

Optimizing Fuzzy Controller using Cuckoo Optimization Algorithm (COA)

Case Study: Computer Numerical Control of a Steam Condenser

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Abstract: One of the demerits of FLC (fuzzy logic controller) is disability in self-tuning which contribute to contingent on knowledge of experts or expert systems. In most cases, tries and errors methodology is used to tune up FLC that could be so time-consuming and may be could not lead to best response. Whereas, meta-heuristic algorithms such as Cuckoo Optimization Algorithm (COA) and Particle Swarm Optimization (PSO) could identify the almost optimum parameters of FLC. COA fuzzy controller is one of the most effective methods in term of conditions which designing FLC on account of insufficient expert knowledge is so problematic. There are several controllers approach to this demand but in this paper with the help of COA, a powerful method for tuning fuzzy logic controller is considered and applied for controlling a steam condenser plant. Finally a comparative study between COA-Fuzzy, PSO-Fuzzy and PID controllers is demonstrated to verify the performance of proposed method.

Keywords: Fuzzy Controller, Optimization, computer numerical control, Steam Condenser, Cuckoo Optimization Algorithm.

1. Introduction

Cuckoo optimization algorithm (COA) is one the recently introduced metaheuristic algorithm. The operation of this algorithm inspired by the spectacular life style of a bird which is called Cuckoo. These birds family have a special lifestyle in terms of egg laying and breeding. As a result, Cuckoo Optimization Algorithm aims to utilize these special characteristics for solving optimization problems. The basis of this algorithm is the same as other swarm intelligence algorithms. Like other algorithms, COA begins its calculations with initial birds and their own eggs. Each initial cuckoo aims to survive in the society and this is the main point of inspiration for COA. According to some predefined factors, each environment has a profit value. Each Cuckoo has to move toward the better environments to be alive and let their eggs breeds. It is obvious that, in this process some Cuckoos or eggs will be demised and in each step of this process, the number of Cuckoos in total population is being decreased. This procedure continues until hopefully there is only one society where all Cuckoos live there [1]. Utilizing the optimization methods to synthesis the self-tuned fuzzy systems has been so widespread in the last few years. Online tuning algorithm is the most important part of such systems [2] [3] [4].

The gradient descent algorithm [5] and genetic algorithm (GA) [6] [7] [8] [9] [10] [11] have been the base point of view for the learning process. Simulated annealing (SA) [12] [13] [14] is yet another choice for solving optimization problems. However, it has seldom gained interest of researchers for learning method and tuning of fuzzy systems. Particle Swarm Optimization (PSO) is the other way for optimizing FLC which is introduced later than the others [15] [16] [17][18]. The ability of COA to finding the best optimal answer, fast convergence, and simplicity in determining the best algorithm parameters and to deal with any type of cost function with huge number of optimization parameters, makes it a better tool than the classical gradient descent algorithm, GA and PSO. The COA fuzzy system is examined by a plant which is a steam condenser pressure control system.

Pressure control in condensers is so common and practical in all industrial fields such as oil and gas industries. There are several different methods to meet this demand as can be demonstrated by for instance PID controller, FLC, and the likes. Fundamentally, pressure control is one of most nonlinear processes in control knowledge and in this paper; this parameter in a steam condenser with minimum overshoot, steady state error and other important parameters in output response is controlled. To put it in other way, typical controller could not tackle this failure. On this condition, one of the best and acceptable methods is COA fuzzy controller. That is why; there is insufficient expert knowledge to tune up FLC. The COA organizes expert knowledge and tunes it up. There are several methods to tune up all or some parameters of FLC like input membership functions, output membership functions and inference rule base. On this paper, the COA tunes up input and output membership functions for achieving to the best performance. In subsequent sections, details of COA fuzzy system, plant, and disturbance are identified and responses is comprised with ordinary FLC.

2. Cuckoo Optimization Algorithm (COA)

In as much as the COA is published recently, brief introduction with COA seems inescapable. Figure 1 depicts flowchart of COA.

Similar to other evolutionary methods, COA begins with an initial population. These initial populations consist of some cuckoos which have their own eggs. Cuckoos lay these eggs in another birds' nests. These nests are called host nests. Merely some of these eggs, which are more similar to the host birds' eggs, have the opportunity to grow up. Otherwise, eggs will be detected by host bird and will be throw away from nest. That is, they will not become a mature Cuckoo. The number of grown eggs is an index for the suitability of the nests for egg laying in that area. As mentioned before, each area has its own profit value. The more profit value has a direct link with more eggs survival rate in that area. Hence, the narrowed area in which more eggs survive will be the parameter that COA is going to optimize. Each Cuckoo searches for the area with the most profit value to lay eggs in and in order to maximize their eggs survival chance. After survived eggs grow and became a mature cuckoo themselves, they make some new societies. The best habitat of all societies will be the destination for the cuckoos amongst other societies. It is remarkable that each Cuckoo has its own egg laying radius parameter. This parameter is being defined according to the number of eggs each cuckoo has and also the cuckoo's distance to the goal point. Then they immigrate toward this goal point and they will inhabit somewhere near this point. Cuckoo starts to lay eggs again in some random nests which are inside her egg laying radius. This process continues until the best are with maximum profit value is being defined. For further details please refer to [1].

Utilizing COA algorithm to optimize a Sugeno type fuzzy controller has been proposed in [23]. They have proposed an optimized controller for a water tank level control system. Their approach was tuning merely triangle shaped output membership functions of a Sugeno type fuzzy controller with six optimization parameters. However, a tank liquid level can be controlled by merely a well-tuned PID controller and utilizing a fuzzy controller is not vital. In this paper we proposed a fuzzy controller which fully tuned by COA. That is, both input membership functions and output membership functions with totally 17 optimization parameters have tuned by COA. A steam condenser pressure control selected because of its well-known complexity and most of the time unfeasibility in controlling with classical controller such as PID controllers.

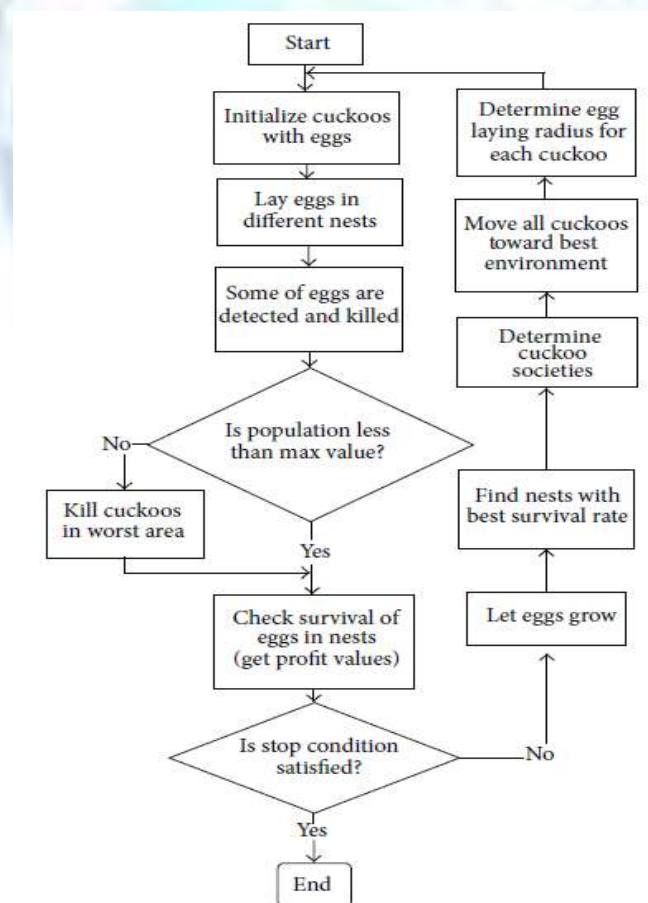


Fig.1 Flowchart of Cuckoo Optimization Algorithm

3. Control process of steam condenser

Steam condensers are so common and practical in all industries such as oil and gas industries. Generally, a lot of parameters in a steam condenser impact on condenser output pressure. In this paper, a dynamic model of steam condenser based on energy balance and cooling water mass balance is utilized, which is shown in figure 2 [19]. As can be seen in this model, there are three input parameters in steam condenser plant. The first input is steam flow rate (FS), the second input is cooling water inlet temperature and finally the third input is cooling water flow rate. Moreover, Output parameter is condenser pressure that is measured by a pressure sensor. In the utilized model of steam condenser, steam flow rate (Fs) is assumed 4 Kg/Sec and cooling water inlet temperature is 60° C and the cooling water flow rate effects output pressure.

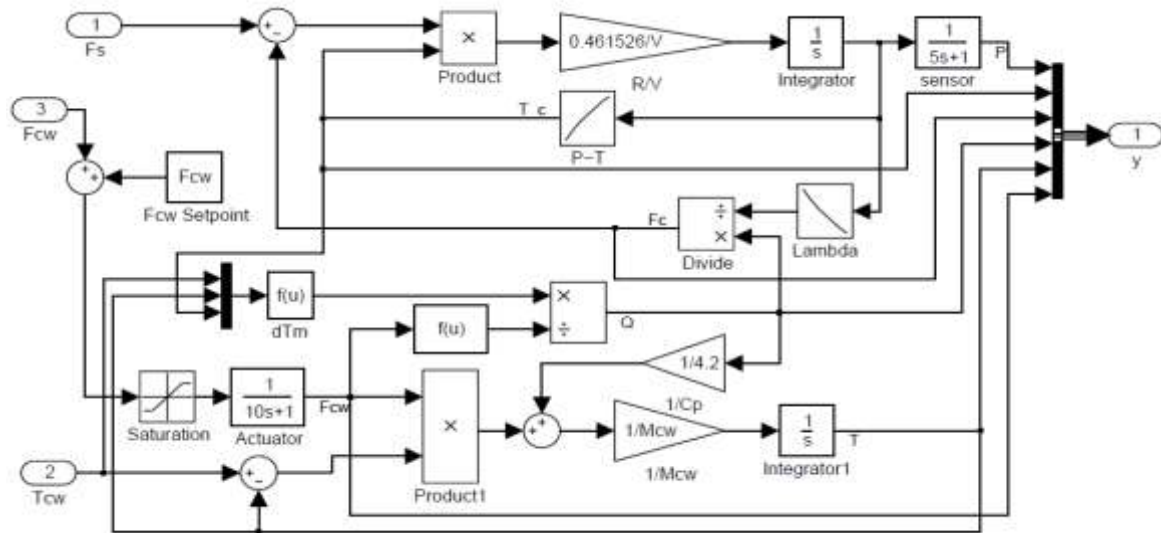


Fig. 2 Simulink model of steam condenser

4. Characteristics of utilized FLC

There are two inputs and one output for FLC that are error signal, derivative of error signal and cooling water flow rate command respectively. Reference signal is a step signal that changes from 90 to 86 KPa. The closed-loop model with pressure, P controlled by proposed COA-FLC is shown in figure 3.

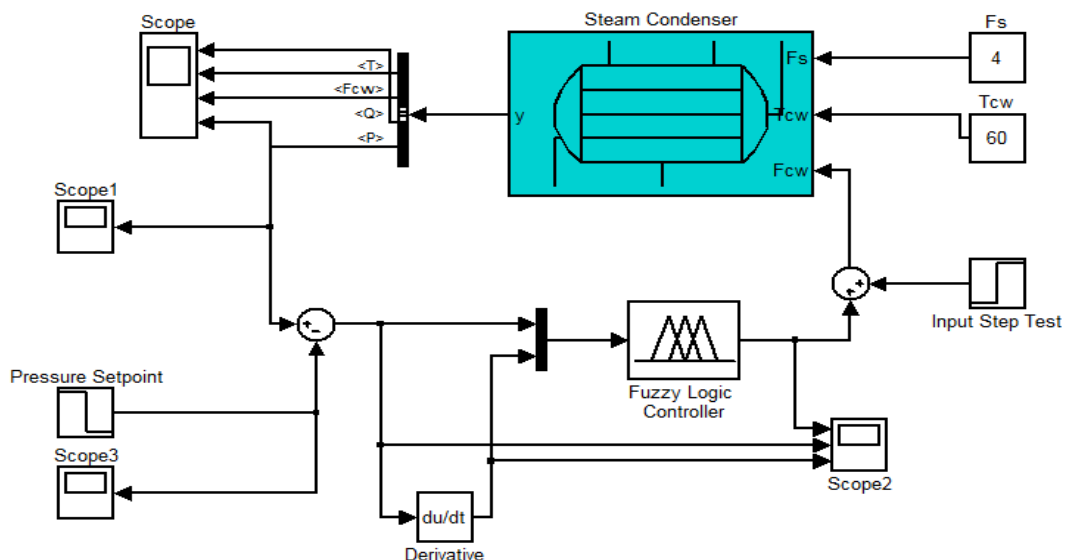


Fig.3 Simulink model of COA-Fuzzy controller.

In term of rule base, 4 rules is intended which is mentioned as follow.

1. If (error is high) and (error derivate is low) then (out is low).
2. If (error is low) and (error derivate is low) then (out is high).
3. If (error is medium) and (error derivate is low) then (out is low)
4. If (error is high) and (error derivate is low), then (out is very high).

The inputs are termed “error” and “d-error” respectively. Range of “error” input is between -3.5 to 5 and center of “el”, “em”, and “eh” memberships are situated in -3.5, 0.75, and 5. As well as range of “d-error” input is between 0.4 to 413 and center of ‘del’, ‘dem’, and ‘deh’ memberships are set in 0, 2.213, and 4.413. Indeed, COA tunes up the Gaussian membership functions spreads and all parameters of triangle membership function of output. Then, in this section, there are 6 parameters for optimizing. Apparently, for faster designing FLC by COA, some limits must be considered, therefore the number of membership functions of output is limited up to five. It should not be forgotten that such as these limitations must not have adverse effect on achieving the best performance. The name of FLC output is ‘out’ and its range is between -20 to 55. Center of first and last membership functions is located in -20 and 55 respectively and the center of each membership function must be before next ones. Moreover, their type is triangular-shaped. The COA undertakes responsibility of tuning positions of other points of triangulars. It creates 11 parameters for optimizing. Regarding to other specifications of FLC, inference engine is product inference engine, fuzzification is singleton, defuzzification is center average or centroid defuzzifier, aggregation is maximum, implication is product, or method is probabilistic or, and method is product [20]. The FLC is designed by Matlab [21]. The key part of designing FLC on this paper is designing output membership functions. Due to insufficient expert knowledge, designing this section is dedicated to The COA. To put it another way, the COA designs the FLC output and input membership functions in order to better response. On next section, method of this task is discussed.

5. Cost function, and COA Parameters

It is taken for granted, each cuckoo position is equal to one style of input and output membership functions and could be attributed to one system performance. In other words, finding the best cuckoo position that yields the best performance is the target of this paper. In fact, features of condenser pressure response could be as cost function. The criteria for evaluating cost function are rise time (Rt), settling time (St), maximum of overshoot (Mo), maximum of undershoot (Mu), and Steady State Error (Ess) of condenser pressure response [22]. It is illustrated in equation (1) and the aim is finding cuckoo position with minimum cost function. This is to say that some weight is intended to each characteristic for changing the influence of each of them.

$$\text{Cost Function} = W1Rt + W2St + W3Mo + W4Mu + W5Ess \quad (1)$$

To achieve details regarding COA parameters please refer [1]. The parameters of COA and PSO are mentioned in table 1 and table 2 respectively.

Table 1. COA Parameters.

COA Parameters	Value
Optimization variables	17
Initial population	50
Minimum number of eggs laying	2
Maximum number of eggs laying	9
Maximum iterations	100
Number of clusters	2
Lambda variable	1
Accuracy	25
Maximum number of cuckoos	100
Parameter of egg laying	1
Population variance	1^{-10}

Table 2. PSO Parameters.

PSO Parameters	Value
Optimization variables	17
Swarm size	20
Personal learning coefficient (C1)	$2.05 * (2/4.1 - \sqrt{2.05^2 - 4 * 2.05})$
Global learning coefficient (C2)	$2.05 * (2/4.1 - \sqrt{2.05^2 - 4 * 2.05})$

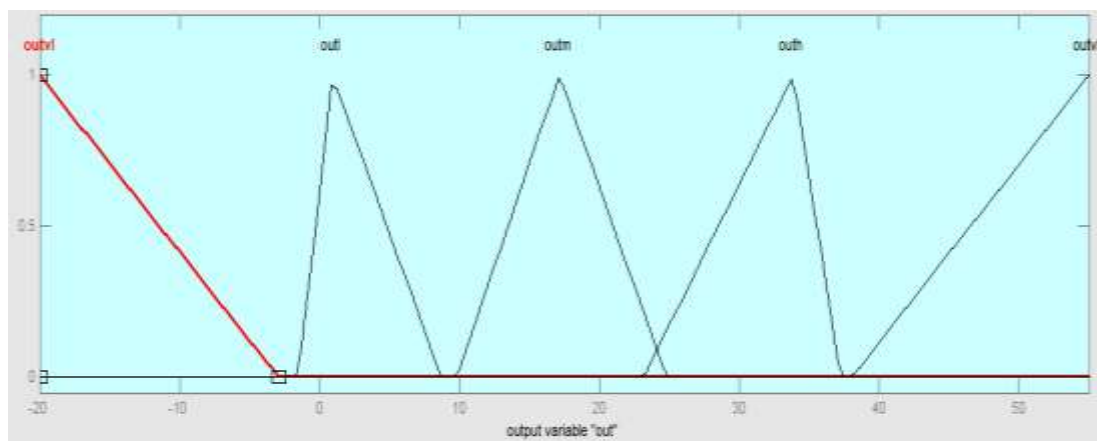


Fig.4 Membership functions of output designed by COA.

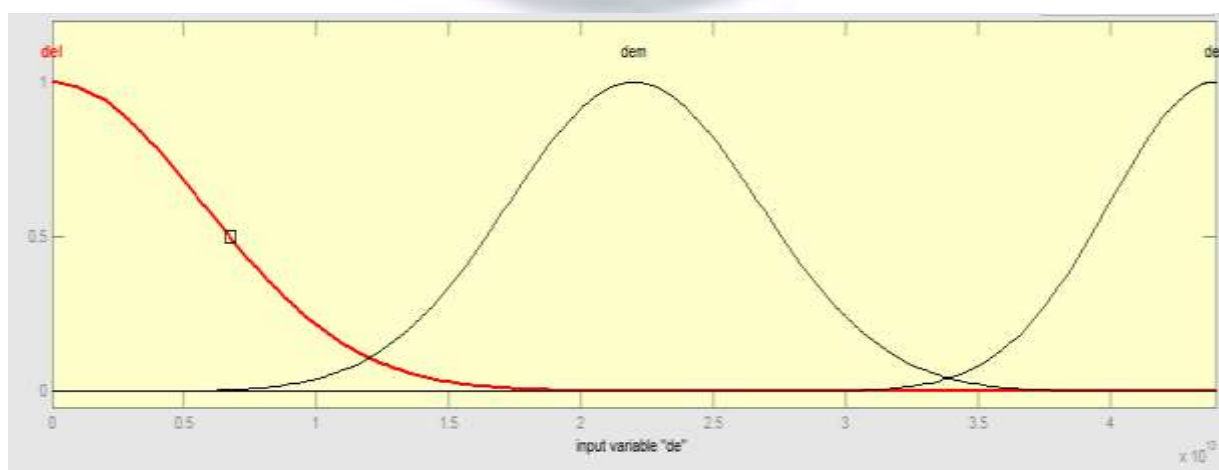
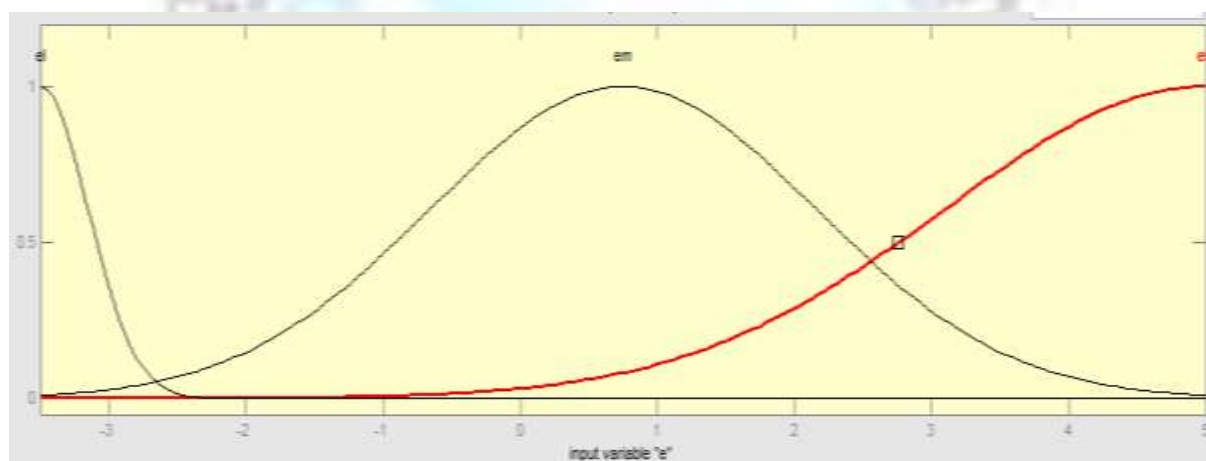


Fig.5 Membership functions of input designed by COA.

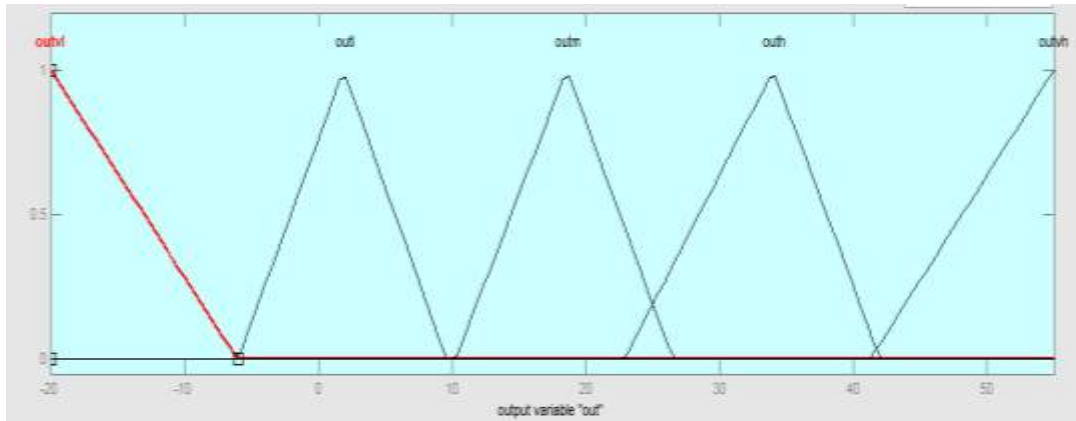


Fig.6 Membership functions of output designed by PSO.

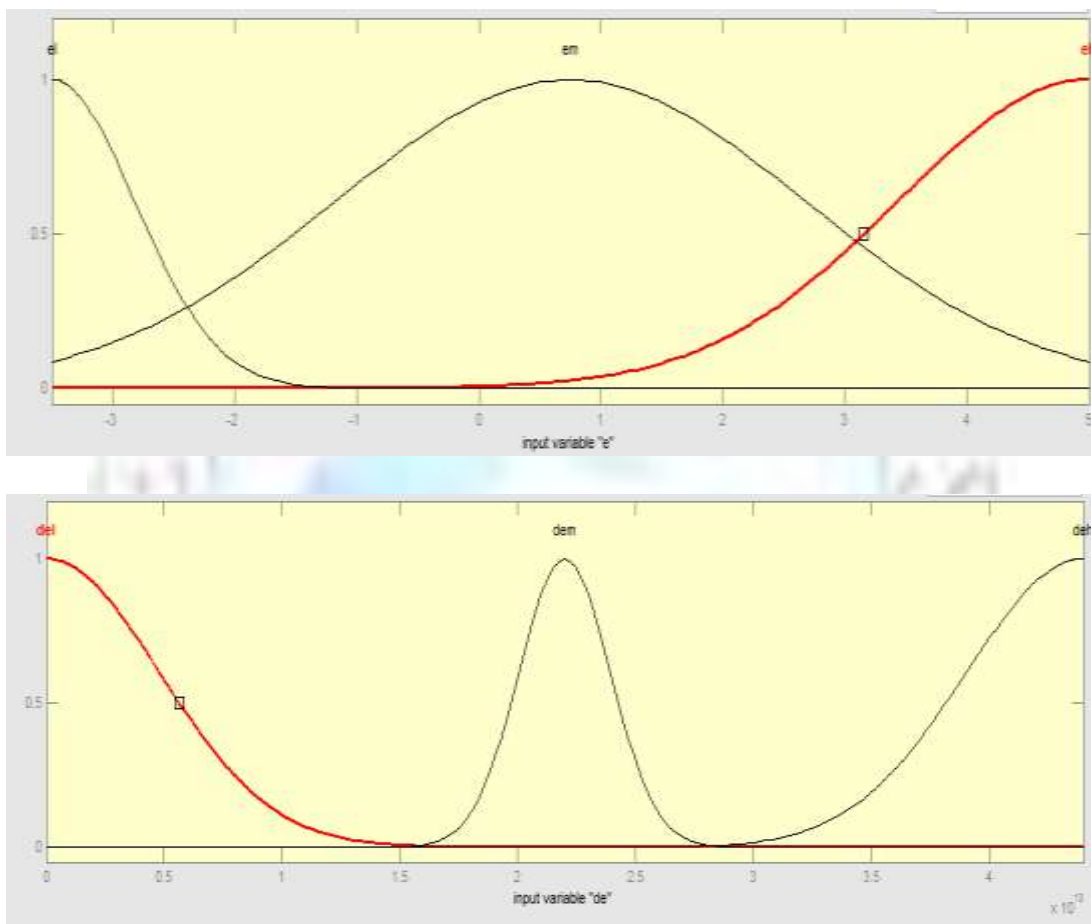


Fig.7 Membership functions of input designed by PSO.

6. Results

The COA and PSO were run 50 times and following results repeat more than others. Style of designed output membership functions that is associated with the best cuckoo position is represented in figure 4. Figure 5 depicts style of designed input membership functions that is related with the best cuckoo position. Fig 6 and 7 also depict the membership functions of outputs and input of FLC tuned by PSO respectively. The input and output membership functions parameters of FLC tuned by COA are mentioned in table3. Comparative results of condenser pressure responses for three controllers including COA-Fuzzy, PSO-Fuzzy and PID controllers is showed in figure 8. In this response weights are $W1=1$, $W2=1$, $W3=1$, $W4=1$, $W5=5$. The COA could tune up FLC parameters promptly within 25 iterations. As can be seen in this Figure, COA-Fuzzy controller has the best performance in terms of overshoots and steady state error. Furthermore, Figure 9 illustrates amount of cost function in each iteration.

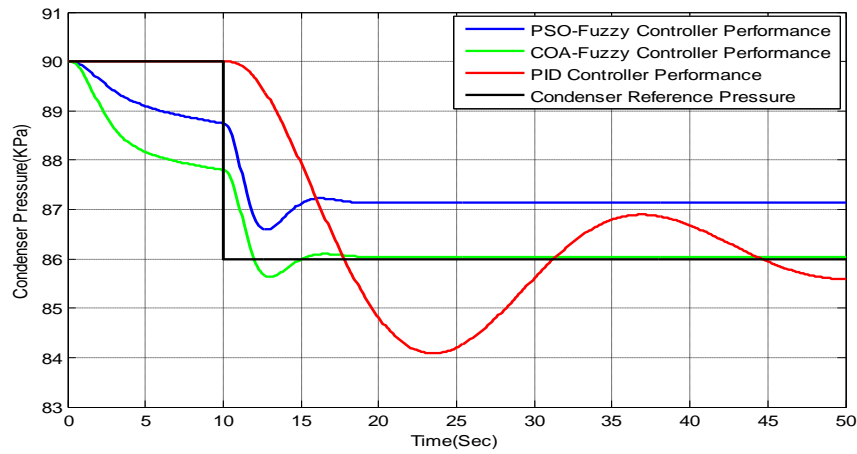


Fig.8 Condenser pressure response of different controller.

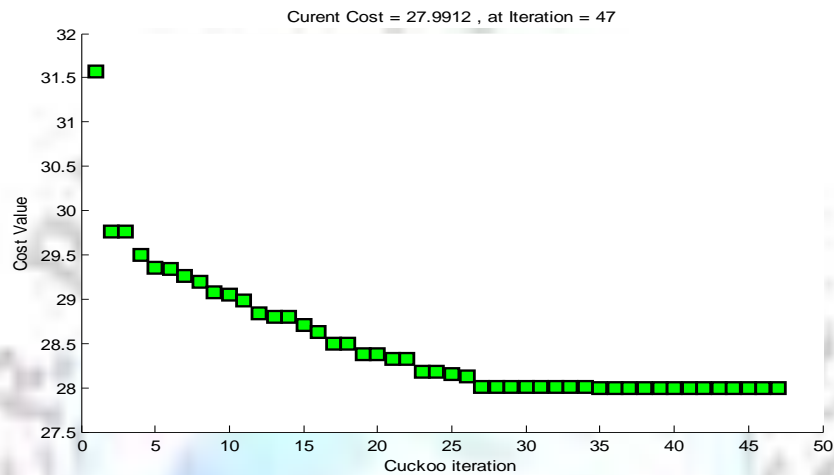


Fig. 9 COA iterations.

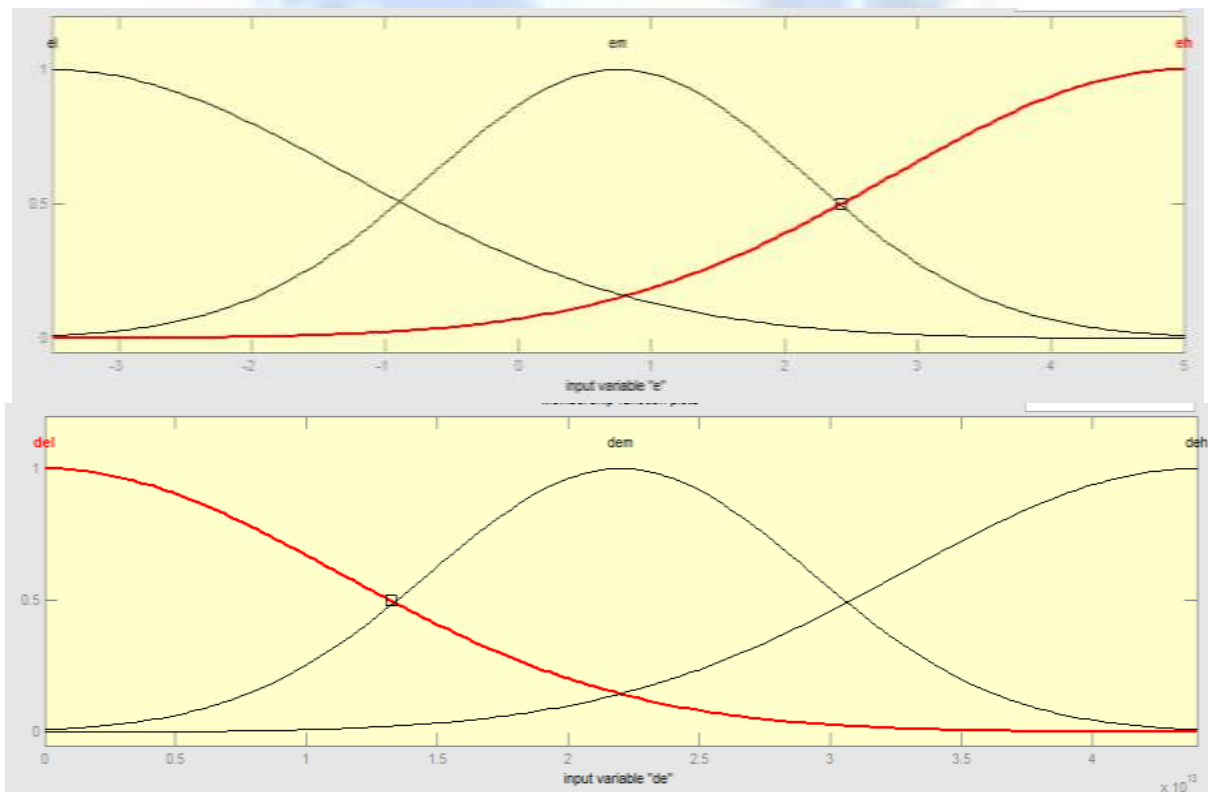


Fig.10 Membership functions of two inputs designed by an expert.

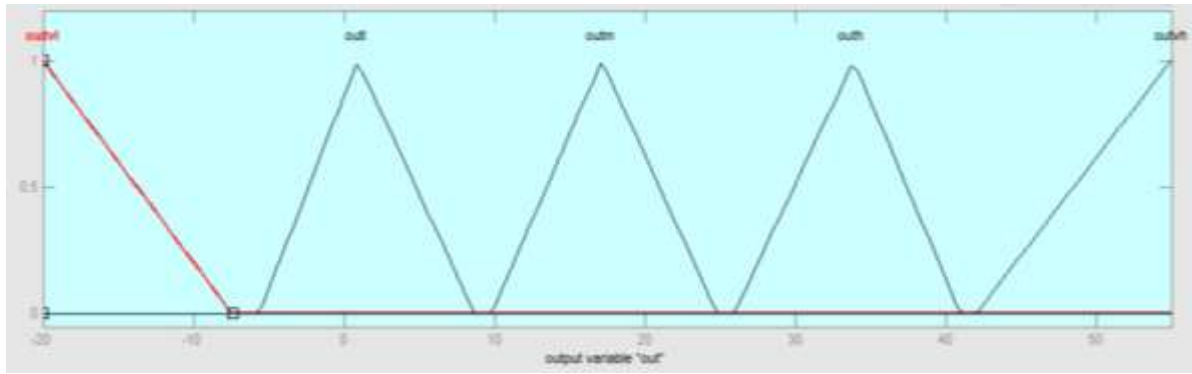


Fig.11 Membership functions of output designed by an expert.

Table 3. Input and output membership functions parameters of FLC tuned by COA.

Feature	Range	Number of membership	Membership Name	Type	C(Center point)	σ (Spread)	First foot	Last foot	Peak
Output	[-20 55]	5	outh (Very high output)	Triangular-shaped			38.05	55	55
			outh (High output)	Triangular-shaped			23.14	37.24	33.89
			outm (Medium output)	Triangular-shaped			9.8	24.82	17.16
			outl (Low output)	Triangular-shaped			-1.5	8.72	0.92
			outvl (Very low output)	Triangular-shaped			-20	-2.9	-20
Input	[0 4.413]	3	deh (High derivative of error)	Gaussian	4.413	4.03612			
			dem (Medium derivative of error)	Gaussian	2.213	4.75612			
			del (Low derivative of error)	Gaussian	0	5.71612			
			eh (High error)	Gaussian	[5]	1.905			
E (Error)	[-3.5 5]	3	em (Medium error)	Gaussian	[0.75]	1.411			
			el (Low error)	Gaussian	[-3.5]	0.347			

To assess COA fuzzy controller with ordinary FLC, response of ordinary FLC is represented in figure 12. The input and output membership functions of ordinary FLC that is designed by an expert is like figure 10 and 11.

As can be seen ordinary FLC response has an enormous steady state error and an unavoidable overshoot. Despite the fact that COA fuzzy controller response to a great extent has been resolved steady state error and overshoot failures.

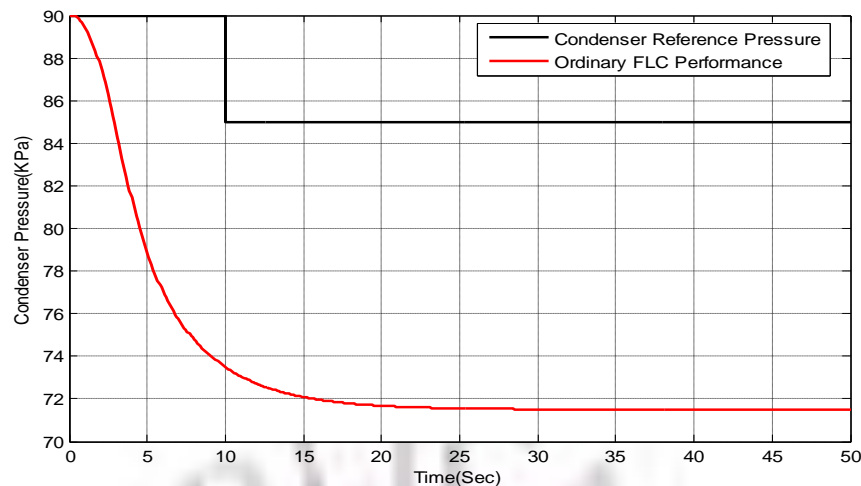


Fig.12 Condenser pressure response of ordinary FLC.

7. Conclusion

One of demerits of FLC is disability in self-tuning which contribute to contingent on knowledge of experts or expert system. Meta-heuristic algorithms such as cuckoo optimization algorithm (COA) and Particle Swarm Optimization (PSO) could identify the almost optimum parameters of FLC that tuning output membership functions for achieving to the best performance.

COA-Fuzzy controller is one of the most effective methods in term of conditions that designing FLC is so problematic. In this paper, COA Fuzzy controller controls steam condenser pressure with high accuracy in ESS. Comparative result approve that COA Fuzzy has superior performance than ordinary FLC and traditional controllers such as PID and PSO Fuzzy controllers. In the final analysis, the COA could demonstrate its capability to tune up FLC parameters promptly with uppermost level of accuracy.

REFERENCES

- [1]. R. Rajabioun, "Cuckoo Optimization Algorithm," Applied Soft Computing, pp. 5508-5518, 13 May 2011.
- [2]. R. Tanscheit and E. Lembessis, "On the behavior and tuning of a fuzzy rulebased self-organizing controller", in Mathematics of the analysis and design of process control, vol.1, 1992, p. 603-612.
- [3]. K. Ahn, D. Truong i Y. Soo, "Self tuning fuzzy PID control for hydraulic load simulator Automation and Systems" in IEEE International Conference on Control, Korea, 2007.
- [4]. E. Gonda, H. Miyata i M. Ohkita, "Self-tuning of fuzzy rules when learning data have a radically changing distribution", Electrical Engineering in Japan, vol. 144, nr 4, p. 63-74, 2003.
- [5]. F. Guelyi P. &Siarry, "Gradient descent method for optimizing various fuzzy rule bases", in Second IEEE international conference on fuzzy systems, 1993.
- [6]. P. Seihwani H. Lee-kwang, "Designing fuzzy logic controllers by genetic algorithms considering their characteristics", in Congress on Evolutionary Computation, 2000.
- [7]. Y. C. Chioui L. W. Lan, "Genetic fuzzy logic controller: an iterative evolution algorithm with new encoding method", Fuzzy Sets and Systems, nr 152, p. 617-635, 2005.
- [8]. R. Alcalá, J. Benitez, J. Casillas, O. Cordon i R. Perez, "Fuzzy control of HVAC systems optimized by genetic algorithms", Applied Intelligence, vol. 2, nr 18, p. 155 - 177, 2003.
- [9]. F. Herrera, M. Lozano i J. L. Verdegay, "Tuning fuzzy logic controllers by genetic algorithms", International Journal of Approximate Reasoning, vol. 12, p. 299-315, 1995.
- [10]. A. Homaifari E. McCormick, "Simultaneous design of membership functions and rule sets for fuzzy controllers using genetic algorithms", IEEE Transactions on Fuzzy Systems, vol. 3, nr 2, p. 129-139, 1995.
- [11]. H. Gurocak, "Genetic-algorithm-based method for tuning fuzzy logic controllers", Fuzzy Sets and Systems, vol. 108, nr 1, p. 39-47, Nov. 1999.
- [12]. H. Youssef, S. Saiti S. Khan, "Topology design of switched enterprise networks using a fuzzy simulated evolution algorithm", Eng. Appl. Artif. Intell., vol. 15, p. 327-340, 2002.
- [13]. L. Ingber i B. Rosen, "Genetic algorithms and very fast simulated reannealing", A comparison. Mathematical and Computer Modeling, vol. 16, nr 11, pp. 87-100, 1992.

- [14]. G. Liu i W. Yang, "Learning and tuning of fuzzy membership functions by simulated annealing algorithm", in IEEE Asia-Pacific conference on circuits and systems, 2000.
- [15]. W. Lei, K. Qi i W. Qidi, "Fuzzy logic based multi-optimum programming in particle swarm optimization", w IEEE International Conference on Networking, Sensing and Control, Tucson, Arizona, USA, 2005.
- [16]. H.-M. Feng, "Self-generation fuzzy modeling systems through hierarchical recursive-based particle swarm optimization", Cybernet. Syst.: Int. J., nr 36, p. 623–639, 2005.
- [17]. Q. Kang, L. Wang i Q. Wu, "Research on fuzzy adaptive optimization strategy of particle swarm algorithm", Int. J. Inform. Technol., vol. 12, nr 3, p. 66–76, 2006.
- [18]. W. Pang, K.-p. Wang, C.-g. Zhou i L.-j. Dong, "Fuzzy discrete particle swarm optimization traveling salesman problem", w Fourth International Conference on Computer and Information Technology, 2004.
- [19]. Yi Cao, "dynamic modeling of steam condenser", Cranfield University, 2008.
- [20]. Zadeh. [Online]. Available: <http://www-bisc.cs.berkeley.edu/zadeh/papers>.
- [21]. "Matlab Help system", Mathworks, 2012.
- [22]. O. Katsuhico, "Modern Control Engineering".
- [23]. Balochian, S., Ebrahimi,E., "Parameter Optimization via Cuckoo Optimization Algorithm of Fuzzy Controller for Liquid Level Control", Journal of Engineering, Journal of Engineering, Vol.2013, Article ID: 982354.

