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Gain tuning PI controllers for boiler turbine unit using a new hybrid jump PSO

Mohamed Sayed [b], Sawsan Morkos Gharghory [a,*], Hanan Ahmed Kamal [b]

[a] *Computers and Systems Department, Electronics Research Institute, Dokki, Cairo, Egypt*

[b] *Electronics and Communication Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt*

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Abstract

In this paper, a new hybrid jump PSO (HJPSO) is proposed for tuning the gains of PI controllers to the boiler turbine unit. HJPSO based Gaussian and Cauchy mutation is proposed to improve the standard PSO performance. The new strategy is based on observing the local and global best particles which are not improved in a predefined number of iterations and moving these particles to a new best position. Besides, forming a new particle that handles the minimum error of each controller to replace the global best particle if it has best fitness. The simulation results show that the proposed algorithm has its ability in optimizing the control parameters and effectively achieved better performance when compared with other PSO algorithms.

Keywords: Boiler-turbine unit; Particle swarm optimization (PSO); Gaussian and Cauchy mutation and PI controller

1. Introduction

Due to the rapid increase in the use of power for both domestic and industrial needs, it is a challenge to meet power demand with the highest reliability and efficiency. At present, the power system industry is largely relying on hydro and thermal stations. The thermal power plants are among quick and comparatively cheap peak load supporting power plants. A boiler turbine unit is one of the common thermal power plants to generate electricity. The electrical power generation is based on boilers for steam generation that is used to rotate steam turbines to generate the required plant electricity. The control system of boiler-turbine unit must support the main objective of the power system, which is to meet the load demand for electric power at all times, at constant voltage and at constant frequency. In addition to the mentioned requirements, maintain the boiler steam pressure and water drum level at the desired values despite variations of the load.

* Corresponding author. Tel.: +20 1228187761.

E-mail addresses: mohs100_5@hotmail.com (M. Sayed), sawsan@eri.sci.eg, sawsan_morcos@yahoo.com (S.M. Gharghory), hanan_ak2003@yahoo.com (H.A. Kamal).

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Boiler-turbine system is usually modeled as a multi-input multi-output (MIMO) nonlinear system. The severe nonlinearity and wide operation range of boiler-turbine plant have resulted in many challenges of power systems control engineers. The dominant behavior of the Boiler-turbine unit is governed through the power and pressure control loops (Garduno-Ramirez and Lee, 2001). Most of the current unit control strategies are evolved from multiple single-input-single-output control loop (decentralized) configurations based on PID control algorithms.

These strategies may be classified into three classes: boiler following (turbine leading) control, turbine following (boiler leading) control, and coordinated boiler-turbine control. The boiler following approach has faster but less stable response to load changes. The turbine following approach has more stable but slower response to load changes. As the high coupling between the electric power and the throttle pressure, different control techniques have been introduced to give better performance than a decentralized one and named coordinated control. The coordinated control coordinates the control inputs based on both the electric power demand and throttles pressure which aim to synthesize the advantages of the two aforementioned approaches while minimizing their disadvantages (Gery, 1988). In recent years, many researchers have forced their attention to control and optimize the performance of the boiler turbine units using different modern control methodologies such as robust control, genetic algorithm based control, fuzzy control, gain scheduling approach and nonlinear control strategy. The work in Moon and Lee (2003) proposed Fuzzy Auto-Regressive Moving Average (FARMA) controllers in controlling the boiler-turbine system. Fuzzy sliding mode controllers and Takagi-Sugeno Fuzzy controllers were proposed respectively in Deepa and Lakshmi (2013) and Garduno-Ramirez and Lee (2000). A combination between Fuzzy logic as a feed-forward controller and other technique as a normal feedback controller were also introduced in Luan et al. (2008). Also, the work in Liu and Niu (2008) proposed a model predictive control (MPC) strategy.

Despite the growing research toward studying and designing a modern and sophisticated control algorithm, PID and PI controllers are still widely used in most industrial control applications such as in real control engineering of thermal power plants. This popularity is due to their structural simplicity, robustness, reliability and broad applicability. The only limitation of PID and PI controllers is the improper choice of the PID parameters which may affect on the stability of the system. The conventional tuning methods were presented in literature including Ziegler-Nichols, pole placement, continuous cycling and more (Cominos and Munro, 2002). Nowadays, intelligent tuning techniques were used and compared to conventional techniques. These include neural network PID control based on connection mechanism (Conradie et al., 2002), and intelligent PID control based on fuzzy logic (Shayeghi et al., 2007; Çetin and Demir, 2008), Genetic Algorithm (GA) (Zain et al., 2009), evolutionary programming (Nagaraj et al., 2008), and PSO (Oliveira et al., 2002). Since its appearance, PSO algorithm has been a promising technique for real world optimization problems due to the simple concept, easy implementation and quick convergence (Kennedy and Eberhart, 1995).

Many efforts on the enhancement of traditional PSO have been proposed, by combining PSO with other evolutionary computation techniques. The research efforts have developed a hybrid method combining GA and PSO for the global optimization as described in (Kao and Erwie, 2008; Robinson et al., 2002; Kamal, 2010). A genetic programming based on adaptable evolutionary hybrid particle swarm optimization algorithm, had been presented in Rashid and Rauf (2010). Another research trend is to merge evolutionary operators like selection, crossover and mutation with PSO to increase the diversity of the population and the ability to escape from the local minima. One approach is to mutate PSO parameters such as the position of the best neighborhood, as well as the inertia weight in Miranda and Fonseca (2002). Another approach is to prevent particles from moving too close to each other (Løvbjerg et al., 2001; Gao and Duan, 2007; Løvbjerg and Krink, 2002). Besides, a new trend of research focuses on improving PSO by using adaptive mutation. Chen (Chen et al., 2006) presented a Gaussian mutation operator with adaptive mutation probability which is dynamically adjusted based on the ratio between the mean and the best value of the fitness function. Yang et al. (Li et al., 2008) used an adaptive operator to select the best type of mutation operations in each generation. Pant (Pant et al., 2008) used an adaptive Cauchy mutation operator in PSO, based on beta distribution. Tang (Tang and Zhao, 2010) proposed Local Search PSO, namely LSPSO by applying an adaptive mutation operator which dynamically adjusts the step size of local search in terms of the size of current search space. The work in Morkos and Kamal (2012), a novel adaptive PSO local best is proposed and applied successfully to optimal tuning of PID controller. Among the research studies in using PSO for boiler turbine unit, Binary PSO and Bacteria Foraging based PSO were proposed for optimal tuning the parameters of PID or PI controllers to boiler turbine unit of two inputs and two outputs as described respectively in literatures (Menhas et al., 2011; Deepa and Lakshmi, 2011). The works in Garduno-Ramirez and Lee (2006), Zaharn et al. (2013) proposed PSO and Differential Evolution to determine the optimum steam pressure set point at every electrical power demand to improve the overall performance.

In this paper, a new hybrid jump PSO based Gaussian and Cauchy mutation called HJPSO is proposed for tuning PI controllers of the boiler turbine unit. Three PI controllers are used to control the positions of fuel flow valve, steam pressure valve and feed-water flow valve. The parameters of PI controllers were optimized by minimizing the error function between the actual outputs and the desired inputs to make the output system traces the input. The proposed HJPSO by Gaussian and Cauchy mutation is performed simultaneously on the local best particles and global best particle in the swarm. Local best particles which are not improved in a predefined number of iterations as a result of falling into local minima are mutated by using Gaussian and Cauchy mutation. The local best particles will jump to a new location if the new fitness value resulting after mutation is better than their current values, otherwise keep them unchanged. Also in each iteration, the global best particle is mutated by Cauchy and Gaussian mutation and replaced its current location with the new location resulting from the best mutation. Besides, a new modification is implemented to improve the fitness of the global best particle. This modification is based on minimizing the error between each output and its corresponding input instead of minimizing the value of summing all three errors. By forming a new particle which contains the best gains of each controller and achieves the minimum value of error between each actual output and the desired input. In case if the fitness value of this new particle is better than the current fitness value of the global best particle, the global best particle is updated by this new particle, otherwise the particle remains without change. The performance of the system is compared with the standard PSO, PSO with Gaussian (GPSO) and PSO with Cauchy (CPSO). Experimental studies of tuning the parameters of PI controllers for boiler turbine unit show that the proposed HJPSO performs better than the other PSO algorithms. The obtained results have higher fitness and faster convergence.

The rest of paper is organized as follows: Section 2 presents the Boiler-Turbine dynamic model, PI controllers and the error function used for optimizing PI parameters. An overview of the standard PSO and a brief description of the proposed Hybrid jump PSO techniques are presented in Section 3. Experimental results and discussions are presented in Section 4. Finally, Section 5 concludes the whole work.

2. The boiler-turbine model and control

2.1. Boiler-turbine model

The Boiler-Turbine model used in this paper is for 160 MW oil-fired boiler-turbine generator unit which was developed by Bell and Astrom (1987). It is a nonlinear model with three inputs and three outputs and is represented by third-order multi inputs multi-outputs (MIMO). The output variables to be regulated are the electrical output (E in MW), the drum pressure (P in kg/cm^2), and the drum water level (L in m), while the inputs to the controllers are the positions of valve actuators that control the mass flow rates of fuel, steam to the turbine and feedwater to the drum.

The dynamic equations with the three state variables of the Boiler-Turbine unit are given as follows:

$$\frac{dE}{dt} = ([0.73u_2 - 0.16]P^{9/8} - E)\frac{1}{10} \tag{1}$$

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2P^{9/8} - 0.15u_3 \tag{2}$$

$$\frac{d\rho_f}{dt} = \frac{(141u_3 - (1.1u_2 - 0.19)P)}{85} \tag{3}$$

where: The inputs u_1, u_2 and u_3 are the positions of valve actuators that control the mass flow rates of fuel, steam to the turbine, and finally the feed-water to the drum. The state variables are electric power (E), drum steam pressure (P), and fluid (steam–water) density (ρ_f). The drum water level output is calculated using the following equations:

$$q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09 \tag{4}$$

$$\alpha_s = (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015) \tag{5}$$

$$L = 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5) \tag{6}$$

where: α_s is the steam quality and q_e is the evaporation rate (kg/s).

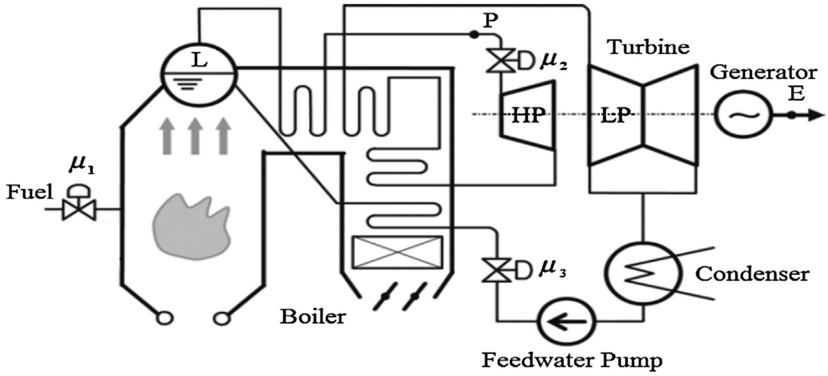

Fig. 1. Boiler-turbine unit schematic diagram.

The positions of valve actuators are constrained to the values between [0,1], and their rates of change (pu/s) are limited to the following values:

$$-0.007 \leq du_1/dt \leq 0.007$$

$$-2 \leq du_2/dt \leq 0.02$$

$$-0.05 \leq du_3/dt \leq 0.05$$

The Boiler-turbine unit schematic diagram is shown in Fig. 1.

2.2. Boiler-turbine control

To regulate the electric power and the steam pressure at the desired set points respectively as well as maintain the drum water level at zero value, three PI controllers are used. The first controller will act on the steam flow valve to track the change in the electrical power, the second controller is used to control the fuel flow valve to track the change in the drum steam pressure and finally the last controller is used to control the feed-water flow valve to keep the drum water level at zero level. The output of each controller depends on the error (e) which is defined as the difference between the set point and the controlled variable. The target of any controller is to minimize the magnitude error as small as possible to improve the steady state response. To achieve the objective of the work and improve the overall system performance, PI controller parameters are tuned to a set of optimum or near optimum parameters by minimizing integral square error of the three controllers using the following equation:

$$I_{ISE} = \int_{t=0}^{n} \alpha_1 * {e_1}^2(t)dt + \alpha_2 * e_2^2(t)dt + \alpha_3 * e_3^2(t)dt \tag{7}$$

where: $e1$ is the error between the desired electrical power and the actual output of electric power plant model, $e2$ is the error in the steam pressure and $e3$ is the error in the drum water level.

α_1, α_2 and α_3 are weighting factors.

Fig. 2 shows the schematic diagram of the power unit and PI controllers tuned by different control strategy algorithms which are described in derails in the following section.

3. Tuning algorithms

3.1. Standard PSO

Particle swarm optimization (PSO) has been introduced by Kennedy and Eberhart in 1995 and is derived from the social-psychological theory. PSO is initialized with a group of random particles (solutions) and then searches for

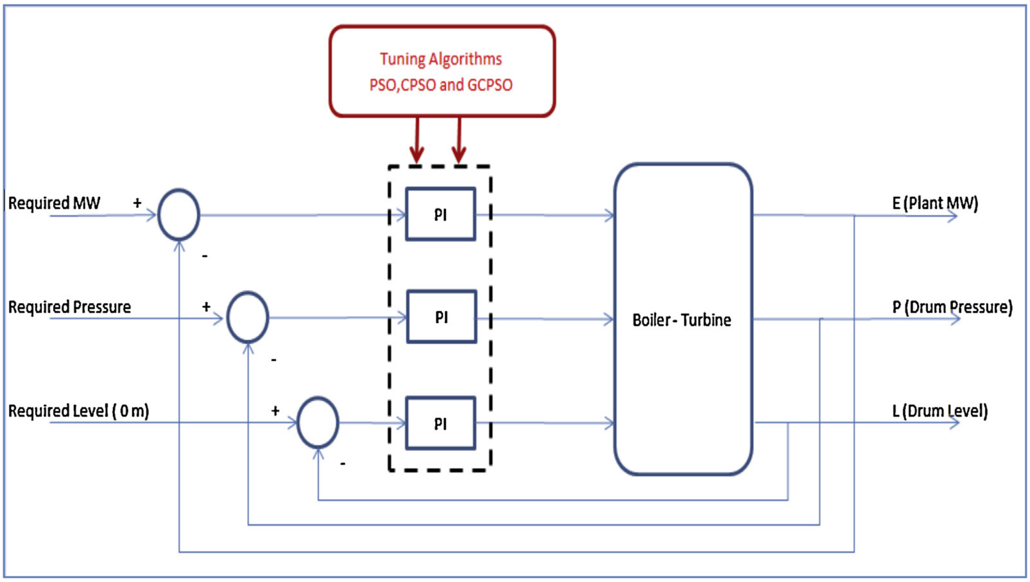

Fig. 2. Boiler-turbine unit with PI controllers tuned by the proposed PSO and different PSO algorithms.

optima by updating generations. Each particle keeps track of the best solution that has achieved so far in the problem search space. This value is called pbest. Another best value that is the overall best value in the swarm and its location is obtained so far by any particle in the group is called gbest. Consequently, the position of any particle is influenced by the best position visited by its experience and the position of the best particle in its neighborhood. The acceleration of a particle toward pbest and gbest locations is weighted by a random numbers that has been generated. Each particle updates its velocity and positions using the following equations:

$$v_i(k+1) = w_i v_i(k) + c_1 rand_1()(\text{pbest} - x_i(k)) + c_2 rand_2()(\text{gbest} - x_i(k)) \tag{8}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{9}$$

where:

$v(k+1)$, $v(k)$ are the particle velocity in iteration number $k+1$, k respectively, $x(k+1)$, $x(k)$ are the particle position in iteration number $k+1$, k respectively. Rand is a random number between (0, 1). $c1$ is called the self-confidence and usually takes values in the range (1.5–2.0), while $c2$ is called the swarm confidence and usually takes the value in the range (2.0–2.5). The inertia weight w is used to achieve a balance in the exploration and exploitation of the search space and plays very important role in PSO convergence behavior. The inertia weight is dynamically reduced from 1.0 to near 0 in each generation based on the following equation.

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}}.iter \tag{10}$$

where: $iter_{max}$ is the maximum number of iterations, and $iter$ is the current number of iteration. $w_{\max}$, and $w_{\min}$ are the maximum and minimum values of inertia weight. The parameters of our proposed PSO are: $c1 = 1.5$, $c2 = 2$, the number of iterations $N = 100$ and the swarm size = 50.

3.2. Hybrid PSO

To increase the diversity of the population and to help PSO jumping out of local minima, different types of hybrid PSO methods are introduced and carried out for tuning the three PI controllers to boiler turbine plant model. The first type is by mutating both of the velocity and the position of the global best particle by Cauchy mutation, the second method is mutated the velocity and the position of the global best particle by Gaussian mutation which is described as follows:

$$V_g = V_g \exp(\delta) \tag{11}$$

$$X_g = X_g + V_g \delta_g \tag{12}$$

where: X_g and V_g represent position and velocity of the global best particle.

δ and δ_g denote Cauchy or Gaussian random numbers with the scale parameter of 1.

Finally the third method is the proposed HJPSO which is described in the following section.

3.3. New HJPSO algorithm

The third technique is a new hybrid jump PSO (HJPSO, which is a modified method to the idea described in Hui (2012). HJPSO is achieved by monitoring the fitness of each local best particle that does not improved in a predefined successive number of iterations which means that this particle is fallen into local minima. This local best particle is mutated by Gaussian and Cauchy random numbers, and then it will jump to a new location if its fitness value resulted from the best mutations is better than its current value. Also, the global best particle is mutated each iteration by Cauchy and Gaussian mutation and updating its value with the best value produced from the two mutations. In addition to that and as in our application where a multiple number of controllers are tuned at the same time, a new modification is proposed to improve the fitness of the global beset particle. By monitoring the performance of each controller and forming a new particle which contains the best parameter gains of each controller that achieve the minimum value of error between the actual outputs and the desired inputs. Finally in case if the fitness value of this new particle is better than the current fitness value of the global best particle, the global best particle is updated with this new particle, otherwise the particle remains without change.

The framework of HJPSO is presented in the following steps:

- Step 1 – Generate initial position and velocity for each particle in the swarm randomly.
- Step 2 – Evaluate the fitness of each particle, and determine the local and the global best fitness for each particle in the swarm.
- Step 3 – Update each particle according to Eqs. (8) and (9).
- Step 4 – Give a predefined value for successive number of iterations in which through it the local best particles are not changing, only five successive iterations are allowed in this proposed algorithm before applying mutation on the unchanged local best particles.
- Step 5 – If the local best value of each particle remains the same for predefined successive iterations, apply Cauchy mutation and Gaussian mutation on this particle, evaluate the particle fitness after the two mutations, and then update its position if its fitness value after mutation is better than its fitness value before mutation.
- Step 6 – Apply Cauchy mutation and Gaussian mutation to the global best particle in each generation, evaluate the fitness of the global best particle after the two mutations, and then update the position of the global best particle if its fitness value after mutation is better than its fitness value before mutation.
- Step 7 – In parallel to the mutated global best particle, generate new particle and choose its parts from all particles parts in the swarm that represent the minimum error of each corresponding controller. Evaluate the fitness of this new particle, if its fitness value is better than the fitness of the current global best particle, updating the global best position with this new particle.
- Step 8 – Determine the local best particles and the new global best particle for the next generation.
- Step 9 – Stop if the stop criterion is satisfied otherwise, go to step 3.

4. Simulation results

To verify the efficiency of the proposed algorithm, experiments have been carried out for optimal tuning of three PI controllers to the boiler turbine plant with three inputs–outputs. The first one is the electrical Power controller that controls the Steam control valve, the second is the pressure controller that controls the fuel control valve and the third controller is the drum water level controller that controls the Feed-water control valve. The performance of the

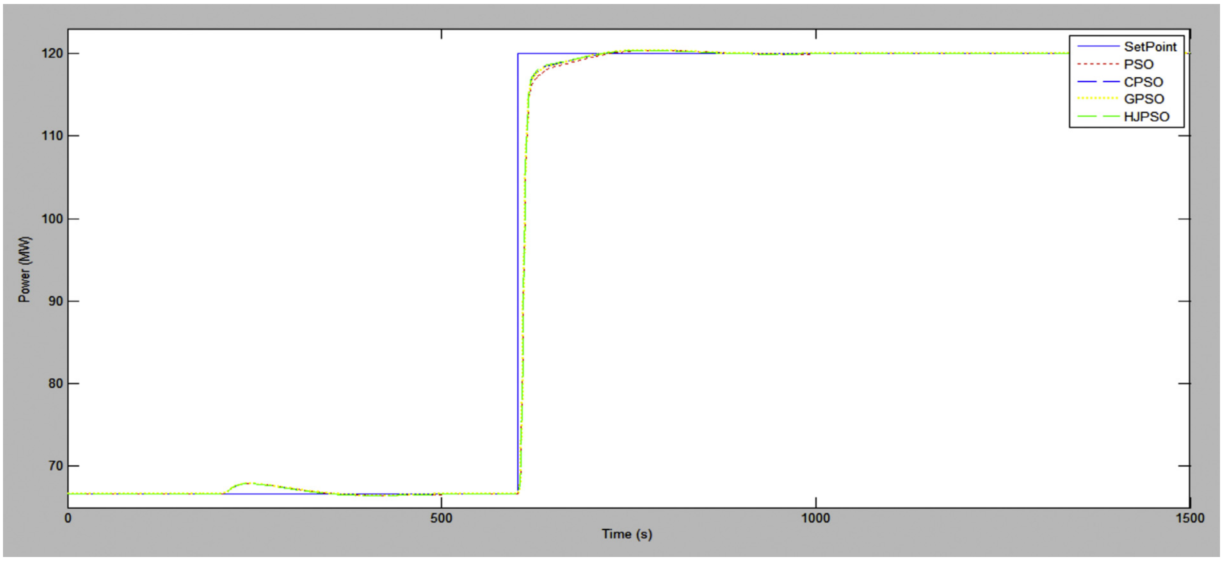

Fig. 3. The electric power output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and step input.

different control strategies are compared based on performance criterion such as peak overshoot, settling time and integral square error (ISE) for the three outputs; electrical power, pressure, and water level. The cost function of PI controllers tuned by the HJPSO, CPSO, GPSO and standard PSO are calculated for 100 generations. The time response of electric power, steam pressure, drum water level of boiler turbine unite after tuning the gains of each PI controller by using the ISE indices and two different set points which are step and ramp are shown in Figs. 3–8 respectively. Also the cost function of the HJPSO, CPSO, GPSO and the standard PSO using ISE with the two set points inputs are shown in Figs. 9–10. Tables 1–4 describe the transient response characteristics of HJPSO, CPSO, GPSO and the standard PSO using ISE performance indices in terms of peak overshoot, settling time, and the value of cost function for both step and ramp inputs. Also the values of the parameters of three PI controllers with both step and ramp inputs are depicted in Tables 5–6.

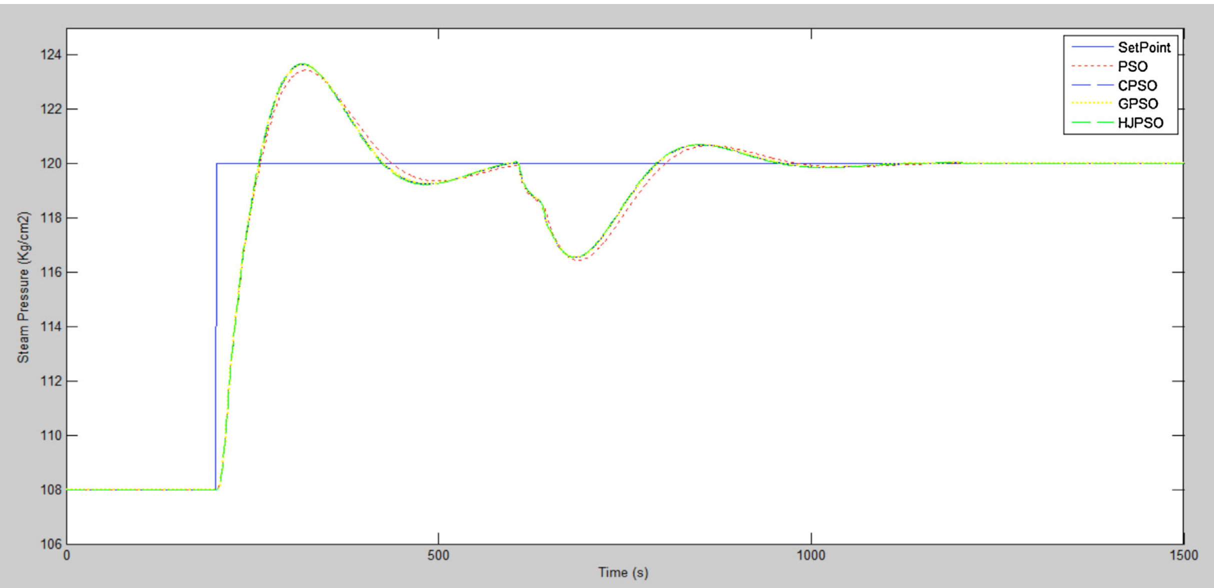

Fig. 4. The steam pressure output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and step input.

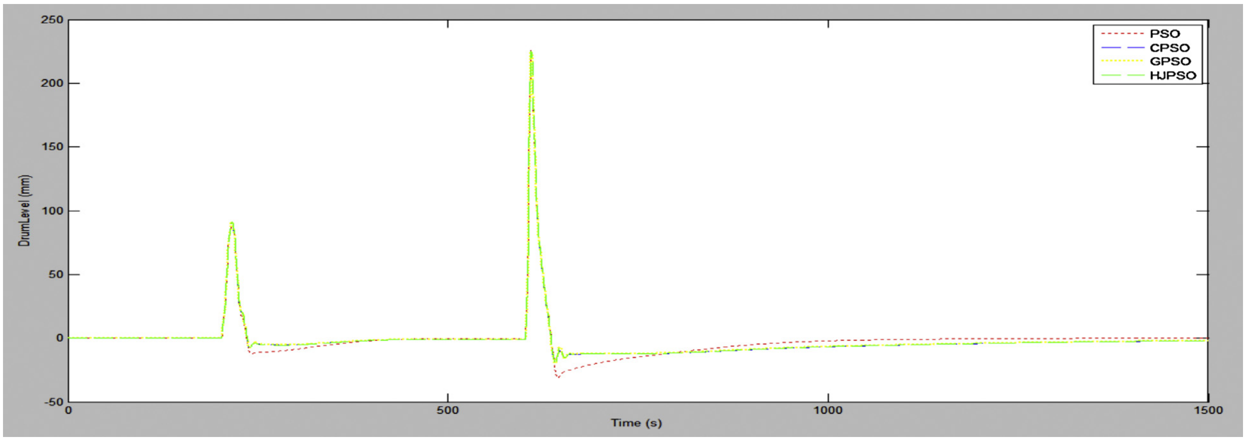

Fig. 5. The drum water level output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and step input.

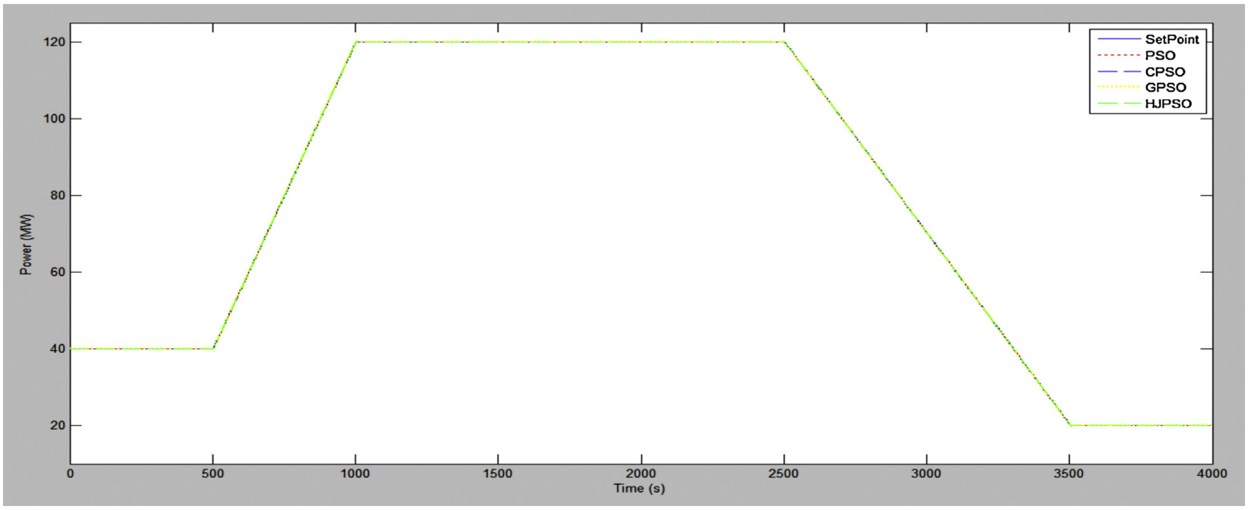

Fig. 6. The electric power output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and with ramp input.

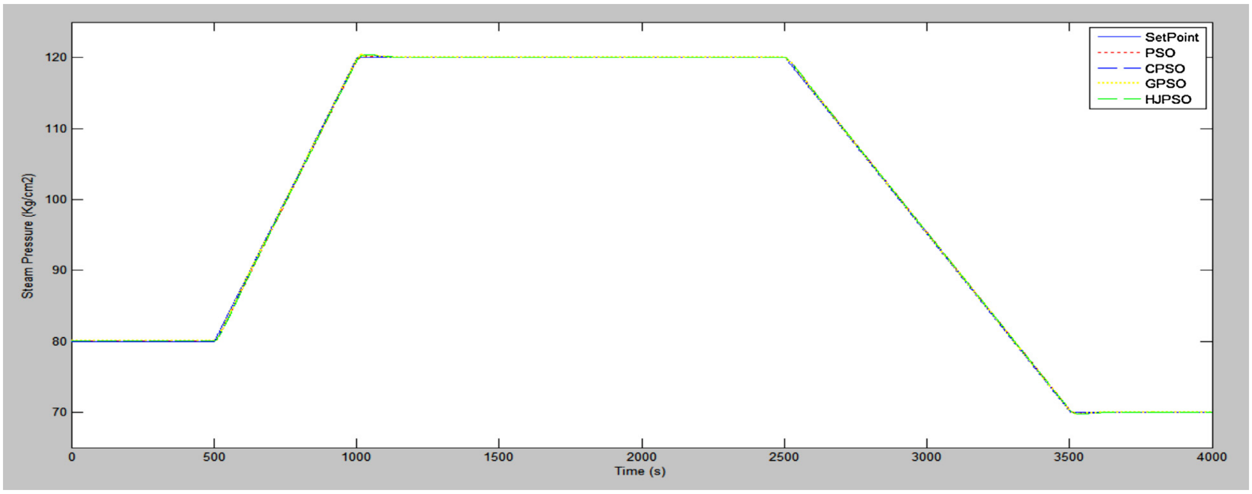

Fig. 7. The steam pressure output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and with ramp input.

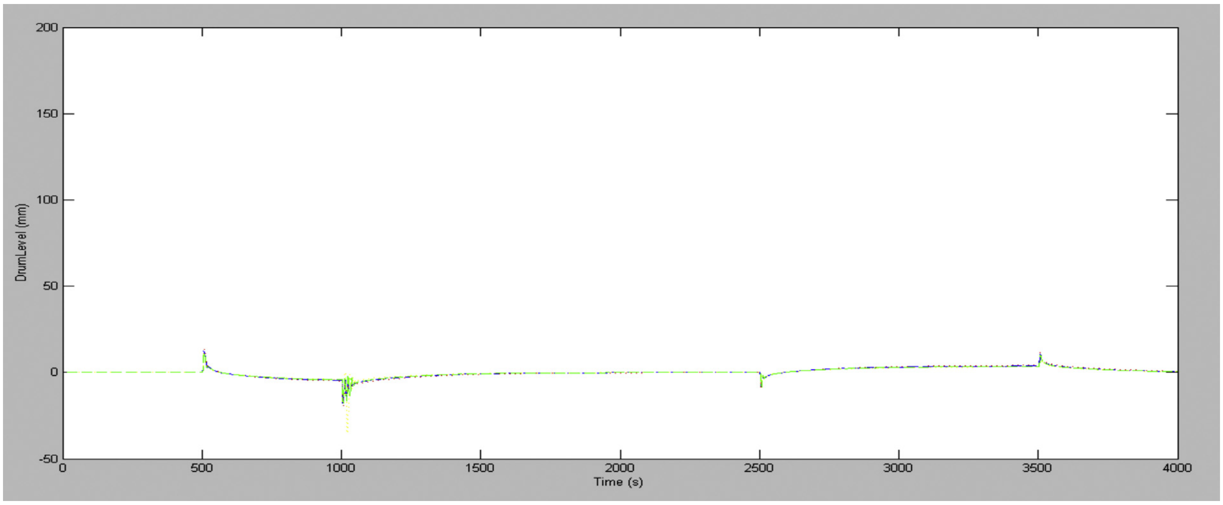

Fig. 8. The Drum water level output with PI controller tuned by the new HJPSO and the other algorithms using ISE indices and with ramp input.

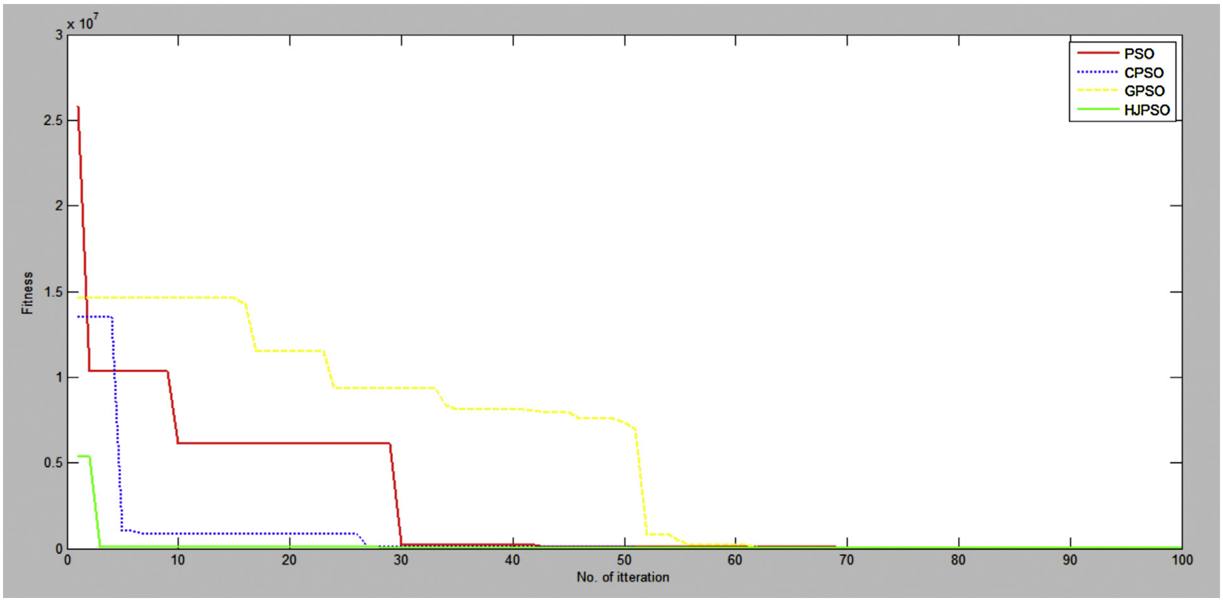

Fig. 9. The cost function of PI controllers tuned by HJPSO and the other hybrid PSO algorithms with step input.

Table 1
Transient response characteristics of electric power with step input and using ISE Criteria.

	Power			
	Peak value (Mp)	Peak time (Tp)	Settling time (Ts)	Cost function value
PSO	120.3788	186	73.1	29667.81
CPSO	120.3736	176	61.9	29270.91
GPSO	120.3767	176	62.7	29259.28
HJPSO	120.3769	174	57.9	29254.5

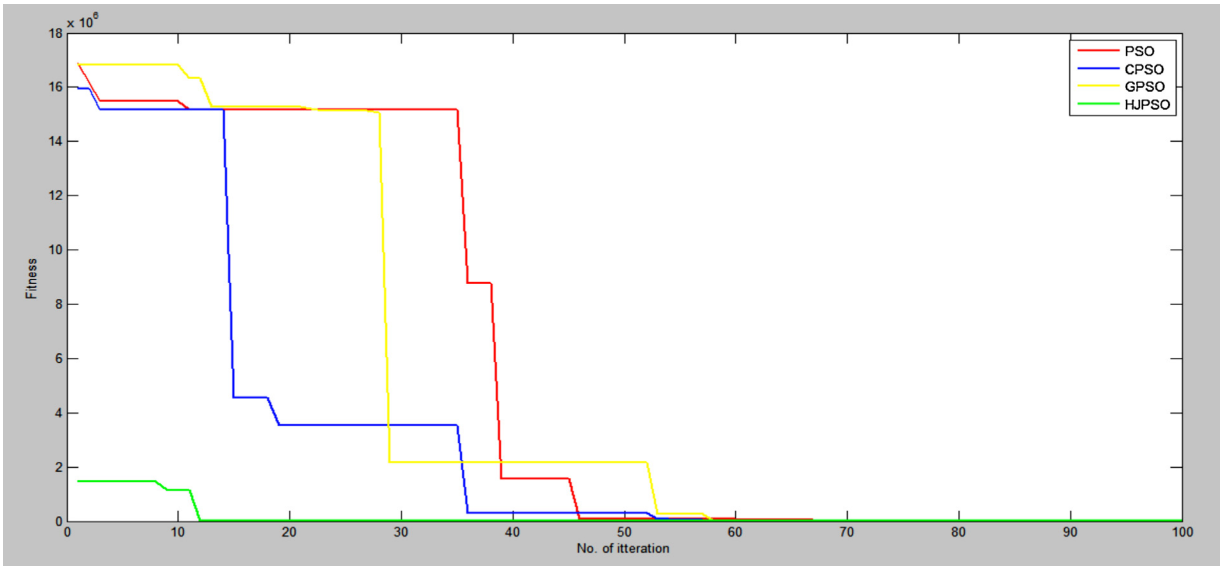

Fig. 10. The cost function of PI controllers tuned by HJPSO and the other hybrid PSO algorithms with ramp input.

Table 2
Transient response characteristics of steam pressure with step input and using ISE criteria.

	Steam pressure			
	Peak value (Mp)	Peak time (Tp)	Settling time (Ts)	Cost function value
PSO	120.4439	121	742.9	29667.81
CPSO	120.653	118	725.6	29270.91
GPSO	123.65	118	725.9	29259.28
HJPSO	123.68	117	723.1	29254.5

Table 3
Transient response characteristics of electric power with ramp input and using ISE criteria.

	Power			
	Peak value (Mp)	Peak time (Tp)	Settling time (Ts)	Cost function value
PSO	120.1718	5	19.9436	539.7547
CPSO	120.0333	4	20	473.779
GPSO	120.0826	4	20	470.1488
HJPSO	120.1995	5	19.8665	464.8748

Table 4
Transient response characteristics of steam pressure with ramp input and using ISE criteria.

	Steam pressure			
	Peak value (Mp)	Peak time (Tp)	Settling time (Ts)	Cost function value
PSO	120.1822	50	69.87	539.7547
CPSO	120.3317	28	69.78	473.779
GPSO	120.5306	20	69.75	470.1488
HJPSO	120.4053	29	69.73	464.8748

Table 5
The controller parameters tuned by the different algorithms with step input.

	MW controller		Pressure controller		Level controller	
	Kp	Ki	Kp	Ki	Kp	Ki
PSO	1.1996	0.0517	2.4262	0.0626	2.6155	0.019
CPSO	1.1877	0.0552	2.3847	0.0676	3.3544	0.0081
GPSO	1.168	0.0549	2.3856	0.0675	3.4659	0.0083
HJPSO	1.1569	0.056	2.3777	0.0686	3.4016	0.0082

Table 6
The controller parameters tuned by the different algorithms with ramp input.

	MW controller		Pressure controller		Level controller	
	Kp	Ki	Kp	Ki	Kp	Ki
PSO	3.5809	0.3916	15.7298	0.1802	2.9956	0.012
CPSO	8.14	0.3013	13.3201	0.3044	3.0554	0.0137
GPSO	8.6709	0.5526	11.8266	0.2784	3.4772	0.0152
HJPSO	3.7169	0.909	10.522	0.2129	3.2251	0.0144

The above simulation results show that HJPSO has a superiority comparing with the other tuning algorithms. As shown, the transient response characteristics of PI controllers tuned by HJPSO in terms of settling time, the cost function and the convergence speed and with both step and ramp inputs is better than the standard PSO, CPSO and the GPSO. HJPSO only has a slightly difference in terms of peak overshoot and peak time values comparing with the other hybrid tuning algorithms which have a slightly better values than it. Also, all the hybrid PSO algorithms achieve the main objective with better performance than the standard PSO.

5. Conclusion

In this paper, a new hybrid jump PSO based Gaussian and Cauchy mutation called HJPSO is proposed for tuning three PI controllers to boiler turbine unit. PI controllers are used to control the positions of fuel flow valve, steam pressure valve and feed-water flow valve. The parameters of PI controllers were optimized by minimizing the error function between the actual outputs and the desired inputs to make the output systems trace each corresponding input in a desired manner. The main idea of HJPSO is based on monitoring the changes of local best fitness in a predefined numbers of iterations. Move the local best particles to a new best place, if the fitness values of the mutated particles are better than their current values. Besides a new modification is employed to the global best particle by generating a new particle which consists of the best parameters of each controller that achieve minimum error and it replaces the position of the global best particle if its fitness value is better than the global best fitness. To verify the efficiency of the proposed HJPSO, different types of hybrid PSO methods are introduced for tuning the three PI controllers to boiler turbine unit and compared with the HJPSO and the standard PSO. As shown, the simulation results prove the robustness and the capability of all the hybrid PSO techniques to achieve the required performance which is better than the standard PSO. The proposed modified method achieves the best result with best convergence speed and with good performance.

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