



Optimization of Automatic Generation Control and Economic Load Dispatch for Two Area Six Unit Interconnected Power System

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HIGHLIGHTS

- Coordination of automatic generation control and economic dispatch lowers running cost.
- Power systems interconnecting is more economic than systems individual operation.
- Novel optimization algorithms are more accurate in tuning the gains of the controllers.
- Without automatic generation control, steady state frequency deviation is not zero.

ABSTRACT

This paper proposes an integrated Economic Load Dispatch (ELD) and Automatic Generation Control (AGC) for interconnected power systems. Based on their participation factor determined from the economic load dispatch calculation, each unit shares the total change in the same control region. In this study, two control areas are considered. Three thermal units are located in each control area. An integral controller (I) is only used for the AGC mechanism's secondary controller and is used for the primary controller for the ELD mechanism. An Improved Grey Wolf Optimizer (IGWO) technique is used to evaluate the optimum parameters of the integral controllers for primary and secondary controllers. An integral time square error (ITSE) has been used as the objective function to tune the suitability of the proposed controller gains. The simulation results demonstrate that the integrated AGC with ELD has the superiority in reducing the overshoot and fast steady state compared with AGC only.

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1. Introduction

The main aim of automatic generation control in interconnected power systems is to maintain zero frequency deviation and balance the generated power with load demand [1]. Since the load demand changes continuously, the operating point of the power system changes, causing the system imposed to deviations in normal frequency and scheduled tie-line power that flows to other areas, which may result in abnormal situations [2]. In traditional automatic generation control (AGC), the frequency and power exchange deviations are combined into a single variable called area control error (ACE), which is used as an input to the conventional controller. The power system's primary goal is to maintain enough generation to satisfy the load at the lowest possible cost. This target must be accomplished to maintain the system frequency under reasonable limits. The control area of the power system is made up of massive integrated generation power units. Uninterruptible electricity supply reduces maintenance costs, and all economic facets of the power grid are important in the power sector. The stable and cost-effective operation of the integrated power grid is dependent on multiple layers of the automatic generation control system, which ensures that generator production corresponds to changes in electrical load demand. The power system's control strategy's primary objective is to eliminate power generation and demand mismatches while keeping the system's frequency within the normal prescribed range. In addition to the (frequency) speed error signal, the speed governor system in each unit changes the prime-mover's mechanical feedback to keep the generation unit speed constant [3]. Automatic generation control is primarily concerned with responses to error signals, which are directly or indirectly affected by the system's governor and turbine dynamics. The governor setpoint of each unit determines who is in charge of the system's primary frequency control. The economic load dispatch feature's key purpose is to reduce the cost role of the overall load demand by changing the unit's participation factor. Load frequency control allows changing the output generation at any time. On the other hand, the

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economic load dispatch would alter the participation factors every few minutes to reduce the system's total generation expense. Many real-world optimization problems have numerous challenges, including high computation costs, nonlinear constraints, dynamic/sharp cost functions, and a large solving area [4]. Despite the fact that perfect algorithms can precisely supply the universal optimum, the time to achieve it grows exponentially in proportion to the number of variables [5].

Algorithms that are metaheuristic or heuristic are known to be among the practical sections of convergent algorithms that can solve complicated problems [6]. One method to classify metaheuristic algorithms is differentiating between their origin, which may be divided into nature-inspired and non-nature-inspired algorithms. Non-nature inspired algorithms are few, like the tabu search [7, 8], adaptive dimensional search [9], and iterated local search [10]. The solver of the problem which is most important is mother nature. In addition, it is a fundamental inspiring source for developing effective algorithms that are nature-inspired and have extended use in solving optimization problems [11]. Nature-inspired algorithms may be evolutionary, swarm intelligence, and physics-based algorithms. The most well-known evolutionary algorithms are genetic algorithm (GA) [12], genetic programming (GP) [13], and differential evolution (DE) [14]. Some popular Physics-based algorithms are big bang-big crunch [15], gravitational search algorithm [16], charged system search [17], ray optimization [18], black hole [19], atom search optimization [20], and henry gas solubility optimization [21]. Swarm intelligence algorithms inspiration is the social creature's collective manner as animal herding, bird group, and ants' searching for food. The most well-known algorithms in this class are particle swarm intelligence (PSO) [22], artificial bee colony [23], krill herd [24], grey wolf optimizer [25], whale optimization algorithm [26], crow search algorithm [27], and harris hawks optimization [28]. The mentioned algorithms have an extending use in solving discrete or continuous problems of optimization [29- 32]. For instance, In 2016, Salim and Afaneen proposed a Fuzzy Logic-based algorithm for the AGC of the Iraqi super grid network power system controller to improve the efficiency of the traditional controller in both usual and abnormal conditions. They got an improved dynamic response [51]. In 2010, an Artificial Neural Network technique was developed by Muthana and Afaneen to alert control room operators to any outage in power system elements (Generating unit or Transmission line) [52]. In 2015, Anmar and Afaneen suggested two approaches to find the most efficient state estimation solution in power systems: Weighted Least Square (WLS) method and Particle Swarm Optimization technique (PSO). Results revealed that the PSO is more accurate and faster [53].

The grey wolf optimizer was suggested in 2014 [36]. It is a population-based swarm intelligence algorithm that mimics the behavior of wolves group hunting. Because it is easy and uses fewer control parameters, GWO is widely used to solve different optimization problems [37, 38]. Since the foundation of GWO in 2014, many alternatives of the fundamental GWO algorithm is introduced to eliminate GWO's drawbacks and offer superior performance [39]. Despite the perfect algorithms' capability to accurately offer the universal optimum, their achievement period is in proportion to the variables number and increases exponentially [5]. Inversely, the random algorithms of optimization are capable of determining optimum solving's through a reasonable period. Although a little number of algorithms have been improved in the non-nature-inspired class, many algorithms are nature-inspired. The grey wolf optimizer (GWO) [25] is an effective metaheuristic inspired by nature, which is newly suggested grounded on the mechanism of group hunting and the wolves' leadership hierarchy in nature. The GW optimizer is considered an efficient metaheuristic algorithm, and it is utilized in solving various optimization problems in many fields like engineering, medical, bioinformatics, and machining learning [40]. The contribution in this paper is the coordination between automatic generation control and economic dispatch using up to date I-GWO optimization algorithm.

The proposed method of controller tuning has been implemented in two areas interconnected power systems. For simulation studies MATLAB/SIMULINK has been used. Optimal parameters of the controller are obtained by minimizing the fitness function. Integration of the square of the area control error, which involves the deviation of frequency and power interchange, has been used to select the fitness function for the I-GWO algorithm. The rest of this study is organized as follows: description of the problem formulation, examined power system models, details of the controller design and optimizer, simulation and analysis of the results, and finally, the study's conclusion.

The paper should be organized into logical parts or sections. Any subsection is given a brief numbered heading. The contents include the introduction that should clearly define the nature of the problem, and the references should be made to previously published papers. Theoretical, experimental, results, discussions, and conclusions form the main sections of the paper. The theoretical section extends the analytical background of the article and develops a new formulation of the problem. Calculations are achieved here using the developed equations, and the modifications should be pointed out. Depending on the suggested research methods, the experimental investigation is achieved, using the testing instruments or designing and manufacturing a test rig. Materials and methods are detailed here. In the results and discussions section, the significance of the obtained results should be pointed out. The citations and the discussions of the kinds of literature should be avoided in this section. Sometimes results and discussions are combined in one section.

2. Research Method

2.1 AGC Model

As shown in Fig 1, the proposed transfer function model is a two-area interconnected thermal power system with a secondary loop controller for AGC mechanism and an ED primary loop controller for economic mechanism. Each control area has a thermal generating station with a controllable Turbine-Governor unit, a power system, and suitable controllers for AGC and ELD concerns. Equivalent transfer functions are used to model the thermal system. Equation (1) depicts the power balance of each control area of a multi-area AGC system.

$$\Delta P_g(s) = \Delta P_{ref}(s) - \frac{\Delta f(s)}{R} \quad (1)$$

Equation (2) shows the transfer mechanism of a hydraulic actuator (Governor).

$$G_H(s) = \frac{\Delta P_V(s)}{\Delta P_G(s)} = \frac{1}{1+T_g s} \quad (2)$$

Equation (3) illustrates the turbine's transfer function

$$G_T(s) = \frac{\Delta P_T(s)}{\Delta P_V(s)} = \frac{1}{1+T_T s} \quad (3)$$

Equation (4) illustrates the tie-line power as a function of frequency.

$$\Delta P_{12}(s) = \frac{2\pi T}{s} (\Delta f_1(s) - \Delta f_2(s)) \quad (4)$$

As shown in equation (5), the total error induced in each control area is estimated as the linear sum of deviations in frequency and tie-line power and is represented as area control error (ACE).

$$ACE_i = B_i \Delta f_i + \sum_{j=1}^n \Delta P_{i-j} \quad (i \neq j) \quad (5)$$

2.2 Economic Load Dispatch (ELD)

The factors that affect power generation at the lowest cost are fuel cost, transmission losses, and generators' operating efficiencies. The minimum cost does not guarantee if the most efficient generating unit is placed in a high fuel cost area. In addition, when the plant location is distant from the center of the load. The losses of transmission may be relatively greater, and consequently, the plant may become excessively uneconomical. Therefore, the problem is to find the power generation of various plants, and as a result, the total cost of operation is minimized. The cost of operation has a significant role in scheduling the economic operation of generating units. In general, the thermal plant input is measured in Btu/h, while the output measuring unit is MW [3].

Practically, the generator i fuel cost can be written as generated real power quadratic function:

$$C_i = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad (6)$$

A characteristic that draws a derivative of the fuel-cost curve against real power is important and called the curve of incremental fuel cost.

$$\frac{dC_i}{dP_i} = 2\gamma_i P_i + \beta_i \quad (7)$$

Equation (8) is to be solved for P_i

$$P_i = \frac{\lambda - \beta_i}{2\gamma_i} \quad (8)$$

The analytic solution may be found for λ , that is

$$\sum_{i=1}^{ng} \frac{\lambda - \beta_i}{2\gamma_i} = P_D \quad (9)$$

or

$$\lambda = \frac{P_D + \sum_{i=1}^{ng} \frac{\beta_i}{2\gamma_i}}{\sum_{i=1}^{ng} \frac{1}{2\gamma_i}} \quad (10)$$

2.3 Coordination of ELD and AGC Using Base Point and Participation Factor Method

This approach assumes that the problem of economic dispatch should be repeatedly solved by shifting generating units from one optimum economic value to another as the demand varies by a small reasonable amount.

We begin with a schedule that has already been established/ the base point. The scheduler then expects a load shift and investigates how often each generating unit needs to be shifted (i.e., "participate") to serve the new load at the most cost-effective operating point.

Assume that the cost versus output power equation has the first and second derivatives (F'_i and F''_i). The machine incremental cost changes from λ^0 to $\lambda^0 + \Delta\lambda$ as the unit load is shifted by a sum ΔP_i . On this single unit, a slight change in output power [1],

$$\Delta\lambda \cong F''_i \Delta P_i \quad (11)$$

This holds for each of the system's N units, implying that

$$\Delta P_1 = \Delta\lambda / F''_1 \quad (12)$$

$$\Delta P_2 = \Delta\lambda / F''_2 \quad (13)$$

$$\Delta P_N = \Delta\lambda / F''_N \quad (14)$$

The number of the individual unit changes is, of course, the overall change in generation (change in total system demand). Generation total change (= system demand total change) is the sum of changes of individual units.

Let the generators total equal demand P_D , where

$$P_D = P_{load} + P_{loss} \quad (15)$$

then

$$\Delta P_D = \Delta P_{D1} + \Delta P_{D2} + \dots + \Delta P_{DN} \quad (16)$$

Each unit participation factor is

$$\left(\frac{\Delta P_i}{\Delta P_D}\right) = \frac{(1/F_i'')}{\sum_i(1/F_i'')} \tag{17}$$

The computer accomplishment of such an economic dispatch scheme is easy. It could be achieved by providing tables of F_i'' values as a function of load levels and devising an easy scheme to look up these data and calculate the factors using the current load plus the expected rise.

A less elegant method of calculating participation factors would be repeated computing of economic dispatch at $P_D^\circ + \Delta P_D$. The participation factors are calculated by subtracting the base-point values of economic generation from the current values of economic generation and dividing the difference by ΔP_D .

If ΔP_D is the total load change in the system, then the following equations represent the generation change of each individual unit:

$$\Delta P_{Gi} = P f_i \times \Delta P_D \tag{18}$$

$$P_{ides} = P f_i \times P_{base} \tag{19}$$

$$\sum_{i=1}^n P f_i = 1 \tag{20}$$

Where “ P_{ides} is the desired output from i^{th} unit and $p f_i$, the participation factors for i^{th} unit and ΔP_{Gi} , the incremental change from the base point generation of the individual unit” [1].

Investigation of Figure 1 shows an overall control system that will try to drive ACE to 0 and drive each unit’s output to its required economic value.

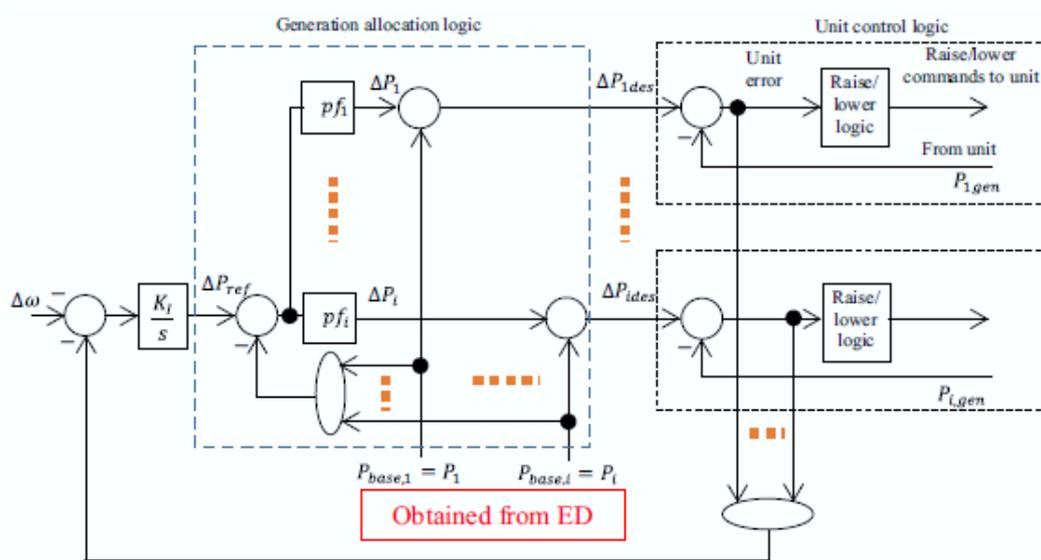


Figure 1: Coordination of AGC with ELD

3. Improved Grey Wolf Optimizer (I-GWO)

The search process in GWO is led by three wolves who are the best in each iteration, demonstrating a powerful convergence towards these three wolves. On the other hand, it is afflicted by a lack of demographic diversity, early convergence, and a disparity between exploitation and exploration [41-45]. Encircling, hunting, and attacking the prey are the stages in wolf hunting.

- Encircling: can be modeled, as in Eqs. (21) and (22).

$$D = |C * X_p(t) - X(t)| \tag{21}$$

$$X(t + 1) = X_p(t) - A * D \tag{22}$$

Where the location of the prey is X_p , X is the wolf location vector, the current iteration is t . A and C are coefficients obtained from Eqs. (23) and (24).

$$A = 2 * A * r1 - a(t) \tag{23}$$

$$C = 2 * r2 \tag{24}$$

Where $r1, r2$ are random vectors between $[0,1]$, and the vector a elements decrease linearly from 2 to 0 over the iterations course given by Eq. (25).

$$a(t) = 2 - (2 * t) / \text{MaxIter} \tag{25}$$

- Hunting: α , β , and δ are assumed to have better information about prey location. Hence, by considering them as the best three solutions, the other wolves' ω are compelled to follow them. The hunting behavior is described by Eqs. (26 - 28).

$$\left. \begin{aligned} D\alpha &= |C1 * X\alpha - X(t)| \\ D\beta &= |C2 * X\beta - X(t)| \\ D\delta &= |C3 * X\delta - X(t)| \end{aligned} \right\} \quad (26)$$

Where C_1 , C_2 , and C_3 are obtained from Eq.

$$\left. \begin{aligned} Xi1(t) &= X\alpha(t) - Ai1 * D\alpha(t), \\ Xi2(t) &= X\beta(t) - Ai2 * D\beta(t), \\ Xi3(t) &= X\delta(t) - Ai3 * D\delta(t) \end{aligned} \right\} \quad (27)$$

Where at iteration t , X_α , X_β , and X_δ are best three solutions obtained firstly, A_1 , A_2 , and A_3 are obtained from Eq. (21), and D_α , D_β , and D_δ are calculated from Eq. (26).

$$X(t + 1) = \frac{Xi1 + Xi2 + Xi3}{3} \quad (28)$$

- Attacking: when the prey stops moving, the hunting process is finished, and wolves begin an attack. As illustrated in Eq. (25), in every iteration, it is updated to change from 2 to 0.

An improvement called improved grey wolf optimizer (I-GWO) is suggested to address GWO's drawbacks. By introducing a new scanning technique known as dimension learning-based hunting, the I-GWO improves the hunting quest strategy. The aforementioned technique is learned through individual wolf hunting actions, and it expands the global search range through multi-neighbor learning. After that, I-GWO brings together candidate wolves in each iteration, resulting from both GWO and DLH strategies to relocate X_i wolf from its current location to a better location. In addition, I-GWO employs an additional selecting and updating step to pick the wolf candidate to win in each iteration and update the current position for the next iteration. The three phases of I-GWO are: initializing, moving, and selecting, and updating. Initializing: during this stage, N wolves are distributed randomly in the range $[li, uj]$ given by Eq. (29).

$$Xij = lj + randj [0, 1] * (Uj - lj), \quad i \in [1, N], j \in [1, D] \quad (29)$$

The i -th wolf location in the t -th iteration is a vector of real values $X_i(t) = \{x_{i1}, x_{i2}, \dots, x_{iD}\}$, where D is the problem dimension number. The wolves' population is stored in a matrix Pop , that has N rows and D columns. The $X_i(t)$ fitness value is obtained from the fitness function, $f(X_i(t))$.

Movement phase: hunting individually is another grey wolves' social manner, motivating to enhance the GWO. The candidate no.1 for the following location of wolf $X_i(t)$ called X_i -GWO ($t+1$) is obtained from Eq. (28).

(DLH) search strategy: besides X_i -GWO ($t+1$), this strategy produces different candidates for the following position of wolf $X_i(t)$ called X_i -DLH ($t+1$). The $R_i(t)$ is measured between the present location of $X_i(t)$ and the candidate location X_i -GWO ($t+1$) from Eq. (29).

$$\begin{aligned} Ri(t) &= |X_i(t) - X_i - GWO(t + 1)| \\ \text{Then, the } X_i(t) \text{ neighbors called } Ni(t) \text{ is formulated by Eq. (30) respected to } \leq Ri \\ \{Xj(t) | Di(Xi(t), Xj(t)) \leq Ri(t), Xj(t) \in Pop \end{aligned} \quad (30)$$

D_i is the measured range between $X_i(t)$ and $X_j(t)$. multi neighbors learning is performed by Eq. (31)

$$Xi - DLH, d(t + 1) = Xi, d(t) + rand * (Xn, d(t) - Xi, d(t)) \quad (31)$$

Selecting and updating phase: choosing the most candidate by comparing X_i -GWO ($t+1$) and X_i -DLH ($t+1$) fitness values by Eq. (32)

$$X_i(t + 1) = \begin{cases} X_{i-GWO}(t + 1), & \text{if } f(X_{i-GWO}) < f(X_{i-DLH}) \\ X_{i-DLH}(t + 1) & \text{otherwise} \end{cases} \quad (32)$$

If the chosen candidate's fitness value is smaller than $X_i(t)$, $X_i(t)$ is modified by the chosen candidate to correct the following position of $X_i(t+1)$. In Pop , on the other hand, $X_i(t)$ remains unchanged. After completing this procedure for each individual, the iterations counter ($iter$) is increased by one, and the search can be repeated until the maximum number of iterations ($Maxiter$) is reached. The obtained results from different experiments and statistical tests prove that I-GWO has better performance than the comparative algorithms [54].

The following steps are the pseudo-code of I-GWO

Input: N, D, Maxiter

Output: The global optimum

1: **Begin**

2: Initializing (N wolves are randomly distributed throughout the search space, and their fitness is calculated.).

3: **For** iter = 2 to Maxiter

4: Find $X\alpha$, $X\beta$, and $X\delta$.

5: **For** i = 1 to N

6: Computing X_{i1} , X_{i2} , X_{i3} by using Eq. (27).

7: Computing $X_{i-GWO}(t+1)$ by using Eq. (28).

8: Calculating $R_i(t)$ by Eq. (10).

9: Constructing neighborhood $X_i(t)$ with radius R_i by Eq. (11).

10: **For** d = 1 to D

11: $X_{i-DLH,d}(t+1) = X_{i,d}(t) + \text{rand} \times (X_{n,d}(t) - X_{r,d}(t))$

12: **End for**

13: Selecting best ($X_{i-GWO}(t+1)$, $X_{i-DLH}(t+1)$).

14: Updating Pop.

15: **End for**

16: **End for**

17: **Return** the global optimum.

18: **End**

4. Controller Structure and Objective Function

For the two-area six units' scheme, the secondary controller for AGC objective and primary controller for ELD controller are considered in this paper. To eliminate the controlled output's steady-state error to match the reference input exactly, the integral term I is used for AGC and ELD. The I controller transfer functions are:

$$TF_I = \frac{K_i}{s} \quad (33)$$

For fixing the controller parameters, an objective function is formulated based on the predicted provisions and restraints. In engineering, the classical implemented objective functions are the IAE (integral-absolute error), ISE (integral-squared error), ITAE (integral-time-multiplied- AE) and ITSE (integral-time-multiplied-ISE), and [46-50].

Most used function is the ISE due to its easier calculation and its permission to separate underdamped from the overdamped system. The elements of negative error are eradicated because the ISE squares it. In addition, the ISE penalizes the errors which are large more than smaller ones and provides fast responses. As time passes, it allows small oscillations. The results explain that the tuning based on ISE has fewer iterations for global convergence than other methods. The ITSE is used as cost function in this paper, and the ITSE function can be expressed as:

$$ITSE = t \int_0^T \{ \Delta F_1^2 + \Delta F_2^2 + \Delta P_{tie12}^2 \} dt \quad (34)$$

T denotes the simulation's time range. ΔF_1 , ΔF_2 , and ΔP_{tie12} are the frequency deviations in area-1, area-2, and the tie-line's power deviation connecting areas 1 and 2, respectively.

5. Simulation Results and Discussion

The proposed solution strategy is illustrated with a two-control-area, six-unit thermal station power system, as shown in Figure 2. The parameters of the transfer function of Figure 2 are listed in the appendix.

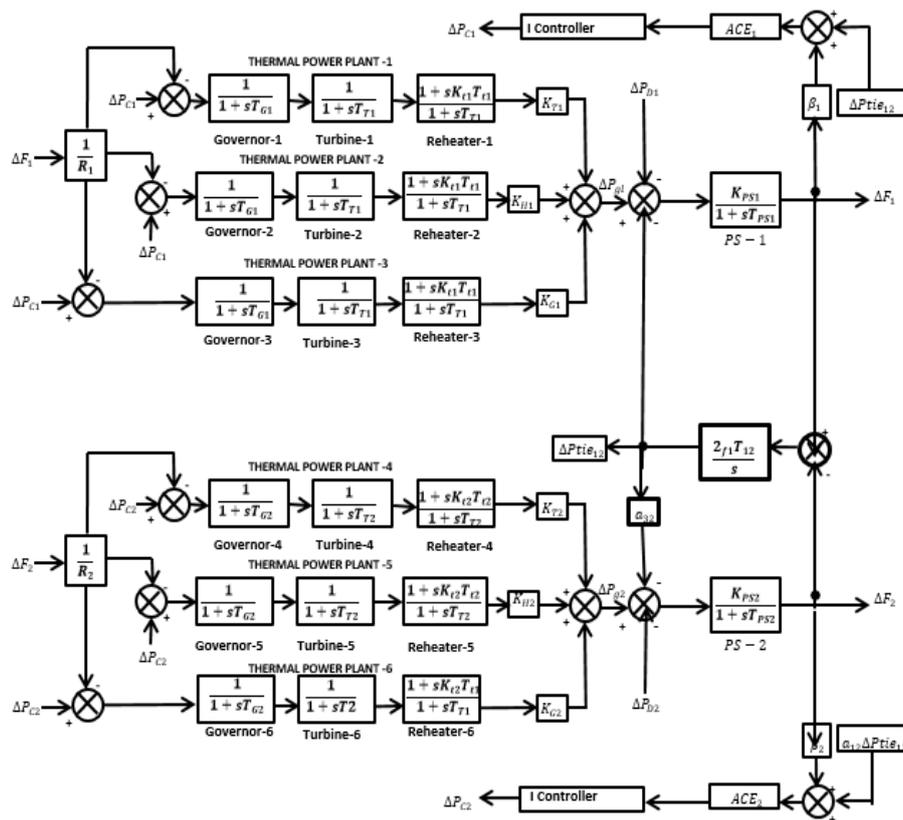


Figure 2: TF model of thermal multi-unit PS

Figure 3 illustrates Simulink of the case study. The green block represents (ITSE) and is illustrated in details in Figure 4. Table 1 shows the input and full output values of economic load dispatch of three generating units that supply each area and the table is discussed below. A 0.05-p.u. step load perturbation (SLP) is applied to the first area (area 1) at the $t=0$ to 400 s to show the efficiency of the I-GWO in solving the system (system load becomes 1050MW). The initial population in this article consists of 20 search agents, with a maximum iteration is equal to 10 iterations. To achieve the desired benefit of economic load dispatch, the ITSE is used as an objective function to tune the parameters of the secondary controller, which operates as an AGC controller, as well as the parameters of the primary controller, which operates as a speed changer for the governor. The optimal value of secondary controllers and primary controllers is also listed in Table 1. In Figure 4, the cost function (J) is seen, with the ITSE value for the I controller is equal to $J= 0.052228$.

At $t=0$ s to 400 s, the behavior of a power system with only AGC and without ED is investigated in the first step. The frequency response, the net tie-line power change, ACE of each area, deviation of mechanical power in each area1, deviation of mechanical power in each area2, and the total mechanical power of each area are shown in Figure 5(a-g), respectively. Obviously, all the dynamic responses during this period are deviated at zero in the steady-state region, which implies the AGC objective is investigated for regulating the own load of each area without interchange power between the two areas. In another period (400 s to 600 s) at the same figure, the integration of ELD with AGC, which is termed as ECO-AGC, is considered in the proposed system with the same SLP (0.05 pu). In addition, all the dynamic responses during this period do not deviate at zero at steady state region, which means that the ECO-AGC objective, is investigated for regulating the load of each area with interchange power between the two area from the area of less operation cost to the area of high operation cost. Finally, for the robust test of the proposed coordination between ELD and AGC based on I-GWO for employing the integral parameters of secondary and primary controllers is considered at the last period in the same figures which is started from 600 s to 1500 s, the ECO-AGC is considered with severe SLP (0.1 pu at area 1). It is evident that all the dynamic responses during this period are responded for economic values. The interchange power through the tie line is increased because the SLP is increased, which means the ECO AGC works economically.

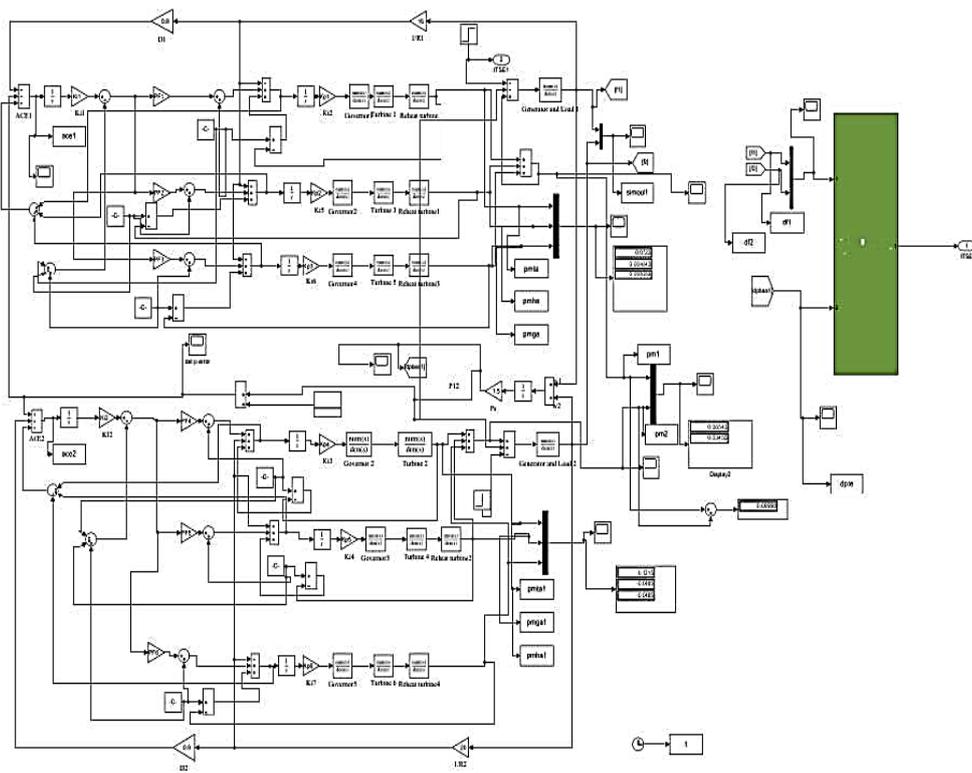
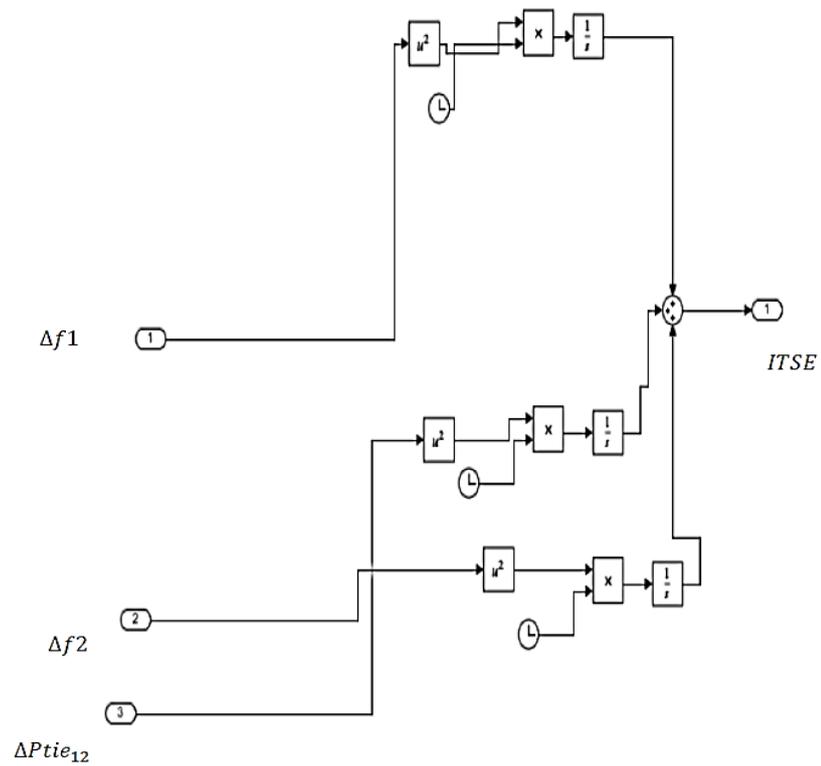


Figure 3: Application of the idea in Figure 1 on two areas six-unit power system



$$ITSE = t \int_0^T \{\Delta F_1^2 + \Delta F_2^2 + \Delta P_{tie12}^2\} dt$$

Figure 4: Details of the green block in Figure 3

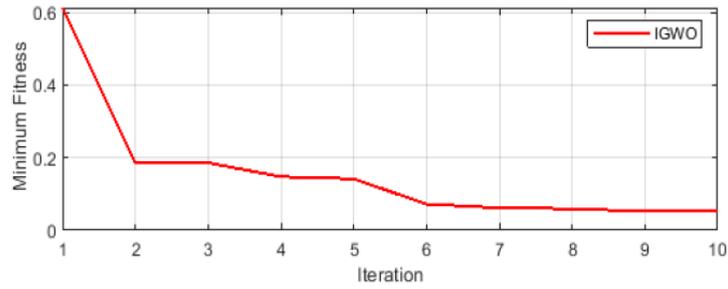
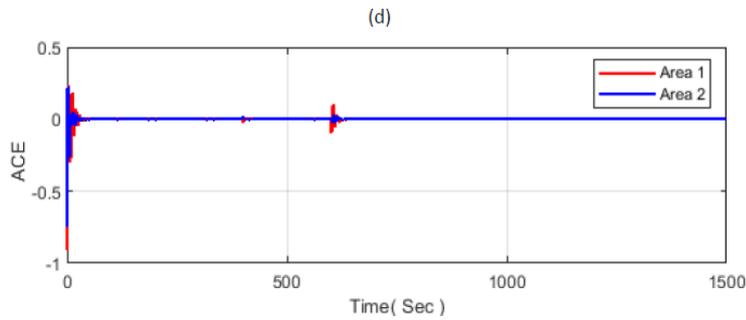
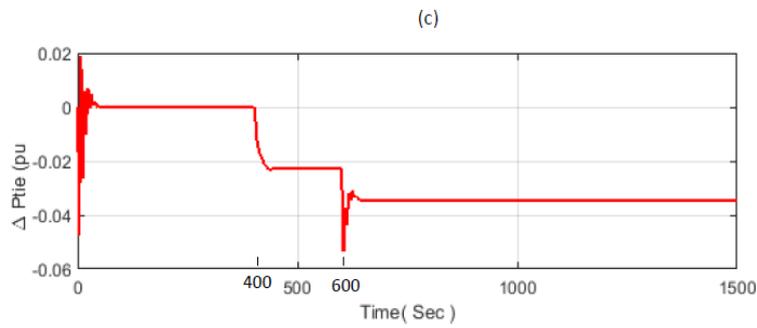
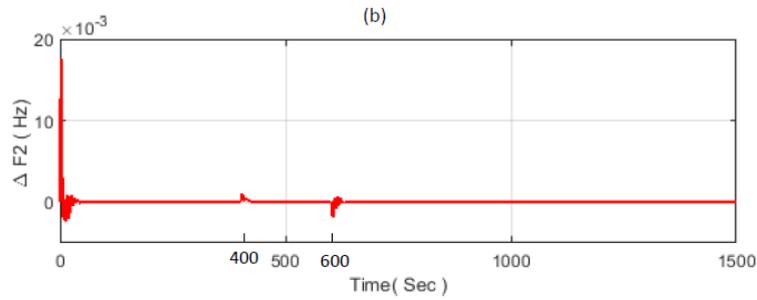
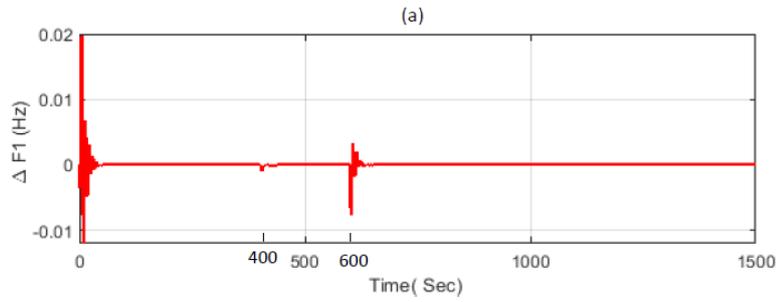


Figure 5: minimum fitness-based ITSE for tuning I parameters (I-GWO)



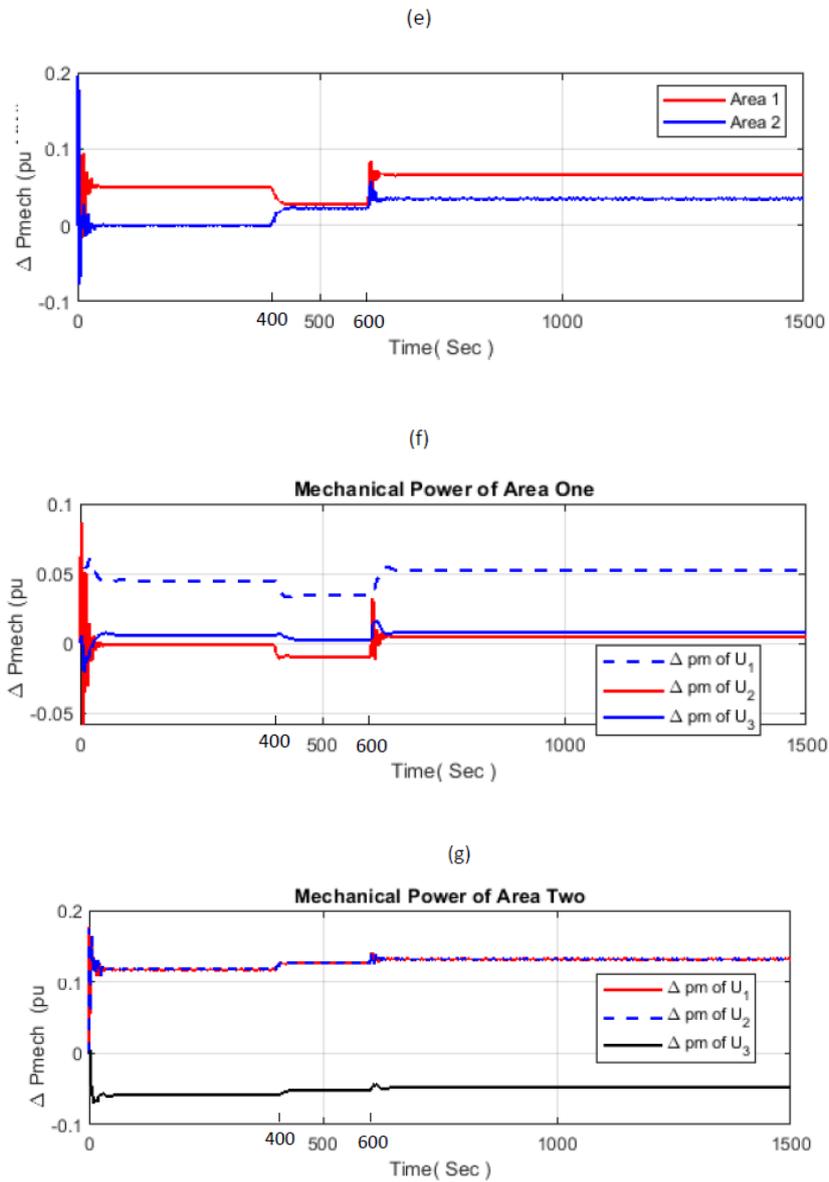


Figure 6: Dynamic responses of ECO-AGC based on I-GWO under 5% and 10% SLP, (a) frequency deviation in area 1, (b) frequency deviation in area 2, (c) tie line power deviation, (d) area control error (ACE) in area 1 and area 2, (e) deviation of mechanical power in area 1, and (f) deviation of mechanical power in area 2, and (g) total mechanical power of each area

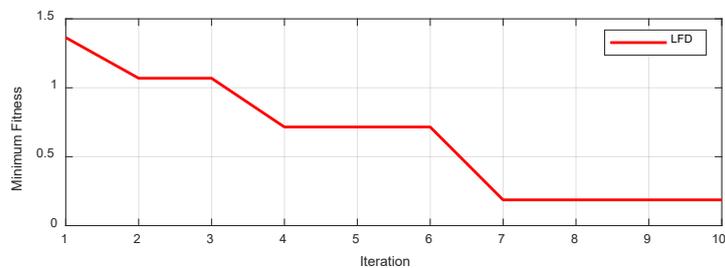
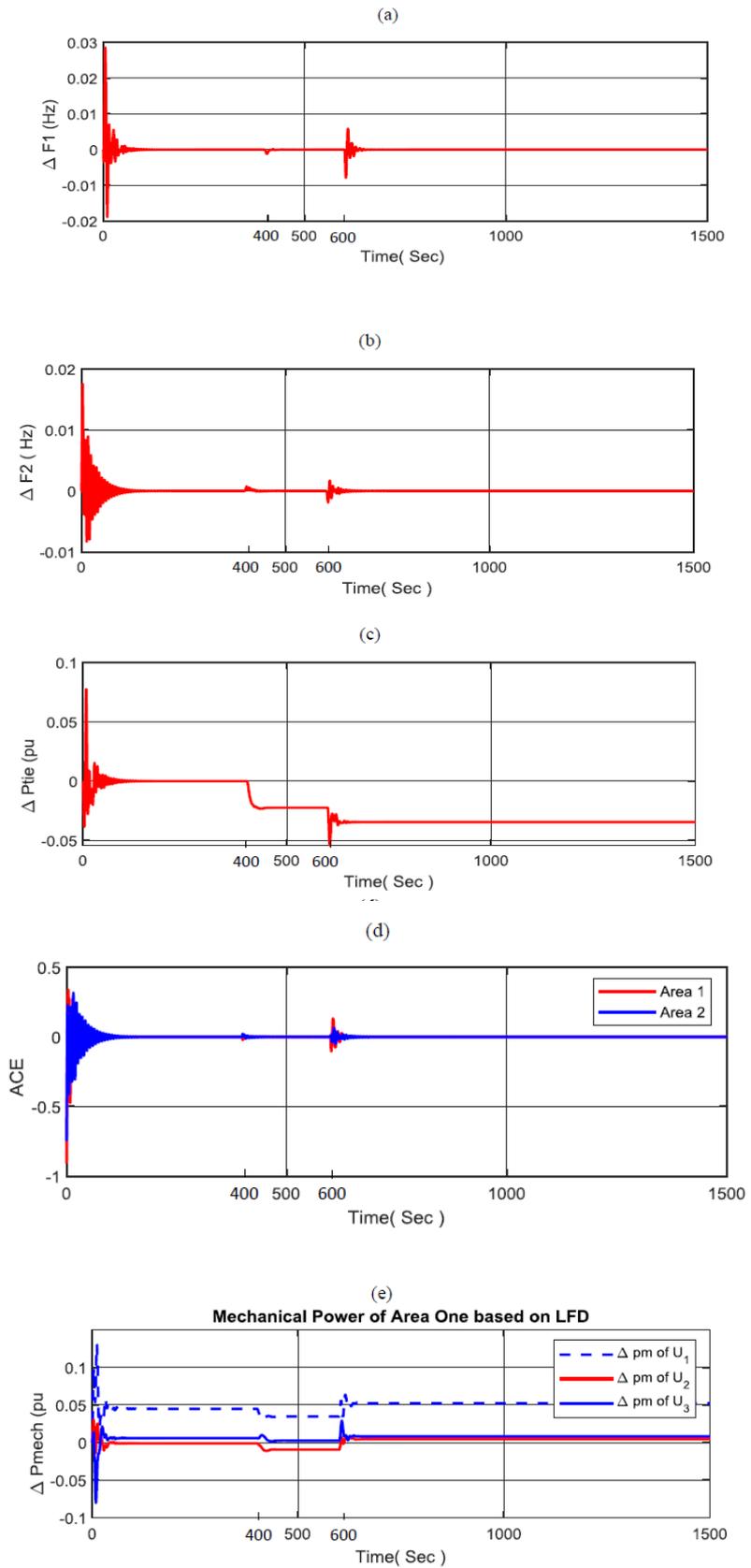


Figure 7: Minimum fitness-based ITSE for tuning I parameters (LFD)



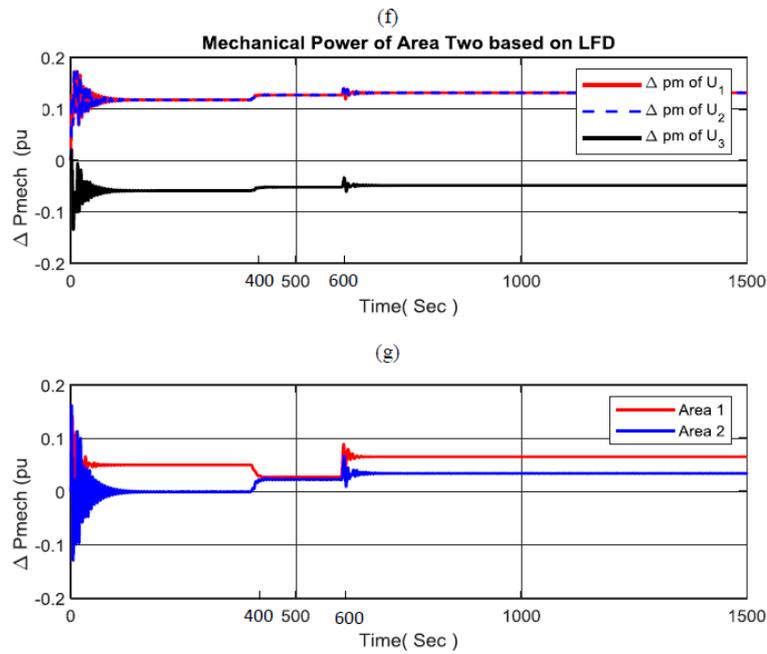


Figure 8: Dynamic responses of ECO-AGC based on LFD [55] under 5% and 10% SLP, (a) frequency deviation in area 1, (b) frequency deviation in area 2, (c) tie line power deviation, (d) area control error (ACE) in area 1 and area 2, (e) deviation of mechanical power in area 1, and (f) deviation of mechanical power in area 2, and (g) total mechanical power of each area

Table 1: Input-output values of the proposed controller and economic load dispatch

Parameter		Area 1		Area 2
Secondary Integral controller gains	K_{i1}	1.1282	K_{i2}	0.23105
Primary Integral controller gains	K_{i1}	0.39481	K_{i4}	0.48976
	K_{i2}	0.43945	K_{i5}	1.1765
	K_{i3}	0.41298	K_{i6}	0.81862
Incremental cost (system lambda) \$/MWh	λ_1	19.117271	λ_2	16.181335
Participation Factor	P_{f1}	0.469974	P_{f4}	0.398268
	P_{f2}	0.377918	P_{f5}	0.300866
	P_{f3}	0.152108	P_{f6}	0.300866
Optimal Dispatch	P_1	525.203762	P_4	524.675325
	P_2	400.000000	P_5	287.662338
	P_3	164.796238	P_6	287.662338
Total generation cost \$/h	C_{T1}	20867.30	C_{T2}	18564.86
Load Demand MW	P_{D1}	1000	P_{D2}	1100
	Unit1	$1122 + 15.84P_1 + 0.003124P_1^2$	Unit4	$950 + 13.41P_4 + 0.002641P_4^2$
Generating Unit Cost Function	Unit2	$620 + 15.70P_2 + 0.003880P_2^2$	Unit5	$560.5 + 14.17P_5 + 0.003496P_5^2$
	Unit3	$156 + 15.94P_3 + 0.009640P_3^2$	Unit6	$560.5 + 14.17P_6 + 0.003496P_6^2$
Constraints MW	Unit1	150min. – 600max.	Unit4	140min. – 590max.
	Unit2	100min. – 400max.	Unit5	110min. – 440max.
	Unit3	50min. – 200max.	Unit6	110min. – 440max.
best objective function		0.052228		

Table 2: I-GWO vs. LFD fitness from 5 runs

	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5	Best fitness	Worst fitness	Average fitness
I-GWO	0.093528	0.078244	0.092878	0.10622	0.096155	0.092878	0.10622	0.093405
LFD	0.14428	0.19556	0.18558	0.28856	0.3290	0.14428	0.3290	0.228596

The parameters inserted in Table1 are:

Optimized AGC integral controller gains for area 1and area 2, K_{i1} and K_{i2} . Optimized primary integral controller of economic dispatch for units 1-6, K_{i1} - K_{i6} . Optimal incremental cost lambda1 and lambda2 for area1 and area2 in \$/MWh

obtained from dispatch program. Optimal power generation of units 1-6 in area1 and2 obtained from dispatch program. The participation factors Pf1-Pf6 for each unit obtained from dispatch program, the summation of the participation factors for each area equals unity. Total generation cost for each area, C_{T1} , and C_{T2} in \$/h obtained from dispatch program based on cost functions of generating units. Load demand in MW for area1 and area2. Cost functions of generating units 1-6 involve the coefficients alpha, beta, and gamma. Inequality constraints (maximum and minimum limits of generated power) for each unit in MW. The best optimal value of the objective function is found by I-GWO (optimization algorithm) after 10 iterations.

With the I-GWO and LFD techniques, the best optimal value of the objective function found and compared and is shown. The comparison between the dynamic responses in Figure 6(a-g) and Figure 8(a-g) explains that I-GWO has superiority over LFD algorithm.

6. Conclusion

This paper proposes an improved GWO algorithm for tuning the primary integral controller (I) and secondary integral (I) controller parameters in a two-area, a six-unit interconnected power system for simultaneous AGC and ELD. Both actions are carried out in the same time frame but on different time scales to demonstrate the benefit of Eco-AGC analysis over traditional AGC. As a result of Eco-AGC activity, there has been an increase in dynamic responses and efficiency index parameters, and all units can help scheduled generation economically. The Eco-AGC is worked in a smooth distribution of affected load variance across units, regardless of power or economics. Without the ED controller, the system becomes more unstable; but, with the ED controller, the system becomes more stable due to the improved optimal control mechanism. Our proposed I-GWO optimized integral (I) controller has been shown to be more effective for AGC and Eco-AGC study and gracefully enhances dynamic system responses under various uncertainties, as demonstrated by various dynamic responses. Future works suggested are to use other types of controller and optimization algorithm. In addition, the application of this procedure on the Iraqi power grid is proposed.

Appendix

$K_{PSi} = 120$, $T_{PSi} = 20$ s, $B_i = 0.425$ puMW/Hz, $T_{ri} = 10$ s, $R_i = 2.4$ Hz/puMW, $T_{Gi} = 0.08$ s, $T_{12} = 0.0866$ puMW/rad, $T_{Ti} = 0.3$ s, $K_{ri} = 0.5$.

Author contribution

All authors contributed equally to this work.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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