN})$ set by the Ziegler_Nichols tuning method as following :

$$\begin{cases} (1-\gamma)K_P^{ZN} < K_P < (1+\gamma)K_P^{ZN} \\ (1-\gamma)K_I^{ZN} < K_I < (1+\gamma)K_I^{ZN} \\ (1-\gamma)K_D^{ZN} < K_D < (1+\gamma)K_D^{ZN} \end{cases} \tag{10}$$

with $\gamma \in [0,1]$

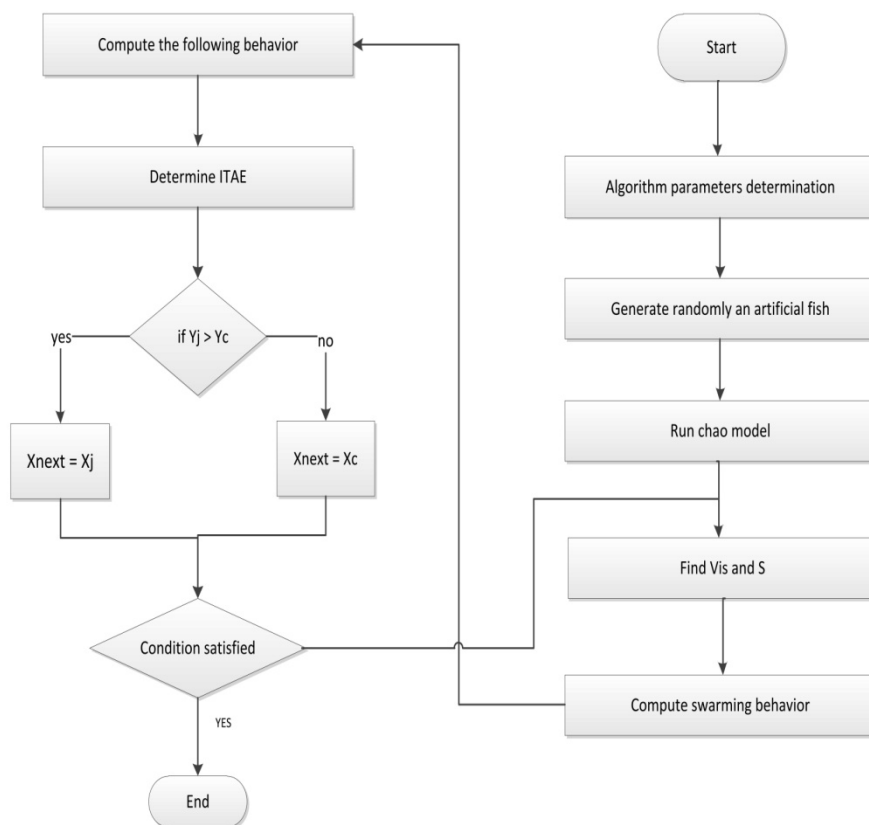The flowchart of the AFSA computing is shown in fig.4.



**Figure.4.** Algorithm based on AFSA improvement

## 4. Simulation and discussion

In this section, the PID improvement is based on the model build in Simulink given in fig.5. The controller process is describe as follow:

$$G(s) = \frac{e^{-0.5s}}{(s+1)^2} \tag{11}$$

Accordind to the previous equation, the Ziegler_Nichols parameters are obtained: $K_P^{ZN} = 2.82$, $T_I^{ZN} = 24.1026$ and $T_D^{ZN} = 3.9610$. And, the AFSA parameters are set as follows: $\alpha$, $S_{min} = 0.0002$, $S = 0.3$, $Vis = 2$, $Vis_{min} = 2$, $\delta = 0.618$, $Mgen = 500$, $\gamma = 0.5$ and $F = 100$.

It can be seen from the following Fig.4 , Fig.5  and the table, the comparison between these three-step responses. The  enhanced step response gives a good response almost without overshoot.
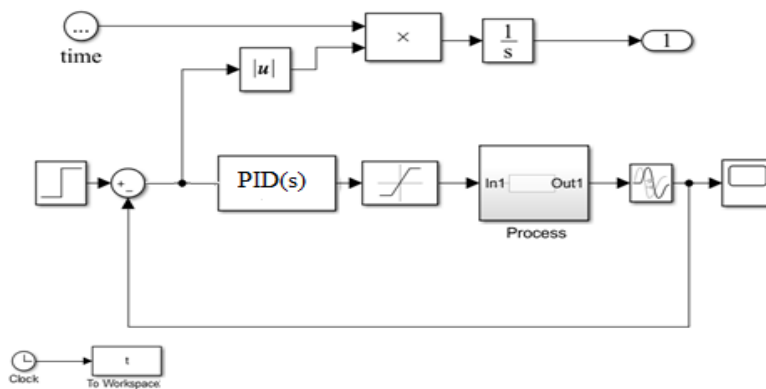


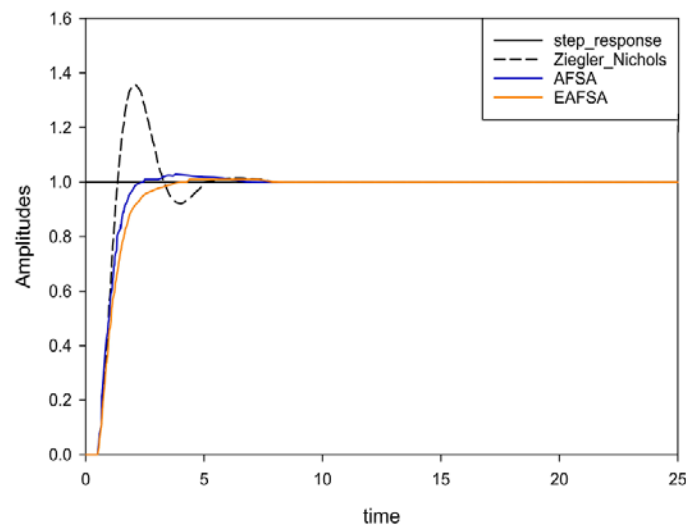**Figure.5.** Simulink model of PID controller



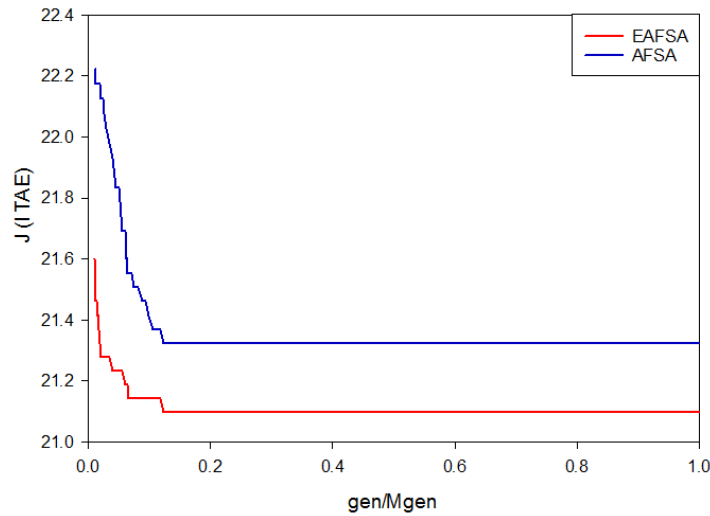**Figure.6.** Step response of Ziegler_Nichols, AFSA and EAFSA design methods

**Figure.7.** fitness curves of AFSA and EAFSA design methods

Table: parameters and performance based on ZN, AFSA and EAFA

|  | $K_P$ | $T_I$ | $T_D$ | $O_p(\%)$ | $t_S(S)$ | $J(ITAE)$ | Y |
|---|---|---|---|---|---|---|---|
| Ziegler-Nichols | 2.8200 | 24.1026 | 3.9610 | 38 | 6.2 | 35.7310 | 0.0280 |
| *AFSA* | 1.7959 | 17.7812 | 6.1574 | 2.48 | 5.3 | 21.4335 | 0.0467 |
| *EAFSA* | 1.5843 | 20.0038 | 5.6041 | 0.12 | 3.4 | 21.2072 | 0.0472 |

The results summarized in the table show that the characteristics (settling time, overshoot, performance) of EAFSA are higher than those of the AFSA:

$$\begin{cases} \Delta t_s = \left| t_s(AFSA) - t_s(EAFSA) \right| = 1.9 \\ \Delta Y = \left| Y(AFSA) - Y(EAFSA) \right| = 5.10^{-3} \\ \Delta O_P = \left| O_P(AFSA) - O_P(EAFSA) \right| = 2.36 \end{cases} \tag{12}$$

The EAFSA is an excellent approach for PID tuning, with considerable advantages like high convergence speed and accuracy, flexibility and less error. Moreover, Fig.7 gives the fitness curves of the AFSA and the EAFSA. In fact, the performance of the system described by the consistency of an artificial fish food $Y = \dfrac{1}{J}$ , shows that the enhanced algorithm leads to good tuning parameters. Simulation results show the achievement and efficiency of the EAFSA. This approach ensures the system, its stability, a fastest response and lowest overshoot.

## 5. Conclusion

The simulated artificial configuration method for the PID parameters could effectively optimize the control results and improve the control system's precision and real-time performance. The paper compared the new EAFSA method with the simultaneous setting methods for the improved AFSA PID parameters; our aim is to improve the PID parameters laid down on AFSA in this study. The results of the simulation show good optimization results for PID parameters and better performance of the

EAFSA.

## 6. References

[1]    K J Aström and T Hägglund  2006  *ISA-The Instrumentation, Systems, and Automation Society Research Triangle* Vol. 461.

[2]    Mercader, K J Aström, A Banos and T Hägglund 2017 *IEEE Transactions on Control Systems Technology* 25 (2) (2017) 441–452.

[3]    A Kumar and K Garg 2015 *International Journal for Scientific Research & Development* 3 (04).

[4]    Y V Hote and  S Jain 2018 *IFAC-PapersOnLine* 51 (4) (2018) 604–609.

[5]    D Fister, I Fister Jr, I Fister and R Safari c 2016 *Robotics and Autonomous Systems* 84(2016) 64–75.

[6]    M Neshat, A Adeli, G Sepidnam, M Sargolzaei and A N Toosi 2012 *International Journal  on Smart Sensing & Intelligent Systems* 5 (1):107-148.

[7]    M Neshat, G Sepidnam, M Sargolzaei and A N Toosi 2014 *Artificial intelligence review* 42 (4) (2014) 965–997.

[8]    Y Luo, J Zhang and  X Li 2007 *IEEE International Conference on Automation and Logistics*, pp. 1058–1062.

[9]    A Salawudeen, B Muazu, Y Shaaban and C Chan 2017 *Journal of Electrical & Electronic Systems* 6 (4). doi: 10.4172/2332-0796.1000243

[10]   M S Amiri, R Ramli and M F Ibrahim 2019 *Applied Mathematical Modelling* 72.17 – 27. doi:doi.org/10.1016/j.apm.2019.03.002.

[11]   V  H  Haji  and  C  A  Monje  2017  Applied  Soft  Computing  58    256 – 264.  doi: https://doi.org/10.1016/j.asoc.2017.04.033.

[12]   M Merchaoui, A Sakly and M F Mimouni 2018 Energy *Conversion and Management* 175 (2018) 151 – 163.doi:https://doi.org/10.1016/j.enconman.2018.08.081.

[13]   W Zhao, C Du and S Jiang 2018 *Computer Methods in Applied Mechanics and Engineering* 339 (2018) 341 –doi:https://doi.org/10.1016/j.cma.2018.04.037.

[14]   Z Cheng and X Hong 2012 *Fifth International Conference on Intelligent Computation Technology and Automation, IEEE*, pp. 265–268.

[15]   Z X Zheng, J Q Li and P Y Duan 2019 *International Conference on Mathematical Modeling and* Computational *Methods in Science and Engineering* (*Mathematics and Computers in Simulation)* 155 (2019) 227 – 243, doi.org/10.1016/j.matcom.2018.04.013.

[16]   S Hussein, B Muhammed, T Sikiru, I Umoh and A Salawudeen 2017 *IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON)*, pp. 554–561.

[17]   W J Zhu and J Bai 2016 *Microelectronics & Computer* 33(2016) 89–93.

[18]   M Misaghi and M Yaghoobi 2019 *Journal of Computational Design and Engineering* https://www.sciencedirect.com/science/article/pii/S2288430018301313.