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Load frequency control of interconnected power system using grey wolf optimization

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ABSTRACT

In this article an attempt has been made to solve load frequency control (LFC) problem in an interconnected power system network equipped with classical PI/PID controller using gray wolf optimization (GWO) technique. Initially, proposed algorithm is used for two-area interconnected non-reheat thermal-thermal power system and then the study is extended to three other realistic power systems, viz. (i) two-area multi-units hydro-thermal, (ii) two-area multi-sources power system having thermal, hydro and gas power plants and (iii) three-unequal-area all thermal power system for better validation of the effectiveness of proposed algorithm. The generation rate constraint (GRC) of the steam turbine is included in the system modeling and dynamic stability of aforesaid systems is investigated in the presence of GRC. The controller gains are optimized by using GWO algorithm employing integral time multiplied absolute error (ITAE) based fitness function. Performance of the proposed GWO algorithm has been compared with comprehensive learning particle swarm optimization (CLPSO), ensemble of mutation and crossover strategies and parameters in differential evolution (EPSDE) and other similar meta-heuristic optimization techniques available in literature for similar test system. Moreover, to demonstrate the robustness of proposed GWO algorithm, sensitivity analysis is performed by varying the operating loading conditions and system parameters in the range of $\pm 50\%$. Simulation results show that GWO has better tuning capability than CLPSO, EPSDE and other similar population-based optimization techniques.

1. Introduction

Owing to the importance of the distribution of electrical power, the power companies are responsible for providing uninterrupted, reliable, efficient and effective power supply to their customers with an acceptable quality. Modern power system network is made up of several controlled areas and for stable operation of power system units, the total generation of each controlled area must match with total load demands plus associated system losses and regulates system frequency and exchanges tie-line power accordingly. This is called as load frequency control (LFC) or automatic generation control (AGC), which plays an important role in power system operation and control [1]. LFC is continuously monitoring the system frequency and tie-line power and calculate net changes of same from their nominal values (known as area control error, ACE), and accordingly control the valve settings of generators so as to keep ACE to its minimum value. AGC drives ACE to zero, automatically both frequency and tie-line power will automatically move to zero [2,3].

Hitherto, several control strategies have been proposed in the area of LFC to improve the system dynamics under the occurrence of the load perturbation. A critical literature review on LFC of conventional and distributed power system networks is available in [4]. It is observed from the literature that due to its simple and user friendly structure, most of the research papers are deal with proportional integral derivative (PID) controller or its alternative to solve LFC problem [1,2,5–7]. In [7], authors proposed several classical controllers like integral (I), proportional integral (PI), integral derivative (ID), PID and integral double derivative (IDD) to solve LFC problem in a multi-area thermal power system. Controller gains were optimized using bacteria foraging optimization algorithm (BFOA) and showed the superiority of the proposed method. Variable structure fuzzy gain scheduling based LFC is proposed in [8] for an interconnected multi-area multi-sources hydro-thermal power system network. Interval type-2 fuzzy controller for four-area LFC is available in [9]. The scaling factor and footprint uncertainties in interval type-2 fuzzy controllers were

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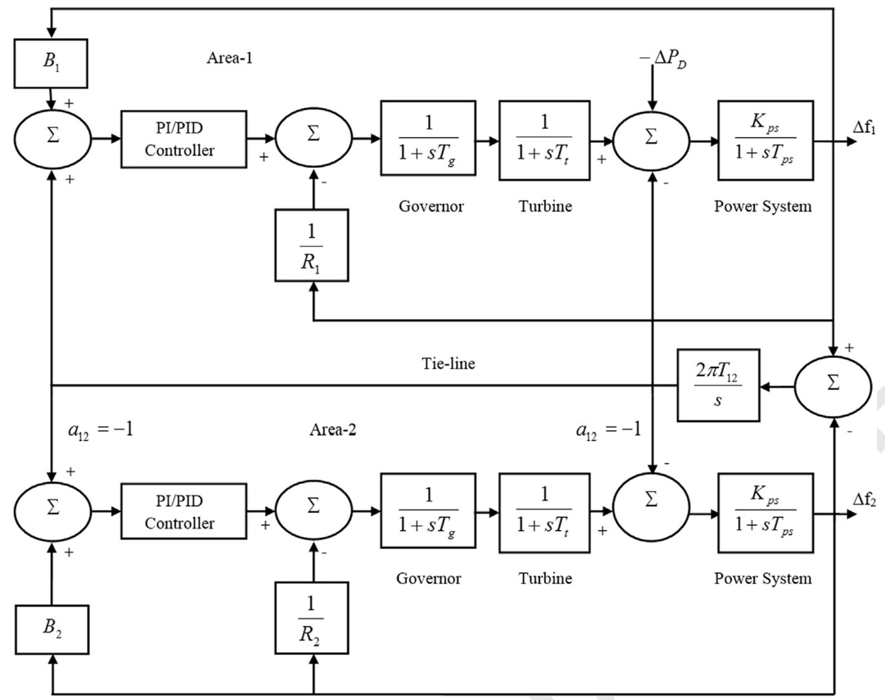

Fig. 1. Block diagram of two-area interconnected non-reheat thermal–thermal power system (test system-1).

optimized using big-bang big crunch (BB-BC) optimization technique. Various others controller based on modern control theory were proposed in the area of LFC to improve system performances under the occurrence of load perturbation like μ-synthesis controller [10], sliding mode controller [11], ANFIS controller [12], non-integer controller [13], observer-based controller [14], neural network controller [15], predictive controller [16], fuzzy logic controller [17], etc.

The modern power system networks are more complex with a large number of uncertainties. The main drawback of LFC is the choice of secondary controller gains. If the gains are not optimally selected, system responses may exhibit large momentary oscillations that may propagate into the wide area resulting in a wide area blackout [18]. This motivates the researchers to design effective and optimum stabilization techniques to die out these large oscillations and retains the system stability. In this context, several meta-heuristic population-based optimization techniques have been introduced in the area of LFC over the last few decades. In [6], teaching learning based optimization (TLBO) technique was proposed for optimal design of classical controller in multi-sources multi-units power system and potentiality of the algorithm was checked with differential evolution (DE) and optimal output feedback controller. DE based LFC was proposed in [19,20] to tune the settings of classical controllers for a multi-area mixed power system network and comparative performances between the classical controllers were also investigated. Farhangi et al. [21] in their recent endeavor, presents a novel approach based intelligent controller on emotional learning for LFC system of a two-area power system with generation rate constraint (GRC) and superiority of the proposed algorithm was investigated with PI, fuzzy logic, hydro-neuro fuzzy (HNF) controller. In [22], authors applied firefly algorithm (FA) with online wavelet filter for an interconnected unequal three area reheat thermal power system considering nonlinearities of the power system. Authors of [23] designed biogeography based optimization (BBO) technique for optimal design of classical controllers and frequency stabilizer like superconducting magnetic energy storage (SMES) to get better dynamic performances of three area hydro-thermal power system with governor dead band (GDB) nonlinearity and investigation revealed that proposed technique effectively died-out the oscillations in frequency and tie-line power compared to ANFIS controller. In [24], artificial bee colony (ABC) algorithm was implemented to solve AGC and effectiveness of the proposed technique was examined with particle swarm optimization (PSO) algorithm using transient analysis method. Shau et al. [25] suggested gravitational search algorithm (GSA) to design PI/PIDF (PID controller with derivative filter) with several classical objective functions for AGC system and showed the superiority of GSA by comparing the results with those of DE, BFOA and genetic algorithm (GA). Later, the study is forwarded to a real system with reheat turbine, GRC and GDB. Panda et al. designed hybrid BFOA–PSO in [26] and effectiveness of same was tested for AGC system and the superiority of hybrid BFOA–PSO was investigated by comparative analysis with PSO, BFOA and GA. Beside this, there are some other optimization algorithms like krill herd algorithm (KHA) [27], chemical reaction optimization [28], oppositional TLBO [29], etc., which are designed and successfully applied to other fields of power system.

Due to the randomness and uncertain dynamic behavior of the power system network, occasionally optimal controllers are also unable to provide better system performances. After the advancement of power electronics components, several researchers proposed various flexible AC transmission systems (FACTS) as frequency stabilizers such as SMES [23,30], thyristor controlled phase shifter (TCPS) [30–32], thyristor controlled series compensator (TCSC) [33], static synchronous series compensator (SSSC) [30], interline power flow controller (IPFC) [34], etc. to give additional damping to the transient responses.

In view of the above discussion, the main aim of the present study is to design and implement a new evolutionary algorithm (EA) known as gray wolf optimization (GWO) for optimal design of PI/PID controller to solve LFC problem. Four different interconnected power system networks with steam turbine nonlinearity are considered to test the effectiveness of proposed GWO algorithm and simulation results are investigated. Integral time multiply of absolute error (ITAE) based fitness function is considered for fine tuning of PI/PID controller gains. The superiority and effectiveness of proposed algorithm is established by comparing transient responses with other population-based meta-heuristic optimization techniques reported in literature such as PSO based fuzzy controller, pattern search (PS) based fuzzy controller, BFOA, DE, GA, hybrid BFOA–PSO, FA, hybrid FA–PS, TLBO,

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Table 1
Nominal values of system parameters.

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
Test System-1 [2,3] (2-area non-reheat thermal-thermal power system)						**Test System-2 [2,3] (multi-area multi-units hydro-thermal power system)**					
f	60 Hz	$T_{P1}=T_{P2}$	20 s	R_1	2.4 Hz/p.u. MW	f	50 Hz	T_{12}	0.0707 s	T_t	0.3 s
$P_{r1}=P_{r2}$	2000 MW	T_{12}	0.545 s	$K_{P1}=K_{P2}$	120	$B_1=B_2$	0.425 p.u. MW/Hz	R_1	2 Hz/p.u. MW	T_g	0.08 s
P_L	1000 MW	a_{12}	−1	$T_{t1}=T_{t2}$	0.3 s	$K_{P1}=K_{P2}$	100	R_2	2.4 Hz/p.u. MW	T_1	48.7 s
GRC	±0.05%±0.025%	$B_1=B_2$	0.425 p.u. MW/Hz	$T_{g1}=T_{g2}$	0.08 s	$T_{P1}=T_{P2}$	20 s	T_w	1 s	K_1	1
						a_{12}	−1	T_R	5 s	T_2	0.513 s
Test system-3 (multi-area multi-sources power system) [6]											
f	60 Hz	T_{12}	0.0433 s	T_{rh}	28.75 s	$R_1=R_2=R_3$	2.4 Hz/p.u. MW	T_{rs}	5 s	T_w	1 s
T_r	10 s	K_T	0.543478	T_{cr}	0.01 s	$K_{P1}=K_{P2}$	68.9566	$B_1=B_2$	0.4312	T_{gh}	0.2 s
K_r	0.5	K_G	0.130438	T_{fc}	0.23 s	$T_{P1}=T_{P2}$	11.49 s	T_t	0.3 s	b_g	0.5
T_{sg}	0.08 s	K_H	0.326084	T_{cd}	0.2 s	c_g	1	X_C	0.6 s	Y_C	1 s
Test system-4 (three-unequal-area all thermal power system) [37]											
f	60 Hz	T_{sg2}	0.06 s	T_{t3}	0.3 s	$D_1=D_3$	0.015 p.u Hz	$2H_3$	0.1247 p.u. s	GRC	3%/min
T_r	10 s	T_{sg3}	0.07 s	B_1	0.3484 p.u. MW/Hz	D_2	0.016 p.u. Hz	T_{12}	0.2 p.u./Hz	R_1	3 Hz/p.u. MW
K_r	0.5	T_{t1}	0.4 s	B_2	0.3827 p.u. MW/Hz	$2H_1$	0.1667 p.u. s	T_{23}	0.12 p.u./Hz	R_2	2.73 Hz/p.u. MW
T_{sg1}	0.08 s	T_{t2}	0.44 s	B_3	0.3692 p.u. MW/Hz	$2H_2$	0.2017 p.u. s	T_{13}	0.25 p.u./Hz	R_3	2.82 Hz/p.u. MW

Zeigler–Nichols (ZN) for the similar test system with same controller structure. Finally, the robustness of the GWO based designed controller is validated under different loading conditions and system parameter variations.

The rest of the paper is organized as follows: The mathematical model of the test systems is illustrated in Section 2. A brief outline of GWO algorithm is available in Section 3. Section 4 gives controller structure with a choice of objective function. Section 5 presents different algorithmic steps of GWO applied to LFC system. Section 6 reports the different simulation results compare to different methodologies. Finally, Section 7 concludes this article.

2. Mathematical model of test system

Initially, a two-area non-reheat thermal–thermal power plant (test system-1) as shown in Fig. 1 is considered for design and analysis purpose. The concerned power system model is widely used in the literature [2,3,5] for investigation of the dynamic behavior of the interconnected system under normal and disturbed condition. Each area has rating of 2000 MW with nominal loading of 1000 MW. Both the control areas are equipped with the speed governor, non-reheat type steam turbine, and power system units. It is assumed that all generators in each area are coherent. In Fig. 1, T_g is the time constant of speed governor, T_t is the time constant of steam turbine, K_{ps} is the gain of power system unit, T_{ps} is time constant of power system unit, B_1 and B_2 are the frequency bias parameter of the respective areas, R_1 and R_2 are the speed regulation parameter of speed governor in area-1 and area-2, respectively, T_{12} is the synchronizing time constant of tie-line, ΔP_D is the load disturbance, Δf_1 and Δf_2 are deviation of frequency in area-1 and area-2, respectively. Nominal values of system parameters are taken from [2,3] and specified in Table 1. The appropriate value of GRC of the steam turbine is included in the system modeling. In practical power system scenario, power generations can only change at a specified maximum limit and therefore, GRC is always considered with steam turbine, otherwise system will experience large momentary disturbances that may cause instability in power system network. The limiting value of GRC in the thermal power plant is 2–5% [2].

3. Optimization techniques

3.1. Gray wolf optimization (GWO)

In today's scenario, computational challenges may exist in finding globally optimized solution from an immensely large solution space. Heuristic optimization techniques have therefore been forwarded which can find the candidate solution from the very large solution space. In the recent time, different meta-heuristic optimization algorithms, as mentioned in Section 1, are proposed to solve nonlinear, complex, real-time problems. In this context, one question may arise: why meta-heuristic optimizations have become more popular? The answer to this question can be summarized into four groups, these are: (i) simplicity, (ii) flexibility, (iii) derivative-free-mechanism, and (iv) local optima avoidance.

Nearly all the well-known meta-heuristic optimization methods are (i) nature inspired, (ii) randomly initialized, and (iii) they have several input parameters those need to be fitted to the problem in hand. The main drawback of conventional methods is the proper selection on input parameters and premature convergence, which results in degradation of computational efficacy and search capability. Beside these, they are also suffering from the long computational time, poor convergence rate, large dimension, no

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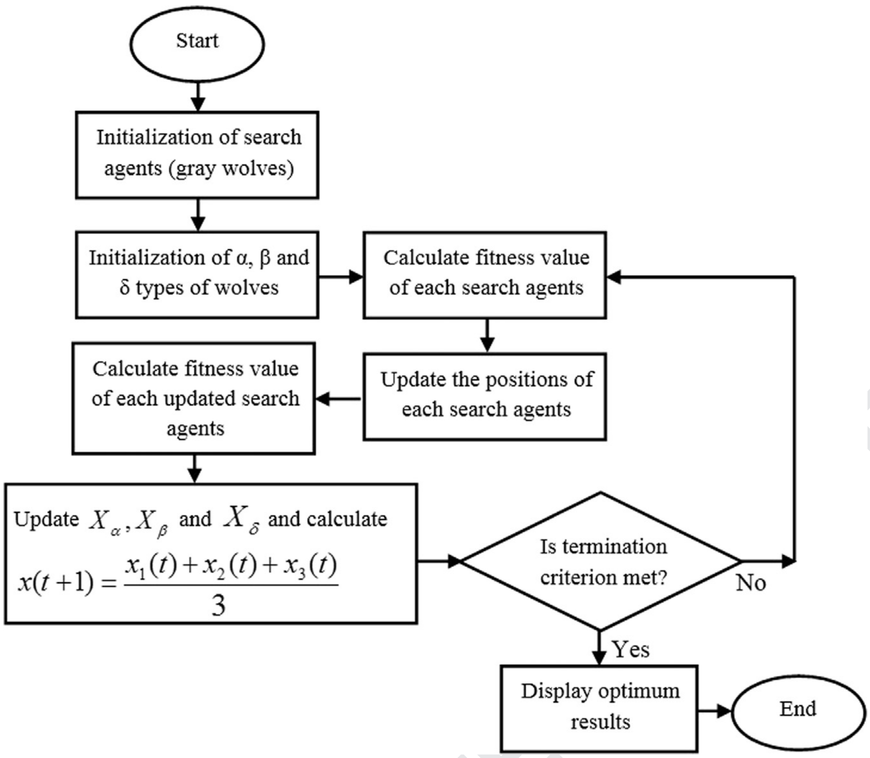

Fig. 2. Flowchart of GWO-algorithm.

Table 2
Optimum values of controller parameters for test system-1.

Controllers	K_{i1}	K_{i2}	K_{p1}	K_{p2}	K_{d1}	K_{d2}	ITAE value
GWO: PI	0.5565	0.0199	0.0630	0.0730	–	–	0.1388
EPSDE: PI	0.8502	0.0334	0.0145	0.0478	–	–	0.1539
CLPSO: PI	0.9661	0.1147	0.0244	0.0150	–	–	0.1949
GWO: PID	1.9107	0.0400	1.0569	1.7486	0.4221	1.1988	0.1340
EPSDE: PID	1.7733	0.1650	0.8599	1.0411	0.3883	1.0110	0.1497
CLPSO: PID	1.7056	0.4286	1.0148	1.7206	0.3844	0.5831	0.1569

Table 3
Comparative performance of ITAE value and settling times for test system-1.

Techniques/parameters	ITAE value	Settling time (s)		
		Δf_1	Δf_2	ΔP_{tie}
Proposed GWO tuned PID	**0.1340**	**1.06**	**3.17**	**3.34**
EPSDE tuned PID	0.1497	2.88	3.37	3.56
CLPSO tuned PID	0.1569	1.89	3.60	3.80
Proposed GWO tuned PI	0.1388	1.70	3.25	3.40
EPSDE tuned PI	0.1539	6.22	7.80	6.67
CLPSO: PI	0.1949	7.19	8.80	7.64
PSO tuned fuzzy PI [3]	0.4470	5.13	6.22	4.83
PS tuned fuzzy PI [3]	0.6334	6.05	7.10	5.56
hPSO-PS tuned fuzzy PI [3]	0.1438	2.26	3.74	2.94
DE tuned PI [20]	0.9911	8.96	8.16	5.75
BFOA tuned PI [20]	1.7975	5.52	7.09	6.35
GA tuned PI [20]	2.7475	10.59	11.39	9.37
Conventional PI [20]	3.7568	45	45	28
hBFOA–PSO tuned PI [26]	1.1865	7.39	7.65	5.73
PSO tuned PI [26]	1.2142	7.37	7.82	5

Bold signifies best results.

guarantee to give the global optimum solution, growing need more computer resources.

The main advantage of GWO algorithm over most of the well-known meta-heuristic algorithms is that the GWO algorithm operation requires no specific input parameters. Additionally, it is straightforward and free from computational complexity. Further, its advantages include – ease of transformation of such concept to the programming language and ease of comprehensibility. In the line of 'no-free-lunch' theorem, there is no meta-heuristic optimization technique well suited for all optimization problems and there is always a room for improvement. Having knowledge of the aforesaid discussion, authors made an attempt to design and implement of load frequency controller utilizing novel optimization method called gray wolf optimization. In the following section, first encouragement of GWO technique is discussed and afterward mathematical modeling of same is presented.

3.1.1. Encouragement of GWO

Gray wolf, also known as timber wolf or western wolf belongs to Canidae family and its scientific name is *Canis lupus*. Gray wolves are normally considered as apex predators (at the top of the food chain) and popularly available in remote areas of North America, Eurasia and northern, eastern and western Africa. The gray wolf optimization (GWO) algorithm is a novel meta-heuristic optimization technique developed by Mirjalili et al. in 2014 [35]. GWO simply mimic the leadership hierarchy and hunting mechanism of gray wolves in nature. Gray wolves mostly prefer to live in the pack (5–12 on average). Four types of gray wolves such as alpha (α), beta (β), delta (δ), and omega (Ω) are employed for simulating the leadership hierarchy, as shown in [35]. Additionally, the hunting mechanism in GWO algorithm involves three main strategies, viz. searching for prey, encircling prey, and attacking prey.

Gray wolves present at the top of the hierarchy are called alpha category wolves and they are the leader of the whole pack. This category of wolves may be male or female and has decision-making power about hunting, sleeping place, time to wake, etc. Their decisions are directed to the pack. However, some kind of democratic behavior is also observed in which they follow other wolves in the pack. In gatherings, the entire pack acknowledges the alpha by holding their tails down. The alpha wolf is also called

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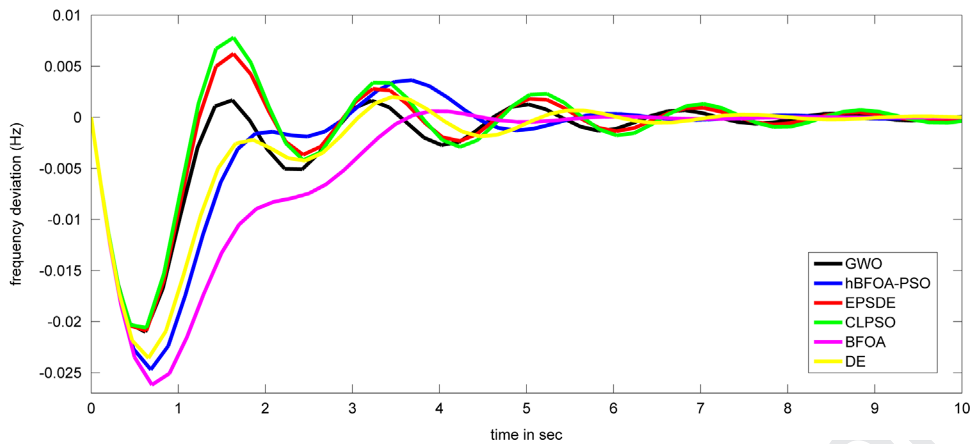

Fig. 3. Changes of frequency with 10% SLP in area-1 for test system-1.

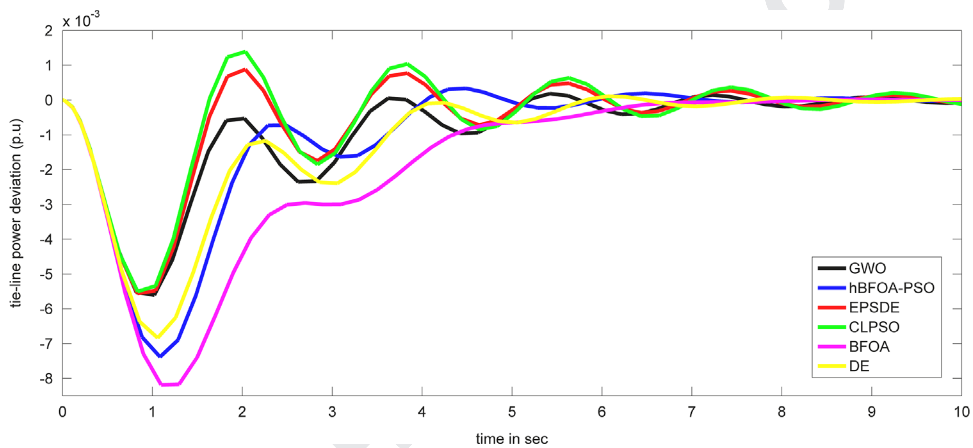

Fig. 4. Changes of tie-line power with 10% SLP in area-1 for test system-1.

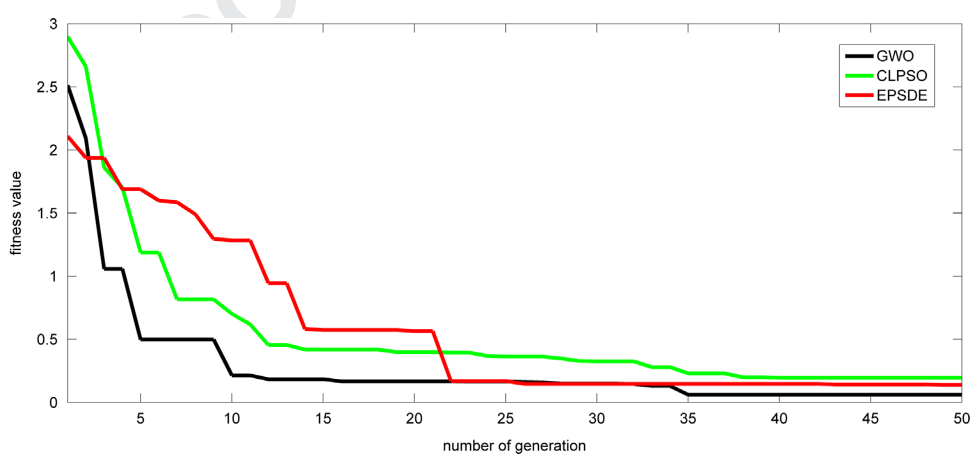

Fig. 5. Convergence profile of proposed algorithms for test system-1 with PI-controller structure.

the dominant wolf since his/her direction should be followed by the entire pack. Interestingly, alpha is not necessarily the strongest member in the hierarchy, it only manages the pack. This shows that the organization and discipline of a pack are much more important than strength.

In the second level of the hierarchy, the gray wolves are named as beta category wolves and they are subordinate of alpha category wolves. They help alphas in the decision-making process and/or other pack activities. The beta wolves can be either male or female. They are probably the best candidate and may transform into the alpha category wolves in case one of the alpha wolves passes away or become very old. The beta wolves respect alpha, but dominant other wolves in the pack. It plays the role of an advisor to alphas and discipliner in the pack.

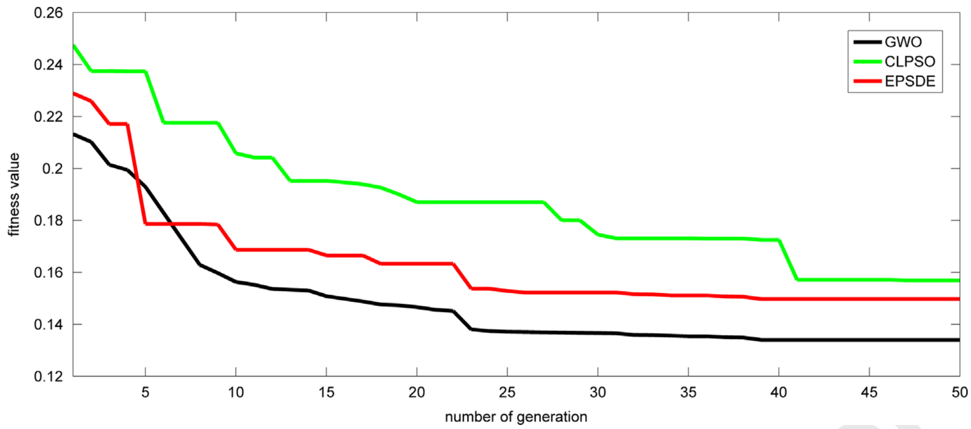

Fig. 6. Convergence profile of proposed algorithms for test system-1 with PID-controller structure.

Table 4
Optimum values of GWO based PID-controller parameters for test system-1with GRC.

Controller gains	GRC$= \pm 0.05$			GRC$= \pm 0.025$		
	GWO	FA [2]	hFA–PS [2]	GWO	FA [2]	hFA–PS [2]
K_{p1}	0.9843	0.3259	0.3834	1.0751	0.5262	0.1898
K_{p2}	1.9892	0.3259	0.3834	1.7904	0.5262	0.1898
K_{i1}	1.9766	0.5743	0.6127	1.9571	0.3404	0.3164
K_{i2}	0.2150	0.5743	0.6127	0.3608	0.3404	0.3164
K_{d1}	0.3463	0.4024	0.4021	0.4165	0.6500	0.4528
K_{d2}	1.0085	0.4024	0.4021	0.7602	0.6500	0.4528
ITAE value	**0.1308**	0.3240	0.2782	**0.1294**	0.8023	0.7405

Bold signifies best results.

Table 5
Comparative performance between different optimization techniques in terms of ITAE value and settling times for test system-1 with GRC.

Optimization algorithms	GRC$= \pm 0.05$ p.u.				GRC$= \pm 0.025$ p.u.			
	Δf_1	Δf_2	ΔP_{tie}	ITAE	Δf_1	Δf_2	ΔP_{tie}	ITAE
GWO	**2.64**	**2.86**	**3.14**	**0.1308**	**2.52**	**3.17**	**3.34**	**0.1294**
hFA–PS [2]	2.8	4.5	4	0.2782	6.9	5.2	7.5	0.7405
FA [2]	3.1	4.9	4.3	0.3240	7.8	6.3	7.9	0.8023
BFOA [2]	4.7	6.4	5.1	0.4788	9	7.9	8.3	1.5078
GA [2]	6.9	8.0	5.7	0.5513	11.1	11.2	11	2.4668
ZN [2]	8.1	9.2	6.7	0.6040	15.3	14.1	15.3	3.4972

Bold signifies best results.

The lowest stage of the hierarchy is occupied by the omega types of wolves. They are basically used as a scapegoat and always follow the decision made by other dominant wolves. They are the worst category of wolves those are allowed to eat. It is noted that omega types of wolves are not so much important in the pack, but the whole pack may face internal fighting in case of losing the omega. This is due to the venting of violence and frustration of all wolves by the omegas. Omegas are always maintaining the dominant structure in the hierarchy and in some cases the omega is also the babysitters in the pack.

The wolves which do not come under alpha, beta and omega categories are grouped under delta or subordinate category. Delta types of wolves always follow the alphas and betas but dominate omegas. Five basic functions performed by delta wolves in the hierarchy, viz. (i) scouts, (ii) sentinels, (iii) elders, (iv) hunters and (v) caretakers. Scouts are responsible for watching the boundaries of the region and aware the pack in case of any hazard. Sentinels protect and promise the safety of the pack. Elders are the experienced wolves (alphas or betas) and their experiences are used to attack prey or any target elements. Hunters help alphas or betas when hunting prey and providing food for the pack. Finally, caretakers are responsible for caring the feeble, sick and injured wolves in the pack.

The main steps of gray wolf hunting are as follows [35]:

(i) Tracking, chasing and approaching the prey.
(ii) Pursuing, encircling and harassing the prey until it stop moving.
(iii) Attack towards the prey.

3.1.2. Mathematical modeling of GWO

In this section, the social hierarchy of wolves, tracking, encircling and attacking prey are discussed followed by the mathematical modeling of GWO algorithm.

3.1.2.1. Social hierarchy. For modeling of the social behavior of the gray wolf, alpha is considered to be the fittest solution followed by beta and delta, respectively, and the rest of the solutions are grouped under omega. In GWO, the hunting (optimization) process is guided by alpha, beta and delta, whereas omega always follows these three wolves.

3.1.2.2. Encircling. To model an encircling behavior of gray wolves around the prey, following equations are considered [35].

$$\vec{D} = \left| \vec{C} \cdot \vec{x_p}(t) - \vec{x}(t) \right| \tag{1}$$

$$\vec{x}(t+1) = \vec{x_p}(t) - \vec{A}\,\vec{D} \tag{2}$$

where t is the current iteration, $\vec{x_p}(t)$ denotes the current position of the victim, and the coefficient vectors $\vec{A}$ and $\vec{C}$ are computed using (3) and (4), respectively.

$$\vec{A} = 2\vec{a}\,\vec{r_1} - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r_2} \tag{4}$$

where $\vec{r_1}$ and $\vec{r_2}$ are two random vectors between [0, 1] and the component of $\vec{a}$ is linearly decreasing from 2 to 0 over each course of the iteration.

3.1.2.3. Hunting. In hunting phase which is basically guided by the alphas, the positions of the gray wolves are updated. Though alphas are the main agents in hunting phase, still occasionally

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betas and deltas also participate in the hunting process. So far we have the candidate solutions of gray wolves in terms of alphas, betas and deltas but we do not know the exact or optimum position of prey. To find the optimum positions, three best solutions (obtained so far) in terms of alpha, beta and delta are saved and remaining solutions including omega are competed. Following formulas are used to update the wolf positions around the prey [35].

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}\,\overrightarrow{X_\alpha} - \overrightarrow{X}\right|, \quad \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}\,\overrightarrow{X_\beta} - \overrightarrow{X}\right|, \quad \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}\,\overrightarrow{X_\delta} - \overrightarrow{X}\right| \tag{5}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}\left(\overrightarrow{D_\alpha}\right), \quad \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}\left(\overrightarrow{D_\beta}\right),$$
$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}\left(\overrightarrow{D_\delta}\right) \tag{6}$$

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{7}$$

It would be observed that final position is random in nature within the circle which is completely defined by the alpha, beta and delta in the search space, whereas other wolves update their position by estimating the prey position.

3.1.2.4. Attacking prey (exploitation). In the above sections, it is discussed that how the gray wolves finish the hunt by attacking prey when it stops moving. In order to mathematically express the model approaching the prey, two parameters, as described below are considered. $\overrightarrow{a}$ is linearly decreasing from 2 to 0 and fluctuations of $\overrightarrow{A}$ is also decreased with $\overrightarrow{a}$. In other words $\overrightarrow{A}$ is a random value between $[-a, a]$. When random value of $\overrightarrow{A}$ is between $[-1, 1]$ the next position of search agent can be any position between the current position and prey position.

3.1.2.5. Search for prey (exploration). Optimum search in gray wolf algorithm is based on the positions of alpha, beta and delta. They diverge from each other when they search for prey and converge during attacking the prey. Mathematically, when the random value of $\overrightarrow{A}$ is greater than 1 or less than -1 then search agent diverges to prey. This emphasizes exploration behavior in GWO algorithm. One more variable in GWO technique helps exploration process is $\overrightarrow{C}$. The random value of $\overrightarrow{C}$ varies between [0, 2], as evident from (4), which effects the prey of defining the distance as in (1). Thus, GWO shows more random behavior throughout the optimization and favoring exploration and local optima avoidance.

Finally, the algorithm steps of GWO may be summarized as follows:

(a) The search process is started with random initialization of candidate solutions (wolves) in the search space.
(b) Alpha, beta and delta wolves are estimated based on the position of prey.

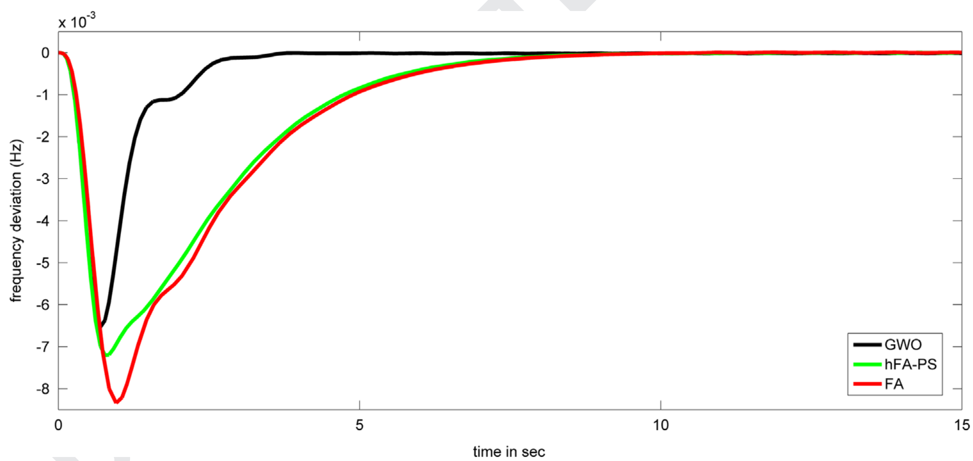

Fig. 7. Changes of frequency with 5% SLP in area-1 considering 0.05 GRC for test system-1.

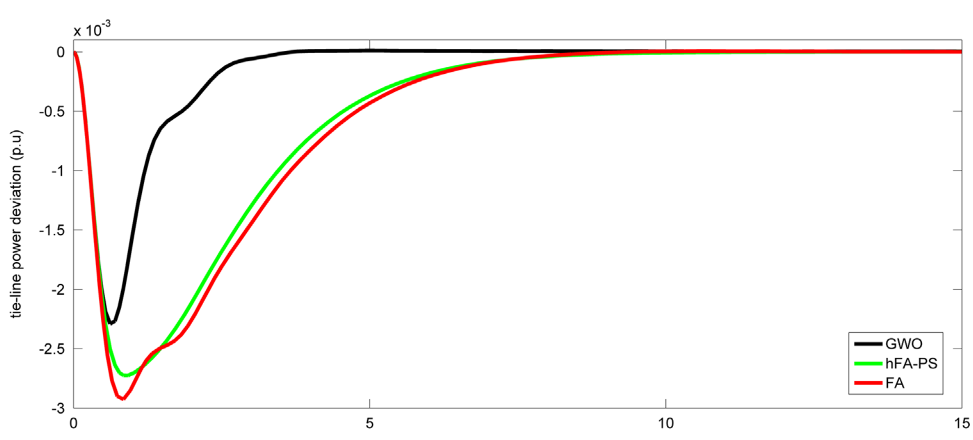

Fig. 8. Changes of tie-line power with 5% SLP in area-1 considering 0.05 GRC for test system-1.

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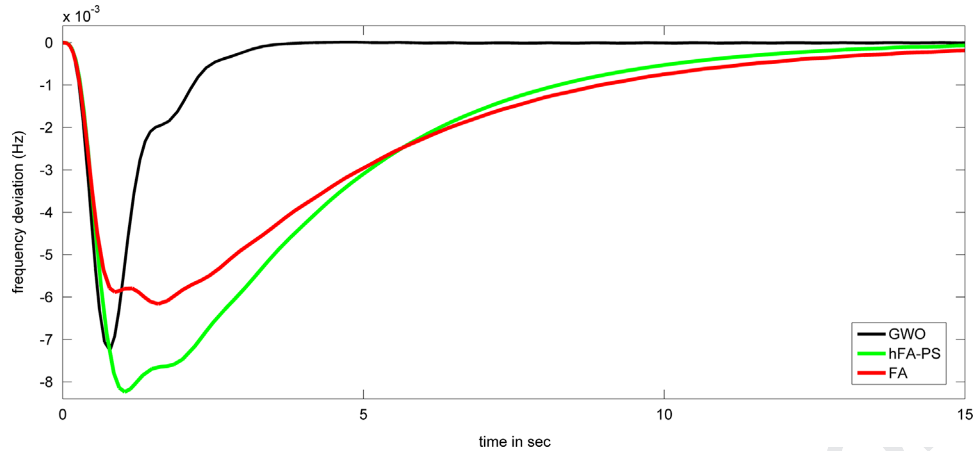

Fig. 9. Changes of frequency with 5% SLP in area-1 considering 0.025 GRC for test system-1.

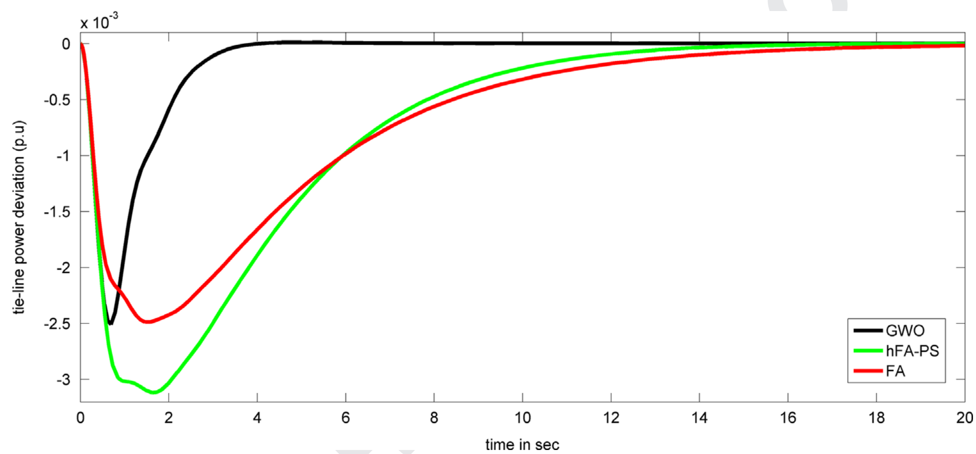

Fig. 10. Changes of tie-line power with 5% SLP in area-1 considering 0.025 GRC for test system-1

Table 6
Optimum gains of GWO based PID-controller, ITAE value, settling time and overshoot using GWO of test system-1 under wide variations of load.

Parameters	ITAE value	Controller gains						Settling time (s)			Overshoot		
		K_{i1}	K_{i2}	K_{p1}	K_{p2}	K_{d1}	K_{d2}	Δf_1	Δf_2	ΔP_{tie}	Δf_1	Δf_2	ΔP_{tie}
Nominal	0.1340	1.9107	0.0400	1.0569	1.7486	0.4221	1.1988	1.06	3.17	3.34	0.0020	9.3×10^{-5}	2.18×10^{-5}
+50%	0.1901	1.9701	0.3942	1.0517	1.9225	0.3767	0.4995	2.35	3.17	3.32	0.0084	9.02×10^{-5}	2.48×10^{-5}
+25%	0.1582	1.9855	0.5456	1.0909	1.9887	0.4040	0.7051	1.31	3.12	3.34	0.0043	6.73×10^{-5}	2.2×10^{-5}
−25%	0.0959	1.9651	0.4395	1.0830	1.8745	0.3922	0.5921	2.30	3.18	3.38	0.0029	3.32×10^{-5}	1.03×10^{-5}
−50%	0.0667	1.8993	0.3813	1.0454	1.8127	0.3822	0.5443	1.28	3.27	3.40	0.0017	2.08×10^{-5}	6.08×10^{-6}

(c) To find the optimum location of prey, each wolf updates its position.
(d) A control parameter, $\vec{a}$ linearly decreases from 2 to 0 for better exploitation and exploration of candidate solutions.
(e) Candidate solutions tend to diverge when $\vec{A} > 1$ and to converge when $\vec{A} < 1$ and at the end GWO gives the optimum solution.

The general flowchart of GWO algorithm is shown in Fig. 2 and for more details about the GWO algorithm; readers are referred to [35].

3.2. Comprehensive learning particle swarm optimization (CLPSO)

As a novel evolutionary computation technique, particle swarm optimization (PSO) has attracted much attention and wide application in the complex optimization fields over the last few decades. PSO mimics the swarm behavior and individual represent points in the *d-dimensional* search space. In conventional PSO, the velocity $\left(V_i^d\right)$ and position $\left({X_i}^d\right)$ of the *i*th-particle are updated using (8) and (9) [36].

$$V_i{}^d \stackrel{update}{\Longleftarrow} V_i{}^d + c_1 rand_i^d\left(pbest_i^d - X_i{}^d\right) + c_2 rand_i^d\left(gbest^d - X_i{}^d\right) \quad (8)$$

$$X_i^d \stackrel{update}{\Longleftarrow} X_i^d + V_i^d \quad (9)$$

where $X_i = \left[X_i^1, X_i^2, \ldots, X_i^d\right]$ is the position of *i*th particle; $V_i = \left[V_i^1, V_i^2, \ldots, V_i^d\right]$ is the velocity of *i*th particle; *pbest* the best previous position of particle yielding the best fitness value; *gbest* the best position discovered by the whole population; c_1 and c_2 are acceleration term that pull each particle toward their optimal position; *rand* is the random number selected between [0, 1].

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Table 7
Q3 Sensitivity analysis of test system-1 with GWO based PID-controller.

Parameter variation	% of change	Proposed GWO based PID-controller				Hybrid PSO–PS based fuzzy PI-controller [3]				DE optimized PI-controller [3]			
		Settling time (s)			ITAE value	Settling time (s)			ITAE value	Settling time (s)			ITAE value
		Δf_1	Δf_2	ΔP_{tie}		Δf_1	Δf_2	ΔP_{tie}		Δf_1	Δf_2	ΔP_{tie}	
Nominal	No change	1.06	3.17	3.34	0.1340	2.26	3.74	2.94	0.1438	8.96	8.16	5.75	0.9962
T_g	+50	2.44	3.17	3.33	0.1312	2.21	3.64	2.81	0.1321	11.13	11.08	7.57	0.9955
	+25	1.71	3.2	3.4	0.1308	2.22	3.70	2.88	0.1386	9.14	9.98	7.45	0.9847
	−25	1.34	3.25	3.36	0.1250	2.28	3.76	2.96	0.1460	7.09	8.06	5.73	1.0012
	−50	1.80	3.59	3.37	0.1342	2.31	3.77	2.97	0.1469	7.03	7.94	5.77	1.0860
T_t	+50	1.89	3.26	3.6	0.1329	1.98	3.61	2.80	0.1348	14.86	14.84	11.05	1.1767
	+25	2.58	3.27	3.49	0.1326	2.16	3.69	2.88	0.1409	11.47	11.45	8.75	1.0028
	−25	1.54	3.08	3.17	0.1257	2.33	3.76	2.95	0.1422	6.66	6.26	5.74	1.0366
	−50	1.31	3.03	3.47	0.1269	2.39	3.74	2.91	0.1354	5.26	6.54	6.00	1.0860
T_{12}	+50	1.63	2.33	2.73	0.1084	2.73	3.51	2.70	0.1361	9.68	9.61	7.33	0.9901
	+25	2.35	2.56	2.90	0.1145	2.56	3.60	2.80	0.1399	9.20	9.35	7.04	0.9875
	−25	2.94	3.61	3.58	0.1497	1.92	3.98	3.14	0.1513	7.74	8.67	6.24	1.0029
	−50	3.04	3.36	3.35	0.1898	3.02	4.48	3.53	0.1917	7.34	7.61	6.69	1.0322

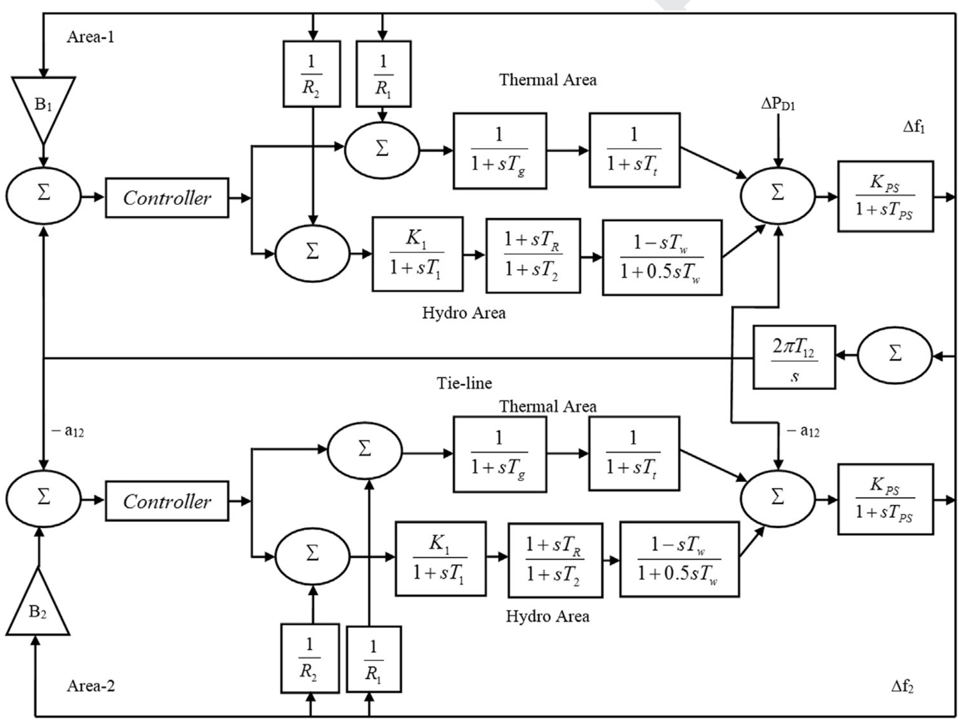

Fig. 11. Block diagram of two-area interconnected multi-units hydro-thermal power system (test system-2).

PSO does not use any evolution operators like crossover and mutation, which may result is degradation of computational ability and search capability. It may easily get trapped in a local optimum when solving multimodal complex problems. To avoid premature convergence and to improve the performance of original PSO, Liang et al. presented a new learning strategy by incorporating a comprehensive learning method into original PSO, namely comprehensive learning particle swarm optimization (CLPSO) [36] in 2006. This strategy ensured that the diversity of the swarm was preserved to discourage premature convergence of original PSO.

In original PSO, *pbest* and *gbest* assist each particle to learn from others and social learning factor is limited to *gbest*. Since all the particles in the swarm learn from the *gbest* even if the current *gbest* is far from the global optimum, particles may easily be absorbed and trapped to the local optimum value if search environment is complex with numerous local solutions. Thus to avoid premature convergence and to accelerate the convergence rate, a comprehensive learning strategy is included in original PSO. In this new technique, particles are allowed to learn from one paradigm (*pbest*) for a few iterations instead of learning from two paradigms, namely, *pbest* and *gbest* for all dimensions. In CLPSO, for each particle, in addition to its own *pbest*, other particles' *pbest* are also used as paradigms. In CLPSO, velocity updating equation is modified as [36]

$$V_i{}^d \overset{update}{\Longleftarrow} w^* V_i{}^d + c^* rand_i^d \left(pbest_{fi(d)}^d - X_i{}^d \right) \tag{10}$$

where $pbest_{fi(d)}^d$ may be any particles' *pbest* or its own *pbest*; w is the inertia weight to balance global and local search ability. For more details regarding CLPSO, readers are referred to [36].

3.3. Ensemble of mutation and crossover strategies and parameters in differential evolution

The effectiveness of differential evolution (DE) is highly depends on the selection of mutation and crossover strategy and associated parameter values. However, different optimization problems have different mutation strategies with different parameter values depending on the nature of optimization problem. Additionally, to solve a specific optimization problem, different mutation strategies with different parameter settings may provide better results during the evolution than a single mutation strategy with unique parameter settings as in conventional DE.

Table 8
Optimum values of PI/PID controller for test system-2 with 1.5% SLP in area-1.

Controller parameter	GWO:PI (ISE)	hFA–PS:PI (ISE)[2]	GWO: PI (ITAE)	hFA–PS: PI (ITAE) [2]	GWO: PID (ITAE)	hFA–PS: PID (ITAE) [2]
K_{p1}	0.5155	0.0476	0.0407	0.0490	1.1641	1.8457
K_{p2}	0.1783	−1.9441	0.0792	−0.7220	1.6009	−0.4525
K_{p3}	1.6259	1.1591	0.8287	1.3594	1.0571	1.2922
K_{p4}	0.0547	−0.5823	0.3354	−1.7002	1.3800	−1.0720
K_{i1}	0.8058	1.4093	0.9747	0.6533	1.8087	1.6563
K_{i2}	1.7824	−0.2675	0.0799	−0.0301	0.0325	0.1378
K_{i3}	0.2142	0.4211	0.2642	0.1119	1.7595	1.8748
K_{i4}	1.7868	−0.4942	1.9854	−0.0827	0.8378	−1.3785
K_{d1}	–	–	–	–	0.6055	0.6109
K_{d2}	–	–	–	–	0.6957	0.4120
K_{d3}	–	–	–	–	0.9952	0.4041
K_{d4}	–	–	–	–	0.4954	0.4541
Fitness value	67.99×10^{-6}	801×10^{-6}	0.0564	0.2285	0.0139	0.0870

Table 9
Settling time and performance index of different optimization techniques for test system-2 with 1.5% SLP in area-1.

Optimization techniques	Settling time (s)			ISE (10^{-6})	ITAE (10^{-3})	ITSE (10^{-6})
	Δf_1	Δf_2	ΔP_{tie}			
hFA–PS tuned PID: ITAE [2]	3.29	5.20	3.92	118.4	87.0	85.7
hFA–PS tuned PI: ITAE [2]	6.43	8.60	5.98	805.0	228.5	862.9
hFA–PS tuned PI: ISE [2]	9.48	15.25	7.15	801.0	333.8	899.9
GA tuned PI: ISE [2]	16.03	25.72	9.84	905.8	625.8	1238
ZN tuned PI: ISE [2]	38.15	38.98	23.99	1079.0	1336	2890
Proposed GWO tuned PID: ITAE	**1.71**	**5.06**	**3.40**	**32.98**	**13.9**	**33.097**
Proposed GWO tuned PI: ITAE	4.09	6.97	3.59	238.86	56.4	251.86
Proposed GWO tuned PI: ISE	6.06	12.7	11.02	67.990	82	73.67

Bold signifies best results.

Ensemble of mutation and crossover strategies and parameters in differential evolution (EPSDE) algorithm consists of a pool of mutation and crossover strategies along with a pool of values for each of associated control parameters competes to produce successful offspring population. EPSDE requires less computational time to generate high quality of solutions and have a stable convergence performance. Each member in the initial population is randomly assigned with a mutation strategy and associated parameter values are taken from the respective pools. The population members (*target vectors*) produce offspring (*trial vectors*) using the assigned mutation strategy and parameter values. If the generated trial vector produced is better than the target vector, the mutation strategy and parameter values are retained with trial vector, which becomes the parent in the next generation. The combination of mutation strategy and the parameter values that produce better offspring than the parent are stored. If the target vector is better than the trial vector, then the target vector is randomly reinitialized with a new mutation strategy and associated parameter values from the respective pools or from the successful combinations stored with equal probability. Four basic steps for successful implementation of EPSDE are enumerated as follows [37]:

Step 1. **Initialization**: Initial population of size 'n_p' is generated using the following pseudo code:

$$
\begin{aligned}
&for\ \ i = 1 : n_p \\
&\qquad for\ \ j = 1 : d \\
&\qquad\qquad pop(i, j) = lb(j) + rand * (ub(j) - lb(j)); \\
&\qquad end \\
&end
\end{aligned}
$$

where d is the number of control variables; $rand$ is a randomly generated number between [0, 1]; $lb$and ub are the lower and upper bounds of control variables.

Step 2. **Mutation**: DE mutates and recombines the population to produce a population of 'n_p' trial vectors. For each trial vector U_i^{k+1} at generation n_p, an associated mutant vector $\rho_i^{(k)} = \{u_{1i}, u_{2i}, \ldots, u_{ni}\}$ can usually be generated by using any

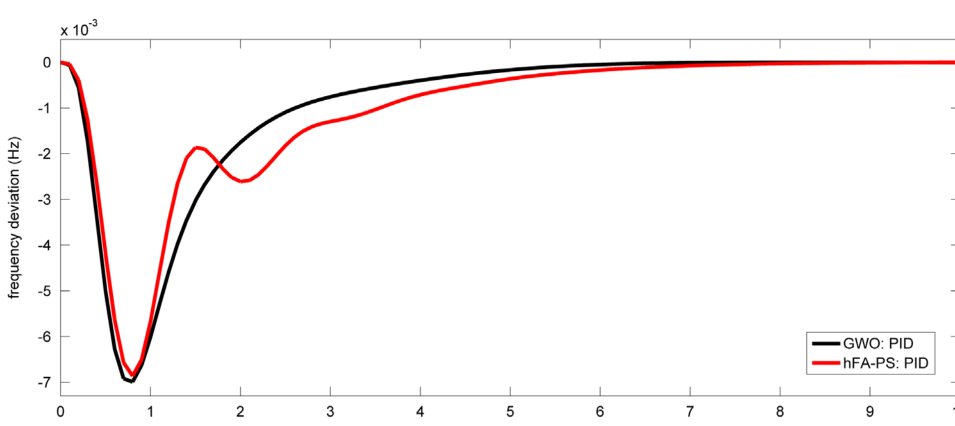

Fig. 12. Changes of frequency with 1.5% SLP in area-1 for test system-2.

one of the five strategies as shown online available code [38].

Step 3. **Crossover**: EPSDE employs a uniform crossover strategy to generate trial vector $\left(t_i^{(k)}\right)$, which is defined as follows:

$$t_i^{(k)} = \begin{cases} \rho_{i,j}^{(k)}, & \text{if} \quad (rand_j \le C_r) \\ u_{i,j}^{(k)}, & \text{otherwise} \end{cases}$$

where C_r is the crossover probability.

Step 4. **Selection**: Fitness function is evaluated for trial vector and target vector, trial vector is selected if it provides better value of the function than target vector as follows:

$$U_i^{k+1} = \begin{cases} t_i^k, & \text{if} \quad \left[f\left(t_i^k\right) \ge f\left(U_i^k\right)\right] \\ U_i^k, & \text{otherwise} \end{cases}$$

The aforesaid procedure, i.e. mutation, crossover and selection, is executed for all target vectors and a new population is created until the termination criterion is met.

4. Controller structure with problem formulation

The main aim of the secondary controller is to regulate frequency and tie-line power deviations to zero as fast as possible after sudden load perturbation and for this, an optimal PI/PID controller is designed using GWO approach. When the controlled areas are interrupted by any sudden load perturbation, the required ACE in each area is used to invoke the controller action such that ACE is reduced to zero. According to IEEE recommended definition of terms of AGC, the ACE in an interconnected power system is defined as a quantity that reflects the deficiency or excess of power within a control area. Mathematically it is defined as in (11).

$$\left.\begin{aligned} ACE_1 &= B_1 \Delta f_1 + \Delta P_{tie} \\ ACE_2 &= B_2 \Delta f_2 - \Delta P_{tie} \end{aligned}\right\} \tag{11}$$

where ACE_1, ACE_2 are the area control error of area-1 and area-2, respectively. The controlled inputs (u_1, u_2) to the plant are obtained as under:

$$\begin{aligned} u_1(t) &= K_p ACE_1 + K_i \int ACE_1 dt + K_d \frac{d(ACE_1)}{dt} \\ u_2(t) &= K_p ACE_2 + K_i \int ACE_2 dt + K_d \frac{d(ACE_2)}{dt} \end{aligned} \tag{12}$$

where K_p, K_i, K_d are the proportional, integral and derivative gains of PID-controller, respectively, which need to be optimized using proposed GWO algorithm. For the optimal selection of PID-controller gains, choice of performance index according to the problem structure is very important so that good dynamic responses under all operating conditions can be achieved. A common problem encountered in control system design is the selection of controller gains. In general, the low value of controller gains offers sluggish system performance, while high value causes an unduly oscillatory system response with the possibility of instability. Somewhere between these extreme levels is the general choice of controller gains that may provide satisfactory system performance.

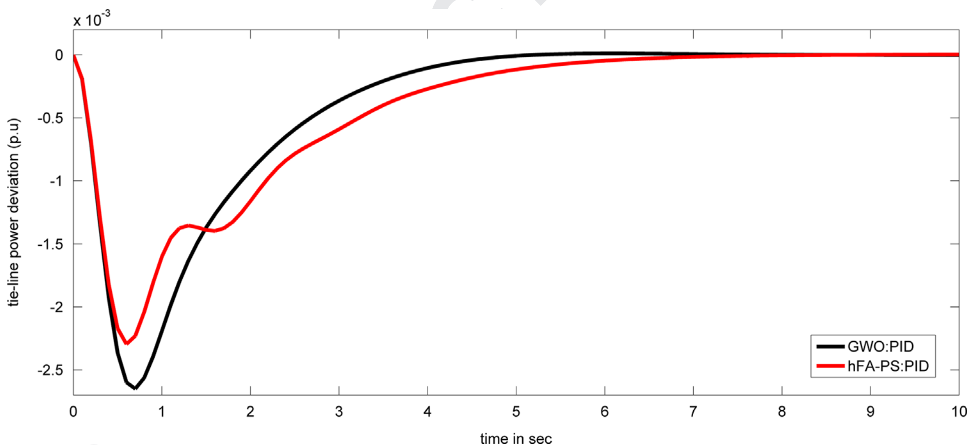

Fig. 13. Changes of tie-line power with 1.5% SLP in area-1 for test system-2.

Table 10
Optimum values of GWO based PID-controller under varied conditions (load, T_H and T_t).

Controller parameters	Loading condition				T_H				T_t			
	+50%	+25%	−25%	−50%	+50%	+25%	−25%	−50%	+50%	+25%	−25%	−50%
K_{i1}	1.9146	1.9020	1.8851	1.8316	1.9645	1.9029	1.9153	1.9366	1.9948	1.8340	1.7927	1.9222
K_{i2}	0.0573	0.0373	0.0885	0.1193	0.1475	0.2335	0.0650	0.0383	0.0284	0.0804	0.0360	0.0377
K_{i3}	1.7238	1.8905	1.9702	1.9321	1.5416	1.7694	1.8084	1.8357	1.9592	1.9136	1.9137	1.1109
K_{i4}	1.1233	1.3032	1.5179	1.2418	1.1446	1.4534	1.4265	1.1812	0.7498	0.6052	1.7778	1.8008
K_{p1}	1.4042	1.0641	1.3152	1.3304	1.4453	1.2911	1.3784	1.2110	1.3881	1.3259	1.0079	1.0083
K_{p2}	1.9705	1.7331	1.8356	1.9140	1.7351	1.9372	1.9095	1.8542	1.5146	1.9519	1.6303	1.7940
K_{p3}	0.6632	1.0664	1.1337	0.4161	0.9743	1.5107	1.0956	0.5633	1.9100	1.4020	0.5201	0.1282
K_{p4}	0.3241	1.3761	1.9696	1.4228	1.7597	1.4359	1.3789	0.9632	1.8514	0.9758	0.8071	1.2262
K_{d1}	0.6419	0.5652	0.6209	0.6304	0.6804	0.6452	0.5967	0.6000	0.8585	0.7371	0.4853	0.4089
K_{d2}	0.5659	0.9622	0.4529	0.3912	0.1725	0.6677	0.5939	0.9261	0.8684	0.8495	0.8973	1.3624
K_{d3}	0.7710	0.6192	0.8951	0.9329	0.8382	0.7495	0.9699	0.4146	0.9441	0.9212	0.6689	0.2542
K_{d4}	1.1993	1.3377	0.6808	1.6145	1.3585	0.6052	1.0045	0.9767	1.2536	1.4995	1.3408	1.7280

Table 11
Optimum values of GWO based PID-controller under varied conditions (T_1, T_2 and T_R).

Controller parameters	T_1				T_2				T_R			
	+50%	+25%	−25%	−50%	+50%	+25%	−25%	−50%	+50%	+25%	−25%	−50%
K_{i1}	1.7600	1.9451	1.9406	1.8815	1.8467	1.9508	1.9510	1.9006	1.9593	1.9356	1.8757	1.9220
K_{i2}	0.0240	0.0831	0.0971	0.1189	0.1773	0.0603	0.0437	0.0557	0.0367	0.1991	0.0189	0.0576
K_{i3}	1.8261	1.9153	1.8512	1.6565	1.7950	1.4881	1.9505	1.9289	1.5970	1.8119	1.9161	1.9296
K_{i4}	1.6466	0.8806	1.0662	1.5096	1.9280	1.9414	1.7395	1.2148	1.6009	1.5581	0.7184	1.4295
K_{p1}	1.1614	1.3102	1.4926	1.4540	1.3218	1.5994	1.2925	1.3730	1.3641	1.6570	1.2282	1.4120
K_{p2}	1.7455	1.9610	1.9366	1.8580	1.8049	1.8573	1.9546	1.7402	1.7213	1.8805	1.0068	1.8560
K_{p3}	0.9011	0.6948	0.6050	1.0375	0.8936	0.9518	1.0610	1.0286	0.9016	0.6624	1.2755	0.5330
K_{p4}	0.7042	1.1357	0.9239	0.9080	1.5193	0.6465	1.0350	1.7614	1.6647	0.9079	1.5046	0.0344
K_{d1}	0.5289	0.5550	0.8010	0.7856	0.5730	0.5941	0.6145	0.6331	0.6915	0.8025	0.5443	0.5479
K_{d2}	0.6535	0.3155	0.6876	0.7075	0.6838	0.2808	0.4198	0.1769	0.5699	0.3774	0.4195	0.1429
K_{d3}	0.7702	0.7400	0.7344	0.9073	1.3458	0.7602	0.5793	0.9336	0.7838	0.8717	0.6766	0.6087
K_{d4}	0.9663	1.3680	0.5058	1.2165	0.9066	0.3485	0.7573	0.5902	0.8597	0.9355	0.0066	0.9858

Table 12
ITAE value and settling time of transient responses under variation of loading condition and system parameter.

Parameter	% of change	Proposed GWO based PID controller				hFA–PS based PID controller [2]			
		ITAE value	Settling time in seconds (2% error band)			ITAE Value	Settling time in seconds (2% error band)		
			Δf_1	Δf_2	ΔP_{tie}		Δf_1	Δf_2	ΔP_{tie}
Nominal	No changes	0.0139	1.71	5.17	4.38	3.1077	48.44	44.44	35.68
Loading condition	+50%	0.0201	1.71	5.33	4.51	3.1718	48.36	44.79	35.73
	+25%	0.0163	2.36	4.53	4.02	3.1098	48.41	44.43	35.69
	−25%	0.0108	1.58	5.10	4.42	3.0536	48.36	44.23	35.62
	−50%	0.0078	1.67	5.29	4.44	3.0479	48.39	44.20	35.65
T_H	+50%	0.0154	2.21	4.99	4.29	3.6068	53.65	54.57	38.40
	+25%	0.0177	1.65	4.75	4.25	3.3034	48.42	49.25	35.75
	−25%	0.0135	1.51	5.37	4.62	2.7961	48.24	39.97	32.89
	−50%	0.0129	2.54	4.80	4.23	2.6265	47.98	39.85	30.19
T_t	+50%	0.0131	2.33	4.34	3.99	5.4230	45.22	66.01	44.41
	+25%	0.0148	1.75	4.95	4.43	3.9785	53.84	55.00	38.64
	−25%	0.0138	1.54	5.00	4.32	2.7684	48.27	40.07	32.92
	−50%	0.0128	1.84	5.05	4.32	2.2550	47.57	39.57	32.79
T_1	+50%	0.0143	1.98	5.00	4.38	3.1071	56.55	52.27	34.22
	+25%	0.0136	1.48	4.91	4.25	3.1044	52.59	53.27	35.04
	−25%	0.0139	1.85	5.37	4.51	3.7196	43.74	50.89	31.61
	−50%	0.0139	1.17	5.75	4.86	5.7071	44.91	48.72	31.06
T_2	+50%	0.0170	1.16	5.47	4.56	3.1916	53.68	45.40	35.74
	+25%	0.0133	1.98	5.67	4.81	3.2640	53.24	44.80	35.62
	−25%	0.0127	2.42	4.77	4.27	3.4983	48.42	49.75	38.43
	−50%	0.0135	1.94	5.10	4.48	4.4884	53.57	55.12	43.71
T_R	+50%	0.0128	1.55	5.34	4.51	3.4059	60.14	51.09	38.04
	+25%	0.0166	1.82	5.63	4.73	3.1091	51.63	47.26	36.56
	−25%	0.0135	1.74	4.68	4.18	5.2457	42.70	49.28	41.55
	−50%	0.0133	1.80	4.86	4.22	16.0689	103.24	103.24	92.64

The essential function of LFC is to minimize the area control error (ACE) and its demanded value to zero as fast as possible. In an optimal control system, the selection of objective function is done either by (i) taking few points of the time response, or (ii) by taking the entire time response, i.e. integral criterion. The integral criterion is the most commonly used performance index in optimal control theory. The commonly used performance indices based on integral criterions are: integral square error (ISE), integral absolute error (IAE), integral time multiplies of square error (ITSE) and ITAE. For any of the possible aforesaid performance indices, best response corresponds to the minimum value of selected objective function and better system specifications like rise time, settling time, overshoot, undershoot, etc.

ISE is a measure of system performances formed by integrating the square error over fixed interval of time. ISE will penalize large errors more than small errors. It exhibits smaller overshoot but albeit large settling time.

IAE is error taken absolute and added over time. It is often used where the digital simulation of a system is being employed; however it is irrelevant to real-time analytical work, because the determination of the absolute value of the error in analytic form is somewhat difficult. It produces slow system response.

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ITAE and ITSE have an additional time multiplier of the error function, which emphasis long duration errors and gives faster time response compare to ISE and IAE. ITAE, what is done is to weight errors which exist after a long time much more heavily than those at the start of the response, resulting faster setting time of system oscillations. ITAE criterion also provides minimum peak overshoot. On the other hand, ITSE criterion based controller offers large controller output for a sudden change in reference value, which is not wanted from the controller design point of view.

It is reported in [2,3,20] that ITAE based objective function remarkably improved system performance compared to aforesaid indices and therefore, it is used as an objective function for optimal design of proposed PI/PID controller. The fitness function or objective function (J) is depicted in (13).

$$J = \int_{t=0}^{t_{final}} t(|\Delta f_1| + |\Delta f_2| + |\Delta P_{tie}|)dt \quad (13)$$

In this context, LFC may be viewed as constrained optimization problem and its constraints are bounded by the controller parameters.

The design problem is formulated as follows:

Minimize J

Subjected to:

$$\left.\begin{array}{l} K_{p,min} \le K_p \le K_{p,max} \\ K_{i,min} \le K_i \le K_{i,max} \end{array}\right\} \text{for PI} - \text{controller} \quad (14)$$

$$\left.\begin{array}{l} K_{p,\ min} \le K_p \le K_{p,\ max} \\ K_{i,\ min} \le K_i \le K_{i,\ max} \\ K_{d,\ min} \le K_d \le K_{d,\ max} \end{array}\right\} \text{for PID} - \text{controller} \quad (15)$$

where, $K_{PID,min}$, $K_{PID,max}$ are the minimum and maximum gains of PI/PID controller parameters, respectively.

5. Implementation of GWO in LFC problem

In this paper, GWO algorithm is implemented to solve LFC problem in multi-area power system network. The algorithmic steps of the proposed method in enumerated as below.

Step 1. Initialize input parameters of GWO algorithm such as *sea rchagents_no* (population size), number of control variables (dimension of the problem) according to the controller structure, upper and lower bounds of the search space, number of elitism parameters and total number of generations.

Step 2. In the initialization process, search agents or gray wolves (i.e., controller parameters such as K_P, K_I, K_D) are randomly generated between upper and lower bounds in the search space.

Step 3. Evaluate the fitness function using (13) and assign alpha, beta, delta wolves in the search space.

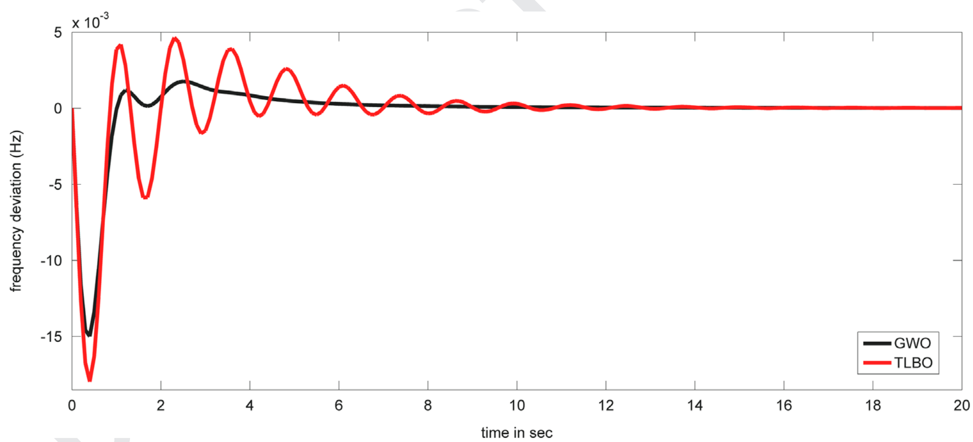

Fig. 14. Changes of frequency with 1% SLP in area-1 for test system-3 considering AC tie-line only.

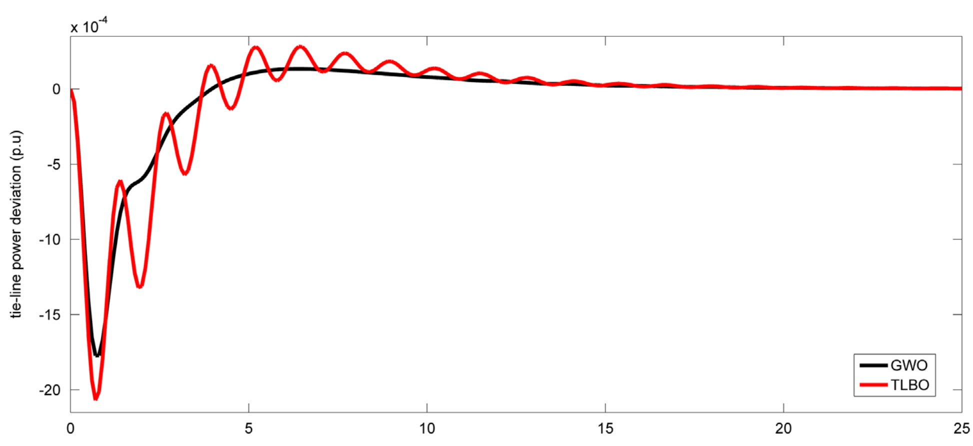

Fig. 15. Changes of tie-line power with 1% SLP in area-1 for test system-3 considering AC tie-line only.

Step 4. Update the positions of alpha, beta and delta using the following pseudo code.

$for\ i = 1 : searchagents\_no$

$\quad if\ \ fitness < alpha$

$\quad\quad alpha \xleftarrow{update} fitness$

$\quad end$

$\quad if\ \ fitness > alpha\ \&\&\ fitness < beta$

$\quad\quad beta \xleftarrow{update} fitness$

$\quad end$

$\quad if\ \ fitness > alpha\ \&\&\ fitness > beta\ \&\&\ fitness < delta$

$\quad\quad delta \xleftarrow{update} fitness$

$\quad end$

end

Step 5. Defining two random numbers r_1, r_2 between [0, 1] and $\vec{a}$ linearly decreasing from 2 to 0.

Step 6. Update the positions of search agents including omega using (5) and (6). Finally, modify the control variables (K_P, K_I, K_D) for the each search agents using (7).

Step 7. Check whether any search agent goes beyond the search space or not and infeasible solutions are replaced by the randomly generated feasible solution set.

Step 8. Sort the positions of search agents obtained in step 6 from the best value to worst value and use for next generation.

Step 9. Go to step 4 until the termination criterion is fulfilled.

6. Simulation results and discussion

To test the effectiveness and superiority of proposed algorithm, four different interconnected power system networks are considered in the present study. Transfer-function model of the test systems are developed in MATLAB/SIMULINK environment and optimization algorithm (GWO) is written in the *m file*. ITAE criterion based objective function (ACE) is minimized using GWO algorithm to find optimum gains of controller parameters. Simulations were conducted on an Intel core (TM) i3 processor 2.4 GHz and 2 GB memory computer in the MATLAB 7.8.0 (R2009a) environment. The dynamic performances of test systems are investigated with 1% SLP in area-1. For successful implementation of GWO algorithm, 40 population size and maximum 100 iterations are taken for the present study.

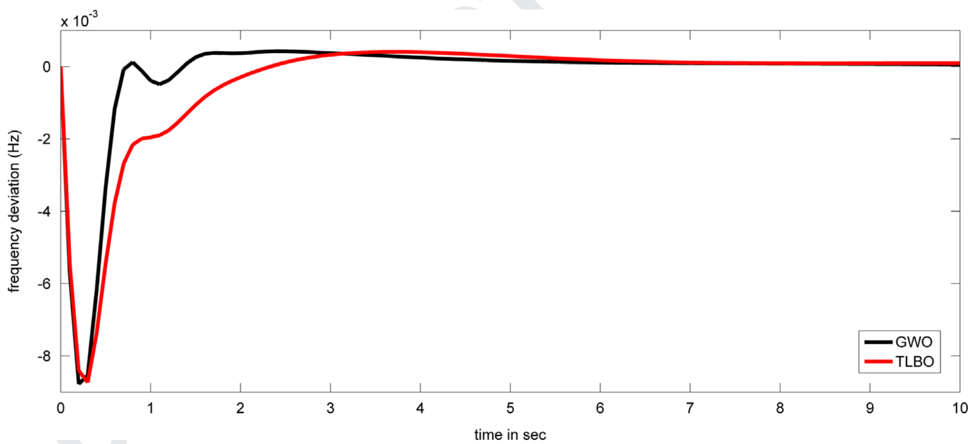

Fig. 16. Changes of frequency with 1% SLP in area-1 for test system-3 considering AC–DC tie-line.

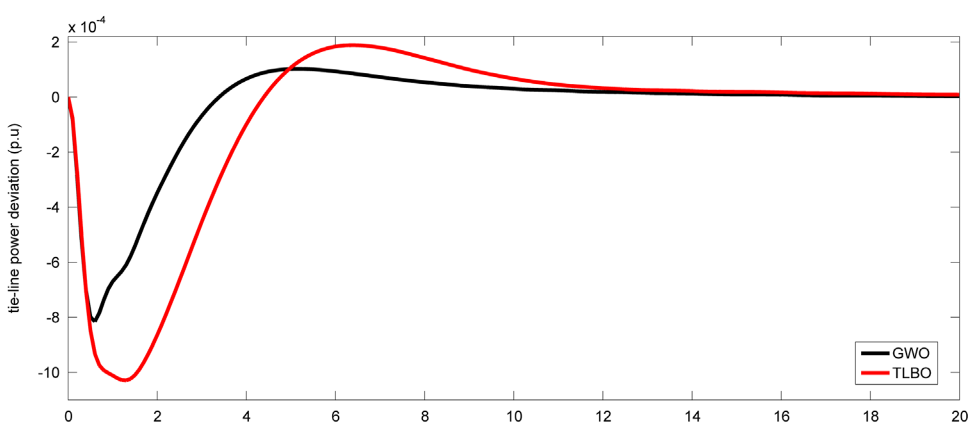

Fig. 17. Changes of tie-line power with 1% SLP in area-1 for test system-3 considering AC–DC tie-line.

6.1. Case study 1 – transient analysis of test system-1

6.1.1. Linear model

At the first instant of study, GWO tuned PI-controller is incorporated to the linearized model of test system-1 as shown in Fig. 1. The nominal values of system parameters are taken from [2,3] and listed in Table 1. The optimum gains of PI-controller using GWO algorithm are provided in Table 2. The performance of proposed GWO technique is compared with other recently published conventional and meta-heuristic techniques such as: CLPSO, EPSDE, PSO tuned fuzzy PI controller [3], PS tuned fuzzy PI controller [3], hPSO–PS tuned fuzzy PI controller [3], DE tuned PI controller [20], BFOA tuned PI controller [20], GA tuned PI controller [20], ZN tuned PI controller [20], hBFOA–PSO tuned PI controller [26], PSO tuned PI controller [26] for the identical power system with similar fitness function and the comparative performances are tabulated in Table 3. It is clearly noted from Table 3 that minimum ITAE value is obtained with GWO technique (ITAE=**0.1388**) compared to CLPSO (ITAE=0.1949), EPSDE (ITAE=0.1539), hPSO–PS based fuzzy PI-controller (ITAE=0.1438), PSO based fuzzy PI-controller (ITAE=0.4470), PS based fuzzy PI-controller (ITAE=0.6334), DE (ITAE=0.9911), BFOA (ITAE=1.7975), GA (ITAE=2.7475), ZN (ITAE=3.7568), hBFOA–PSO (ITAE=1.1865), PSO (ITAE=1.2142). The ITAE value with GWO algorithm is improved by 9.81% (EPSDE), 28.8% (CLPSO), 3.48% (hPSO–PS tuned fuzzy), 69.94% (PSO tuned fuzzy), 78.08% (PS tuned fuzzy), 85.9% (DE), 92.77% (BFOA), 94.9% (GA), 96.3% (ZN), 88.3% (hBFOA–PSO), and 88.56% (PSO). Hence, it can be concluded from the aforesaid discussion that GWO algorithm gives minimum fitness value compared to EPSDE, CLPSO and other optimization algorithms as shown in Table 3.

The dynamic performance of test system-1 is evaluated with 10% SLP in area-1 and the output responses are presented in Figs. 3 and 4. To investigate the superiority of proposed algorithm, the simulation results are compared with BFOA [20], DE [20], hBFOA–PSO [26] optimized PI-controller for the similar test system are also shown in Figs. 3 and 4. The settling time of frequency and tie-line power oscillations with the proposed GWO and other optimization techniques are listed in Table 3. It is clearly noted from Figs. 3 and 4 and Table 3 that proposed GWO algorithm gives better transient performances compared to other optimization approaches reported in the literature.

For further improvement of dynamic responses, PID-controller is introduced in LFC loop and its gains are optimally determined by the proposed GWO method. At the end of the optimization, optimal controller settings are noted down and shown in Table 2. Critical observation of Table 3 reveals that minimum fitness value is obtained with GWO based PID controller (ITAE=**0.1340**) compared to CLPSO based PID controller (ITAE=0.1569), EPSDE based PID controller (ITAE=0.1497) and improvement of fitness value with GWO is 14.6% (CLPSO), 10.5% (EPSDE). The convergence characteristics of GWO algorithm with PI and PID controller structure are shown in Figs. 5 and 6, respectively. For the better comparison, the convergence characteristics of CLPSO and EPSDE

Table 13
Optimum values of controller parameters and performance index with GWO optimized PI/PID controller for test system-4 after 1% SLP in area-1.

Evolutionary algorithm (EA)	Controller gains									ITAE value	Minimum damping ration
	K_{i1}	K_{i2}	K_{i3}	K_{p1}	K_{p2}	K_{p3}	K_{d1}	K_{d2}	K_{d3}		
hGSA–PS [37]	−0.2950	−1.6073	−0.7871	0.1535	0.9489	−1.2751	–	–	–	4.6435	0.0028
Proposed GWO	0.2961	0.0434	0.3325	0.0020	0.0747	0.1622	–	–	–	2.6168	0.0219
hGSA–PS [37]	−0.6539	−1.2491	−0.7123	0.1297	0.8660	−1.2828	0.3846	0.1943	1.8050	0.6508	0.1563
Proposed GWO	1.9851	1.9507	1.9895	1.9635	1.9072	1.9859	0.9432	1.7668	1.2111	0.1083	0.1083

Settling time of system frequencies and tie-line power oscillations

EA's	Δf_1	Δf_2	Δf_3	ΔP_{12}	ΔP_{23}	ΔP_{13}	EA's	Δf_1	Δf_2	Δf_3	ΔP_{12}	ΔP_{23}	ΔP_{13}
hGSA–PS: PI [37]	14.66	13.65	13.67	14.14	11.23	12.09	hGSA–PS: PID [37]	8.26	8.16	9.37	11.84	7.47	9.40
GWO: PI [Proposed]	12.04	13.62	8.10	14.10	10.93	11.32	GWO: PID	6.26	6.78	4.70	10.59	5.74	6.70
% of improvement	18.14	0.219	40.75	0.283	2.74	6.37	% of improvement	24.21	16.91	49.83	10.55	23.16	28.72

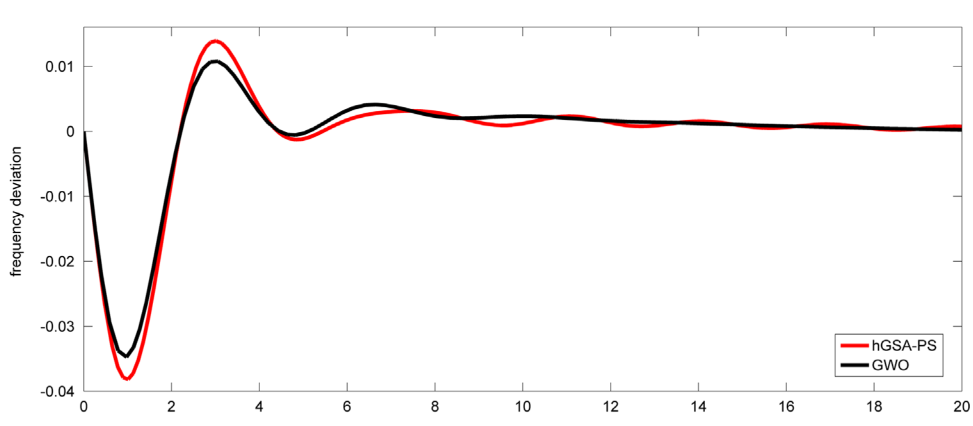

Fig. 18. Changes of frequency with PI-controller after 1% SLP in area-1 for test system-4.

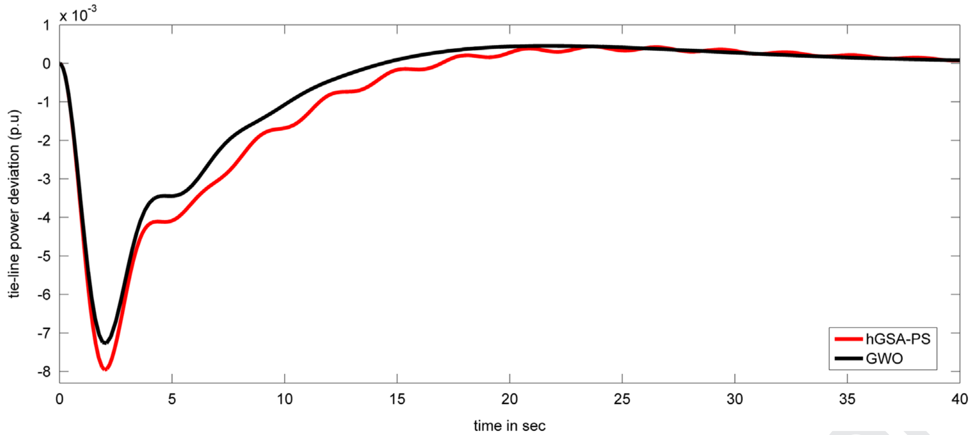

Fig. 19. Changes of tie-line power with PI-controller after 1% SLP in area-1 for test system-4.

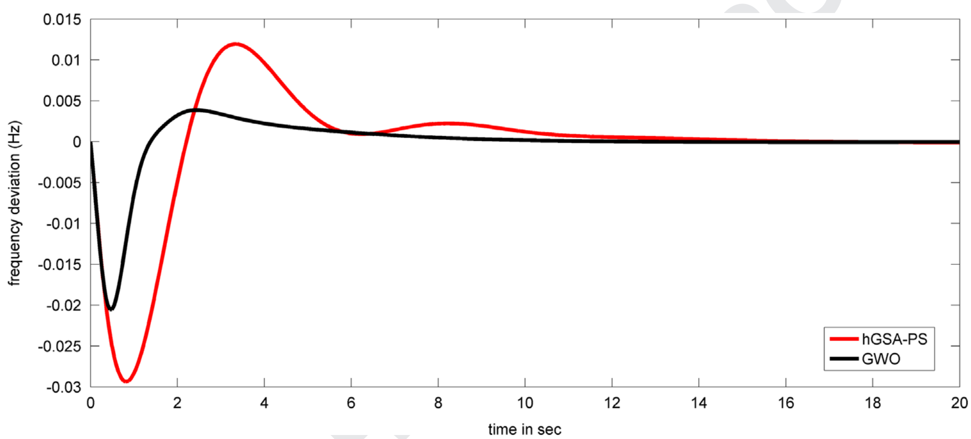

Fig. 20. Changes of frequency with PID-controller after 1% SLP in area-1 for test system-4.

are also given in Figs. 5 and 6 for the similar controller structure. Critical observation of Figs. 5 and 6 reveals that GWO algorithm yields greater convergence performance in terms of fitness value, the rate of convergence and computational efficiency. Settling times of Δf_1, Δf_2 and ΔP_{tie}oscillations are noted down from the output responses and given in Table 3. Percentage of improvement of settling time with GWO optimized PID controller is 37.6% (Δf_1), 2.46% (Δf_2) and 1.76% (ΔP_{tie}), respectively, compared to GWO based PI-controller. It is clearly observed from the simulation results, Table 2 and Figs. 5 and 6, that dynamic stability of concerned power system is improved remarkably with GWO-tuned PID-controller. Hence, in the succeeding sections, the study is carried out with GWO based PID-controller.

6.1.2. *Non-linear model with GRC*

In order to establish the superiority of proposed GWO algorithm, the study is extended to a nonlinear system considering the appropriate value of GRC of the steam turbine. GRC imposes a practical constraint on response speed of the turbine. In actual practice, power generation can only be changed at a specified rate and therefore, it is realistic to consider a limiter in the form of GRC with the steam turbine. If it is not taken into consideration, then generators will experience a large momentary oscillation which may cause instability to the power system. Two GRC values of $\pm$ 0.025 p.u. and $\pm$0.05 p.u.[2] are considered for the present study and dynamic behavior of the test system is investigated with 5% SLP in area-1. The optimum settings of PID-controller with GRC ($\pm$0.025, $\pm$0.05) are listed in Table 4. The performance of proposed GWO algorithm is compared with some recently published [2] meta-heuristic optimization techniques such as hFA–PS, FA, BFOA, GA, ZN and comparative results are shown in Table 5. It is clearly viewed from Table 5 that with identical controller structure, objective function (ITAE) and same GRC value ($\pm$0.05), a minimum ITAE value is obtained with GWO algorithm (ITAE=0.1308) compared to hFA–PS (ITAE=0.2782), FA (ITAE=0.3240), BFOA (ITAE=0.4788), GA (ITAE=0.5513) and ZN (ITAE=0.6040). Improvement of objective function with GWO is 52.9% (hFA–PS), 59.6% (FA), 72.7% (BFOA), 76.3% (GA) and 78.3% (ZN) compared to other optimization techniques listed in Table 5. The dynamics of the nonlinear test system with $\pm$0.05 GRC after 5% SLP are shown in Figs. 7 and 8. The settling times of Δf_1, Δf_2 and ΔP_{tie} with proposed GWO algorithm is noted down from Figs. 7 and 8 and compared with hFA–PS, FA, BFOA, GA, ZN, which is shown in Table 5. It is concluded from Table 5 and Figs. 7 and 8 that proposed GWO outperform other optimization techniques reported before.

A similar study is performed with $\pm$0.025 value of GRC and optimum settings of PID controller, ITAE value and settling time of Δf_1, Δf_2, ΔP_{tie} are reported in Tables 4 and 5. Changes in frequency and tie-line power after 5% SLP in area-1 are displayed in Figs. 9 and 10. It is further observed from Tables 4 and 5 and Figs. 9 and 10 that with the lower value of GRC, GWO technique gives superior performance than that obtained with hFA–PS, FA, BFOA, GA, and ZN.

6.1.3. *Sensitivity analysis of test system-1*

Sensitivity analysis is performed to exhibit the robustness of proposed GWO based PID controller for variations of loading

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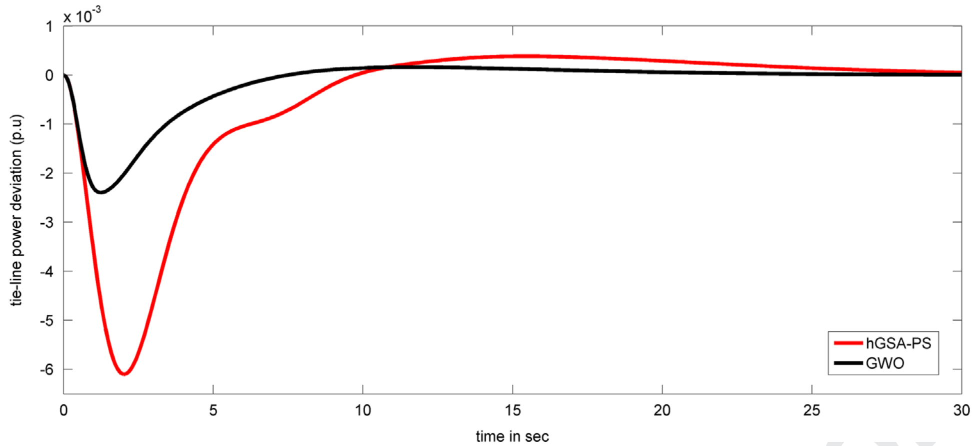

Fig. 21. Changes of tie-line power with PID-controller after 1% SLP in area-1 for test system-4.

conditions and system parameters in the range of $\pm 50\%$ in step of 25% taking one at a time. The PID-controller employed in both areas are optimized simultaneously by using GWO algorithm and optimum values of controller gains, minimum ITAE values, overshoots and settling times of frequency, tie-line power deviations under different loading conditions are depicted in Table 6. It is clearly observed from Table 6 that system performances are barely changed when loading condition is varied between $\pm 50\%$ from their nominal settings, especially the setting time of frequency and tie-line power oscillations.

Additionally, to show the ability and efficacy of designed PID-controller, system parameters are also varying in the range of $\pm 50\%$ from their nominal settings. The changed parameters are the time constant of speed governor(T_g), time constant of steam turbine (T_t) and synchronizing time constant of tie-line (T_{12}). Minimum fitness value, setting time of frequency and tie-line power oscillations under these uncertainty conditions are presented in Table 7. An extensive comparative analysis is made with the results obtained by GWO algorithm and those of hPSO–PS based fuzzy controller [3], DE [3] for the identical test system and same rages of parameter variations as shown in Table 7. The analysis reveals that proposed GWO tuned PID controller gives superior performances as compared to hPSO–PS based controller, DE-based controller. Hence, it can be concluded from the aforesaid discussion that GWO-based PID controller performs satisfactorily under uncertainty conditions and is also quite robust.

6.2. Case study 2 – transient analysis of test system-2

To demonstrate the superiority of proposed GWO algorithm, authors have conducted another simulation. This time, multi-area multi-source hydro-thermal power system network [2,3] as shown in Fig. 11 is considered and dynamic responses are investigated. The nominal settings of system parameters are tabulated in Table 1 and 1.5% SLP in area-1 is considered to study the dynamic behavior of same. Two more objective functions based on ISE and ITSE criterion are considered in addition with (13) for better comparison of proposed algorithm. The objective functions are defined as follows:

$$ISE = J = \int_{t=0}^{t_{sim}} \left[(\Delta f_1)^2 + (\Delta f_2)^2 + (\Delta P_{tie})^2\right] dt \tag{16}$$

$$ITSE = J = \int_{t=0}^{t_{sim}} t\left[(\Delta f_1)^2 + (\Delta f_2)^2 + (\Delta P_{tie})^2\right] dt \tag{17}$$

PI/PID-controllers are simultaneously optimized using proposed GWO algorithm and at the end of the optimization, the optimum gains of designed controller are depicted in Table 8. Minimum fitness value and settling time of frequency and tie-line power deviations are shown in Table 9. The tuning ability of proposed GWO algorithm is established by comparing the results with some recently published [2] optimization techniques like hFA–PS, GA and ZN for the similar test system and same controller structure. Figs. 12 and 13 and Table 9 show the comparative analysis between proposed GWO algorithm and hFA–PS, GA, ZN methods. Critical examination of Figs. 12 and 13 and Table 9 clearly reveals that minimum objective function (both ISE and ITAE) is achieved with GWO based PI-controller compared to hFA–PS, GA and ZN tuned PI-controllers. The ISE is further minimized by 91.5% (hFA–PS), 92.49% (GA) and 93.69% (ZN) with GWO technique. Similarly, ITAE is minimized with GWO by 75.3% (hFA–PS), 90.9% (GA) and 95.8% (ZN). Improvement of settling time of Δf_1, Δf_2, and ΔP_{tie} with GWO optimized PI-controller is 56.8%, 54.3% and 49.8%, respectively, as compared to hFA–PS tuned PI-controller. Having knowledge of the aforementioned discussion, it is concluded that proposed GWO algorithm exhibits better performance than that of classical and modern optimization techniques reported in Table 9.

GWO tuned PID-controller is added to the existing test system for further improvement of system dynamics. Optimum settings of PID-controller, fitness values and settling times of Δf_1,Δf_2, and ΔP_{tie} are given in Tables 8 and 9. It is clearly noted from Table 8 that fitness value with GWO optimized PID-controller is reduced by 84% as compared to hFA–PS based PID-controller. Transient responses of the concerned power system with proposed controller is shown in Figs. 12 and 13. System performance index, i.e. settling time of Δf_1, Δf_2,and ΔP_{tie} are noted down from Figs. 12 and 13 and presented in Table 9. The settling time of frequency and tie-line power oscillations is improved by 48%, 2.69% and 13.3%, respectively, with GWO based PID-controller compared to hFA–PS tuned PID-controller.

Additionally, sensitivity analysis is performed to evaluate the effectiveness and robustness of designed controller for wide variations of loading conditions and system parameters in the range of $\pm 50\%$ of nominal setting. The changed parameters are time constants of speed governor (T_g), steam turbine (T_t), hydro-governor (T_1), hydraulic amplifier (T_2), reset time of hydraulic amplifier (T_R) and in all cases ITAE based objective function is employed to tune the controller gains. The tuned parameters under normal and varied conditions are given in Tables 10 and 11. To illustrate the superiority of designed controller, ITAE value, settling times of Δf_1, Δf_2, and ΔP_{tie} are compared with the results obtained by hFA–PS based PID-controller [2] and depicted in Table 12. The transient analysis reveals that proposed GWO based PID-controller outperforms hFA–PS based PID-controller and controller gains are robust to wide variations of system parameters and loading conditions.

6.3. Case study 3 – transient analysis of test system-3

One more complicated and realistic test system of two-area multi-units multi-sources interconnected power system network having thermal, hydro and gas power plants is considered for further verification of the effectiveness of the proposed GWO algorithm. The transfer-function model of test system-3 is available in [6] and nominal values of system parameters are tabulated in Table 1. GWO algorithm is applied to tune the settings of PID-controller without and with DC link between two controlled areas. 1% SLP in area-1 is considered for the present study. To illustrate the superiority of designed controllers, changes of frequency and tie-line power obtained using GWO tuned PID-controller are compared with TLBO based PID-controller [6] and are shown in Figs. 14–17. It is clearly evident from Figs. 14–17 that proposed GWO based PID-controller gives better system dynamics than TLBO based PID-controller.

6.4. Case study 4 – transient analysis of test system-4

To demonstrate the ability of proposed GWO algorithm in LFC area, the study is further extended to complicated, nonlinear and realistic power system unit which is widely available in the literature [39,40]. The investigation has been made on three-unequal-area all thermal power plant of area-1: 2000 MW, area-2: 4000 MW and area-3: 8000 MW. Classical PI/PID controllers are used as a secondary controller for the concerned test system and its gains are optimally selected by applying proposed GWO algorithm employing ITAE based fitness function. The time delay is one of the most important physical constraints encountered in the power system. With the rapid progression of the power system network, growing of physical setup, functionality and complexity of the system, the time delay is now become a major issue in LFC system design and synthesis. However, to get an accurate insight of the system dynamics, it has to be considered during the study. The time delay in transmission system can be expressed by the following transcendental equation:

$$G_{TD}(s) = e^{-sT} = \frac{1 - sT/2 + s^2T^2/12}{1 + sT/2 + s^2T^2/12} \quad (18)$$

The linear transfer function form of time delay nonlinearity, as defined in (18), is obtained using 2nd order Pade approximation method and T in (18) is the amount of time delay given to the output response, whose value is set to 50 ms for present study [39]. Generation rate constraint (GRC) of steam turbine and governor dead band (GDB) nonlinearities are also included in the system modeling for better assessment of the concerned power system unit. The nonlinear model of three-unequal-area all thermal power system is available in [39] and nominal values of system parameters are specified in Table 1. 1% step load perturbation (SLP) is applied to area-1 for examining the dynamic behavior of the test system and to establish the superiority of GWO algorithm, output results are compared with hybrid gravitational search algorithm (hGSA)–pattern search (PS) optimized PI/PID controller. Optimal controller parameters, minimum ITAE value with proposed GWO algorithm are listed in Table 13. It is clearly evident from Table 13 that minimum ITAE value is obtained with GWO-tuned PID controller (ITAE = 0.1083) compare to hGSA–PS (ITAE = 0.1563) and percentage of improvement is 30.71%. Similarly, the percentage of improvement of ITAE value with GWO based PI-controller is 46.3% than hGSA–PS optimized PI-controller. The change in frequency and change in tie-line power after SLP with GWO-optimized PI/PID controllers are displayed in Figs. 18–21 (only four figures are shown). For the better comparison between GWO and hGSA–PS algorithms, the output results are displayed on the same figures. The system performance, i.e. setting time of frequency and tie-line power oscillations are noted down from Figs. 18 to 21 and presented in Table 13. Critical observation of Table 13 and Figs. 18–21 reveals that proposed GWO optimized PID controller gives better system response in terms of minimum settling time, minimum fitness value than that obtained with hGSA–PS algorithm. Hence, it may be concluded from the aforesaid discussion that proposed GWO outperforms hGSA–PS algorithm.

7. Conclusion

This article presents design and implementation of a new evolutionary algorithm namely GWO for the first time to find an effective and optimal solution of LFC problem in the power system. An extensively used two-area non-reheat thermal power system without and with GRC of the steam turbine is considered at the first instant and PI/PID controller parameters are optimized employing GWO, CLPSO and EPSDE algorithms using ITAE based objective function. To show the superiority of the proposed GWO algorithm, simulation results are compared with those of some classical and meta-heuristic optimization techniques like CLPSO, EPSDE, hFA–PS, FA, hPSO–PS, PSO, DE, hBFOA–PSO, GA, ZN, etc. for the similar test system and significant improvement is observed with GWO optimized PID controller. Sensitivity analysis is performed to illustrate the robustness of designed controller by varying the system parameters and operating loading conditions. Time domain simulation yields that proposed controller is quite robust and gives satisfactory performance under uncertainty conditions. Additionally, three realistic test systems, viz. two-area multi-units hydro-thermal system, two-area multi-units multi-sources thermal–hydro-gas system and three-unequal-area all thermal power plant, are investigated for validations of the effectiveness of proposed GWO algorithm in LFC area. To make the study realistic, different power system nonlinearities like GRC, GDB, and time delay of the transmission system are included in the system. Simulation results exhibit that proposed GWO tuned PID-controller can effectively handle the aforesaid nonlinearities and improved system performance remarkably.

Some advanced control algorithm may be applied to the proposed area in LFC system to improve the system dynamics under the disturbed condition in future. In the present analysis, authors have considered single load perturbation, i.e. 1% of nominal value at $t = 0$ s to identify the effectiveness and robustness of designed controller. But, in actual practice power system is always experiences random load variation with different magnitude during the whole day. So, in future we will consider such type of load pattern to revise the dynamics of given power systems. Additionally, we will include different power system stabilizers in coordination with LFC for further advancement of system stability. This research work can further be extended by considering the contingency analysis.

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