ELECTRICAL & ELECTRONIC ENGINEERING | RESEARCH ARTICLE

Grey wolf optimizer based regulator design for automatic generation control of interconnected power system

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Abstract: This paper presents an application of grey wolf optimizer (GWO) in order to find the parameters of primary governor loop for successful Automatic Generation Control of two areas’ interconnected power system. Two standard objective functions, Integral Square Error and Integral Time Absolute Error (ITAE), have been employed to carry out this parameter estimation process. Eigenvalues along with dynamic response analysis reveals that criterion of ITAE yields better performance. The comparison of the regulator performance obtained from GWO is carried out with Genetic Algorithm (GA), Particle Swarm Optimization, and Gravitational Search Algorithm. Different types of perturbations and load changes are incorporated in order to establish the efficacy of the obtained design. It is observed that GWO outperforms all three optimization methods. The optimization performance of GWO is compared with other algorithms on the basis of standard deviations in the values of parameters and objective functions.

Keywords: automatic generation control (AGC); integral square error (ISE); grey wolf optimizer (GWO); gravitational search algorithm (GSA); genetic algorithm (GA)

1. Introduction

Ongoing electricity demand and exponential growth in population have laid a heavy burden on conventional generation, transmission, and distribution system. To match high load demands with exponential increment of utilities at transmission and distribution ends, the problem of the power system operation and control emerged as a challenging design problem. Automatic generation control (AGC) is a common denominator used to maintain the fair balance between the real power generation, system load demand, and associated system losses (Nanda & Kaul, 1978). IEEE defines...
AGC as “The regulation of the power output of electric generators with in a prescribed area in response to changes in system frequency, tie-line loading, or the relation of these to each other, so as to maintain the scheduled system frequency and/or the establish interchange with other areas within predetermined limits” (IEEE Standard Definitions of Terms, 1970).

Figure 1 shows the schematic diagram of load frequency control (LFC) and automatic voltage regulator (AVR) of a turbo generator. The automatic control of turbo generator consists of two major loops, i.e. LFC loop and AVR loop. The LFC loop controls the real power output and frequency of the system and AVR loop regulates the magnitude of terminal voltage of all the generators and the reactive power output. The AGC works on two control modes. In primary control, speed governors are responsible for the operation of control valve of turbine power input. The secondary control is slow and maintains the tie line power interchange.

A rich literature survey on existing AGC techniques was reported in Ibraheem and Kumar (2005). In the paper, the authors explained AGC schemes, types of power system models, control techniques, control strategies, sensitivity features, etc. The critical issue was to obtain the modeling of an interconnected power system near any operating equilibrium, Elgerd (1983) and Sadat (1999). Over the past few years, many researchers have done significant researches on the subject of better AGC of large interconnected power systems. Some of the approaches were based on Pole Placement Technique (Sivaramakishana, Hariharan, & Srisailam, 1984), coefficient diagram method (CDM) Bernard, Mohamed, Qudaih, and Mitani (2014) and Ali, Mohamed, Qudaih, and Mitani (2014), neural networks (NN) (Kannah, Tripathy, Malik, & Hope, 1984; Kothari, Satsangi, & Nanda, 1981; Valk et al., 1985), fuzzy logic (FL) (Banerjee, Mukherjee, & Ghoshal, 2014; Sahu, Pati, Mohanty, & Panda, 2015; Sudha & Vijaya Santhi, 2012; Wu, Er, & Gao, 2001), Super Magnetic Energy Storage Device (Pandan, Sahu, & Panda, 2014), and evolutionary algorithms (EA) (Abdel-Magid & Abido, 2003; Abdel-Magid & Dawoud, 1996; Debbarma, Chandra Saikia, & Sinha, 2014; Emary, Zawbaa, Grosan, & Hassenian, 2015; Gozde, Cengiz Taplamacioglu, & Kocaarslan, 2012; Mirjalili, 2015; Mirjalili, Mirjalili, & Lewis, 2014; Muro, Escobedo, Spector, & Coppinger, 2011; Nanda & Mishra, 2009; Puja, Chandra, & Nidul, 2014; Rout, Sahu, & Panda, 2013; Sahu, Panda, & Padhan, 2014; Saxena, Gupta, & Gupta, 2012; Song, Sulaiman, & Mohamed, 2014; Song et al., 2015). In view of the literature survey, it has been observed that CDM is an algebraic way to solve these compensator design problems. The process of obtaining coefficients is time-consuming and not suitable for fast and online applications. Adaptive leaning paradigms like neural networks (Kannah et al., 1984; Kothari et al., 1981; Valk et al., 1985) are based
on data generation. Learning of the network is dependent on data-sets. This time-consuming activity makes the approach very lethargic and inappropriate. Fuzzy logic Wu et al. (2001) and Sahu et al. (2015) models are based on uncertainty modeling. Models are based on approximation often failed to maintain the accuracy on real-world problems as thousands of fuzzy models are based on conjunction, disjunction, implications, and defuzzification choices. In AGC problems, high degree of precision is required.

The traditional approach is to optimize the parameters of the secondary loop of governor; however, in this study, it has been shown by the authors that the effect of primary governor loop parameters on the controller setting is predominant. Now a days, meta-heuristic techniques are used to solve these problems due to their flexibility, avoidance of local optima, and derivation-free mechanism. Some of these approaches include gravitational search algorithm (GSA) (Sahu et al., 2014), particle swarm optimization (PSO) (Abdel-Magid & Abido, 2003), genetic algorithm (GA) (Abdel-Magid & Dawoud, 1996), bacterial foraging (BF) (Nanda & Mishra, 2009), differential evolution (DE) (Rout et al., 2013), artificial bee colony (ABC) (Gozde et al., 2012), firefly algorithm (FA) (Debbarma et al., 2014), and cuckoo search (CS) (Puja et al., 2014). Investigations have been carried out using PSO (Abdel-Magid & Abido, 2003) and GA (Abdel-Magid & Dawoud, 1996) and found that they are getting trapped at local optima. These difficulties were overcome by bacterial foraging (BF) technique. Nanda and Mishra (2009) implemented BF technique with integral controller. The resulting performance was better as compared to classical and GA methods. Some new algorithms like ABC (Gozde et al., 2012), FA (Debbarma et al., 2014), CS (Puja et al., 2014), etc. were also successfully applied in AGC. Debbarma et al. (2014) presented the FA to design fractional controller gains. A comparison was presented by authors with the conventional Proportional Integral and Differential Controllers. Shivaie, Kazemi, and Ameli (2015) presented a modified harmony search algorithm to solve the LFC.

In this work, a digital simulation is used with grey wolf optimizer (GWO) to optimize the parameter of AGC for two areas’ system. Mirjalili et al. (2014) proposed a population-based algorithm known as GWO inspired by nature of grey wolf in 2014. It mimics the leadership hierarchy and the hunting behavior of grey wolf (Muro et al., 2011). This algorithm shows a very promising response to deal with the optimization process of uni-modal, multi-modal, fixed dimension multi-modal and composite functions. The algorithm outperforms other conventional population-based techniques. The comparison was based on ability of exploration, exploitation, local optima avoidance, and convergence (Muro et al., 2011). For population-based techniques, exploration and exploitation are the common features. However, there is no mathematical analogy found between these two features. In fact, these two features are contradicting in nature. Exploration of search space for potential solutions and the exploitation performance to converge on the global optima are the main features of any algorithm and moreover responsible for the performance of the algorithm. Exploitation process is controlled by control parameters. GWO maintains a fair balance between the exploration and exploitation phenomena. Recently, GWO has been applied on real optical engineering (Mirjalili et al., 2014), combined economic load dispatch problem (Song et al., 2014), and parameter estimation in surface waves (Song et al., 2015). Mirjalili (2015) employed GWO for the training of multi-layer perceptron; further, the performance of this perceptron is tested on three function approximation sets and five classification problems. The performance of GWO-trained MLP is superior to well-known evolutionary trainers like GA, PSO, and Evolution Strategy. Song et al. (2015) applied GWO as a powerful surface wave dispersion curve inversion scheme. The proposed scheme is benchmarked on noise-free, noisy, and field data. Further, the results of algorithms were compared with the conventional techniques. Emary et al. (2015) proposed a classification-based fitness function to eliminate the redundant, irrelevant, and noisy data. This fitness function is optimized through GWO. GWO performed feature selection and classification task efficiently. Salient features of the algorithm are described below:

(1) This algorithm is based on the leadership hierarchy and hunting behavior of the grey wolf. The simplicity of the algorithm allows scientists to simulate the natural concepts in a lucid manner.
(2) The noteworthy feature of this algorithm is that it has less control parameters and possesses a derivative-free mechanism. This mechanism is a boon and advocates the superiority of GWO to avoid local optima trap.

(3) Algorithm is flexible and can be applied to many real-world problems without changing the main structure.

(4) This algorithm can be applied to non-differentiable, stochastic, and discontinuous functions.

In view of the above literature survey, salient features of this algorithm become the primary motivation to apply GWO in AGC regulator design. In this paper, two standard objective functions, integral time-multiplied absolute error (ITAE) and integral squared error (ISE), are used for the analysis which are function of time and error.

In Section 2, a brief description of the modeling of two areas' interconnected system, its investigation, and the proposed approach is presented. Section 3 describes the grey wolf optimization technique. Section 4 exhibits the dynamic responses of frequency deviation in both the areas and the tie line power at different loading conditions. Section 6, the conclusion, shows the efficacy of the proposed approach by comparing it with GSA (Sahu et al., 2014), PSO (Abdel-Magid & Abido, 2003) and GA (Abdel-Magid & Dawoud, 1996).

2. System modeling

2.1. AGC model

The two areas' non-reheat thermal interconnected power system is shown in Figure 2. The main components of the power system include speed governor, turbine, rotating mass, and load. The inputs of the power system are controller output \( u \), load disturbance \( \Delta P_L \), and tie line power \( \Delta P_{tie} \), while the outputs are frequency deviations \( \Delta f \) and area control error ACE. The ACE signal controls the steady-state errors of frequency deviation and tie power deviation. Mathematically, ACE can be defined as

\[
ACE = B\Delta f + \Delta P_{tie}
\]  

where \( B \) indicates the frequency bias parameter.

The operating behavior of the power system is dynamic, so it must be assumed that the parameters of the system are linear. For the mathematical modeling, transfer function is used.

The transfer function of a governor is represented by Elgerd (1983):

\[
G_g(s) = \frac{1}{1 + sT_g}
\]  

Turbine is represented by the transfer function as (Elgerd, 1983):

\[
G_t(s) = \frac{1}{1 + sT_t}
\]  

The transfer function of rotating mass and load (Elgerd, 1983):

\[
G_L(s) = \frac{K_p}{1 + sT_p}
\]  

where \( T_p = \frac{2H}{P} \) and \( K_p = \frac{1}{D} \).

\( \Delta P_g \) and \( \Delta P_L \) are the two inputs of rotating mass and load with \( \Delta f(s) \) being the output and represented by Elgerd (1983).
\[
\Delta f(s) = G_c(s)[\Delta P_e(s) - \Delta P_g(s)]
\] (5)

2.2. System investigated

The system is investigated on the two equal thermal areas connected by a weak tie line having the same generation capacity of 1,000 MVA. The parameters of the system are taken from (Sadat, 1999). A sudden step perturbation of 0.1875 p.u. occurs in area 1 and 0.1275 p.u. in area 2. The transfer function model of two areas' thermal system is shown in Figure 2. The system is implemented using MATLAB 2013 and run on a Pentium IV CPU, 2.69 GHz, and 1.84-GB RAM computer (MATLAB, http://www.mathworks.com).

2.3. The proposed approach

The controller used in AGC system is PI controller as it determines the difference between set point and reference point as well as removes the steady-state error. For the design of PI controller, parameters' proportional gain \(K_P\) and integral gain \(K_I\) are essential. However, in this work, for the ease and simplicity of optimization process, we consider proportional gain 1. Area control errors are the input of the controllers for area 1 and area 2 which are defined as

\[
ACE_1 = B_1 \Delta f_1 + \Delta P_{tie}
\] (6)

\[
ACE_2 = B_2 \Delta f_2 + \Delta P_{tie}
\] (7)

where \(B_1 = \frac{1}{R_1} + D_1\) and \(B_2 = \frac{1}{R_2} + D_2\).

The output of the controllers are \(u_1\) and \(u_2\) and are obtained as

\[
u_1 = K_{p1} ACE_1 + K_{i1} \int ACE_1
\] (8)
In this paper, the estimation of integral gains and parameters of primary governor loop are based on
two objective functions (ITAE and ISE) which are mentioned in Equations (10) and (11). It aims to
reduce the steady-state error to zero and maximize the damping ratio of the system.

\[ u_2 = K_p \cdot ACE_2 + K_i \int ACE_2 \quad (9) \]

The problematic constraints are the parameters of AGC regulator which contains integral gains,
speed regulations, and the frequency sensitivity coefficients as they are bounded with the limits.
These parameters are system specific. Hence, the design problem can be formulated as

\[
\text{Minimize } J \\
\text{Subjected to} \\
K_{i_{\text{min}}} \leq K_i \leq K_{i_{\text{max}}} \\
R_{\text{min}} \leq R \leq R_{\text{max}} \\
D_{\text{min}} \leq D \leq D_{\text{max}}
\quad (12)(13)(14)
\]

where \( J \) is the objective function \( (J_1 \text{ and } J_2) \).

3. Grey wolf optimizer

A recent population-based swarm intelligence technique, called GWO, inspired by the nature of grey
wolf is discussed in this section. This technique was proposed by Mirjalili et al. (2014) in 2014. In
GWO, the leadership hierarchy and the hunting behavior of grey wolf are mimicked. Grey wolves
belong to Canidae family and prefer to live in a pack of 5–12 members on average. This pack is cat-
egorized into four groups, namely: alpha, beta, delta, and omega for the simulation of leadership
hierarchy. They have very strict social-dominant hierarchy.

Alphas are the first level and are the leaders of the pack. Alphas are the decision-makers regarding
hunting, sleeping place, and time to wake up and that decision will be followed by the pack. Hence,
the alpha wolf is also known as the dominant wolf. Alpha is not essentially the strongest member in
the pack, but good in organizing and disciplining the pack.

Beta comes in the second level on the hierarchy of grey wolves. Betas help alpha wolves in deci-
sion-making and the activities of the pack. Betas are the best candidates to get the position of alpha
in case of the alpha wolves pass away or become very old. The beta supports alpha's command
throughout the pack.

Delta is the third level in the pack. Delta wolves have to submit alpha and beta, but they dominate
omega. The scouts, elders, hunters, sentinel, and care takers belong to this group.

Omega wolves have the lowest ranking in the pack. They always have to surrender to all other
dominant wolves. Omega is not a main member, but everyone face fighting and problems in case of
losing an omega.
As hunting is also an interesting behavior of grey wolves, the three important steps of hunting are employed to carry out the optimization, which are: searching for prey, encircling the prey, and attacking the prey. According to Muro et al. (2011), the main stages of grey wolf hunting are tracking, chasing, pursuing, encircling, and attacking the prey.

In the mathematical modeling of social hierarchy of wolf, alpha (α) is considered as the fittest solution, beta (β) and delta (δ) are the second- and the third-best fittest solutions, respectively, in designing GWO. The rest of the candidate solutions are considered as omega (ω). The hunting is guided by α, β, and δ. The ω wolves follow α, β, and δ wolves.

For the modeling of encircling the prey, the following equations are proposed.

\[
\vec{D} = | \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) | \tag{15}
\]

\[
\vec{X}(t + 1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{16}
\]

where \( t \) represents current iteration, \( \vec{A} \) and \( \vec{C} \) are coefficient vectors, \( \vec{X}_p \) is the position vector of the prey, and \( \vec{X} \) is the position vector of the grey wolf. The vectors \( \vec{A} \) and \( \vec{C} \) can be calculated as follows:

\[
\vec{A} = 2\bar{a} \cdot r_1 - \bar{a} \tag{17}
\]

\[
\vec{C} = 2 \cdot r_2 \tag{18}
\]

The components of \( \bar{a} \) are decreased linearly from 2 to 0 over the course of iterations and \( r_1, r_2 \) are random vectors in \([0, 1]\). Figure 3 shows the 3D position of prey at \((X^*, Y^*, Z^*)\) and grey wolf at \((X, Y, Z)\) with its possible next locations.
During hunting, the first three best solutions ($\alpha$, $\beta$, and $\delta$) obtained are saved and coerce other search agents (including the omega) to update their positions according to the best search agent. The following are the proposed formula.

\[
\vec{D}_u = |\vec{C}_1 \cdot \vec{X}_u - \vec{X}|, \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|
\]  

(19)

\[
\vec{X}_1' = \vec{X}_u - \vec{A}_1 \cdot (\vec{D}_u), \vec{X}_2' = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \vec{X}_3' = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta)
\]  

(20)

\[
\vec{X}(t + 1) = \frac{\vec{X}_1' + \vec{X}_2' + \vec{X}_3'}{3}
\]  

(21)

Figure 4 shows the updating position of search agent according to the alpha, beta, and delta. It can be observed that alpha, beta, and delta estimate the position of the prey and other wolves update their position stochastically around the prey and the final position is randomly within the circle.

The searching of grey wolves depends on the position of the alpha, beta, and delta. For searching, they diverge from each other. Mathematically, $\vec{A}$ varies with random values greater than 1 or less than $-1$ to oblige the search agent to diverge from the prey. This brings out exploration and allows GWO algorithm to search globally. If $|A| > 1$, grey wolves diverges from the prey to find the fitter prey.

When the prey stops moving, the grey wolf finishes its hunt by attacking it. If $|A| < 1$, grey wolves converge toward the prey and attack it. The vector $A$ is a random value in the interval $[-a, a]$. This process is known as exploitation.

**Figure 4.** Position updating in GWO.
4. Results and analysis

This section presents the critical analysis of regulator performance on two areas' interconnected thermal units under different load perturbations in both areas. Table 1 shows the optimal parameters of integral regulator with primary governor loop constants, namely: frequency sensitivity coefficient ‘$D$’ and speed regulation ‘$R$’. The values obtained from the optimization process of proposed GWO technique with GSA, PSO, and GA from objective functions $J_1$ (ITAE) and $J_2$ (ISE) are shown in this table. The lowest value of integral regulator gain and the highest value of $R$ are obtained with GWO optimization process, which shows that controller setting obtained from this technique is more robust as compared to others (Nanda & Mishra, 2009). Table 2 shows the values of system modes (eigenvalues) and the minimum damping ratio obtained from the objective functions $J_1$ and $J_2$ by the proposed GWO-tuned AGC regulator. These values are compared with the regulator obtained by modern heuristic optimization algorithms GSA, PSO, and GA. For stability studies, eigenvalues are important, as they give the information about the system’s behavior when the system is subjected to any physical disturbance. Both real and imaginary parts have their interpretation and physical significance. Oscillatory instability is due to the real positive part of the complex conjugate eigenvalues. These eigenvalues are also known as swing modes. It is observed from Table 2 that when the system is tested with GA-tuned AGC regulator with criteria $J_2$, the swing modes possess positive real part (0.0361). Real positive part indicates the oscillation of growing amplitude. The real part of the complex conjugate eigenvalue shows the damping behavior which represents the damping oscillations, meaning: larger the magnitude, more the rate of decay. Imaginary components show the frequency of oscillations. With PSO setting $J_2$, the response contains high frequency modes (2.69 Hz and 2.18 Hz). Higher frequency modes are not good for control equipment’s health. On the other hand, GWO regulator not only possesses moderate values of frequency oscillation (1.49 Hz, 1.73 Hz), but also contains larger real negative parts ($-0.4638, -0.2848, -0.29, -0.05$) as compared with other regulators. The eigenvalues after the employment of GWO AGC regulator possess bigger negative part as compared with any other algorithms which indicates that the system is comparatively stable. The values of minimum damping ratio, when the optimization process is carried out by objective function $J_1$, are 0.1875 for GWO, 0.1601 for GSA, 0.1345 for PSO, and 0.1668 for GA. It is observed that the system’s damping performance is comparatively improved with GWO technique. However, less value of damping ratios is obtained by GA as compared to any other algorithm. Prima facie design obtained by the $J_2$ criteria is rejected due to the positive real part in GA regulator, appearance of higher frequencies of oscillations in all regulators, and smaller negative real part of the system’s modes. To justify this: firstly, the responses of GWO-based regulator are taken into consideration with both the objective functions $J_1$ and $J_2$. It is then compared with the GSA (Sahu et al., 2014), PSO (Abdel-Magid & Abido, 2003), and GA (Abdel-Magid & Dawoud, 1996). Figure 5 shows three dynamic responses obtained from GWO. The frequency deviation of area 1 is shown in Figure 5(a–d). Deviation in the tie line power is shown in Figure 5(e) and the frequency deviation of area 2 is shown in Figure 5(f). Figure 5(a–d) shows the frequency deviation in area 1 with increase in load for the two objective functions $J_1$ and $J_2$ with changes in loads as:

| Table 1. Optimized parameters of AGC regulator |
|-----------------------------------------------|
| Parameters | GWO | GSA (Sahu et al., 2014) | PSO (Abdel-Magid & Abido, 2003) | GA (Abdel-Magid & Dawoud, 1996) |
|------------|-----|-------------------------|---------------------------|-----------------------------|
| K11        | 0.2072 | 0.3817               | 0.3131                  | 0.3031          |
| K12        | 0.2055 | 0.2153               | 0.1091                  | 0.3063          |
| R1         | 0.0555 | 0.0401               | 0.0581                  | 0.0794          |
| R2         | 0.0689 | 0.0657               | 0.0531                  | 0.0737          |
| D1         | 0.5943 | 0.5889               | 0.4756                  | 0.7591          |
| D2         | 0.5507 | 0.8946               | 0.6097                  | 0.8950          |
Figure 5(a)—load is increased by 10% in area 1.

Figure 5(b)—load is increased by 20% in area 2.

Figure 5(c)—load is increased by 10% in area 1 and 20% in area 2.

Figure 5(d)—load is increased and decreased by ±25% and ±50% from their nominal values in area 1.

The critical analysis of these responses suggests that the overshoot and the settling time of ITAE (J1) are less than ISE (J2) in all conditions and achieve better dynamic performance. Due to the superior performance of J1, ITAE is considered in further cases. It can be observed in Figure 5(d) that as the load increases, the oscillations in the system are less with GWO (J1) regulator and dampen quickly as compared with GWO (J2) regulator. Figure 5(e) and Figure 5(f) shows the response of tie line power and frequency deviation in area 2 for the range ±25%–±50% of the nominal load. In Figure 5(f) it is observed that there is negligible effect of variation of load on the frequency deviation in area 2 when increased in area 1. It is also empirical to judge with the responses obtained under different conditions that although both regulators achieve zero steady-state error, the regulator tuned with the criteria J1 obtained less settling time. The effect of the increment in the load in areas is not prominently seen in the response with J1 setting. It can be concluded from Figure 5 that overall robust regulator design can be obtained with criteria J1.

The comparisons of all the algorithms are examined by the four cases.

Case A: Load change in area 1 by 10%. The dynamic responses of $\Delta f_1$, $\Delta f_2$, and $\Delta P_{tie}$ are given in Figures 6–8 for all the algorithms. Figure 9 shows the representation of OS, ST, and FOD under all cases.

Case B: Load change in area 2 by 20%. Figures 10–12 show the dynamic responses of the system.

Case C: Load is increased in area 1 by 25%. In Figures 13–15, the system dynamic responses are shown.
Case D: Load is decreased in area 1 by 25% and its responses are given in Figures 16–18.

It is observed from Figures 6–8 that GWO-based controller exhibits the better dynamic performance as compared with others. Percentage overshoot and settling time are much less in these cases. The low oscillatory response exhibited by GWO is also good for the equipment’s health. Figure 9 shows the preliminary calculations for all the algorithms under all cases to show the effectiveness of proposed GWO over GSA (Sahu et al., 2014), PSO (Abdel-Magid & Abido, 2003) and GA (Abdel-Magid & Dawoud, 1996). It has been observed that minimum value of settling time is obtained from GWO-based regulator. This value is considered as a close replica of dynamic
performance of controller. It is also empirical to mention here that for frequency deviation in area 1, the settling time obtained from GWO is 4.7, whereas from GSA, PSO, and GA, settling times are 7.1, 7.8, and 6.6, respectively. The frequency deviation in area 2 also shows that the value of settling time is less when GWO is used. The value of settling time, when frequency deviation, in area 2 is 5.4 for GWO, 7.2 for GSA, 7.8 for PSO, and 8.7 for GA. It is also interesting to observe that with the 10% increase in the load, PSO gives erroneous results and the flow of tie line power behaves in a different manner. Hence, critical analysis of dynamic responses clearly reveals the better dynamic performance exhibited by GWO. By examining the responses in Figures 10-12, it is clearly seen that the
settling time and peak overshoot are less when load changes in area 2 are by 20%. It can be observed from the Figure 11 that when area 2 observes 20% increase, GA-based controller is not able to mitigate the frequency oscillations. This inculcates oscillatory instability in the system. However, GWO-based controller shows a better dynamic response and yields a satisfactory performance over a wide range of loading conditions. For case B, the settling time of GWO is 4.9, 6.4, 7.1, and 7.3 for GSA, PSO, and GA, respectively. This analysis can be seen in Figure 9. Figures 13 and 14 show the frequency deviations of areas 1 and 2. Figure 9 illustrates the overshoot, settling time, and FOD of case 3 when load is increased in area 1 by 25%. From dynamic response and graphical representation of overshoot, settling time, and FOD, it is clear that GWO provides competitive results as compared to all other algorithms. The dynamic responses for case D are shown in Figures 16–18 and it has been observed that GWO-tuned controller yields a better dynamic performance. The minimum
settling time is obtained from GWO which is 4.1 for frequency deviation in area 1 and 4.5 for frequency deviation in area 2. However, in case of GSA, the settling time is 6.1. An oscillatory response is obtained by the GA-, GSA-, and PSO-tuned controllers.

The eigenvalues obtained from J1 and J2 for each case of all the algorithms are provided in Table 3. It has been observed that all modes which come from GWO technique lie in the left half of the s-plane and thus sustain the stability of the system. However, in case of GA, few modes lie in the right half of s-plane and make the system unstable. This phenomenon can be observed in Figures 11 and 12. It can also be observed that the modes obtained after the realization of controller through J1 criterion possess a bigger negative part, and in few operating cases, like B, C, and D, this
phenomenon is more prominent. Eigenvalues are true replica of the system’s behavior. In different operating cases, these calculations show different behaviors of the system.

5. Optimization performance

Around 100 trials of optimization are carried out to judge the efficiency of the optimization process carried out by all the above-said algorithms. To provide a fair comparison, population size (100) and maximum number of iterations (1,000) are kept the same. Stopping criterion for the optimization process is maximum run of the iteration. To observe the optimization process in a critical way, the standard deviations of optimized parameters of the regulator along with the values of objective functions are calculated and shown in Table 4. It is observed that high values of standard deviations are obtained in regulator parameters and values of objective functions when optimization process is handled by GSA. Comparatively large values of standard deviations are found in GA and PSO for base load conditions when it is compared with GWO. High values of standard deviation are observed in speed regulation parameters after each run of optimization obtained with GA regulators (J1 and J2). The impact of speed regulation parameters on the dynamic response is shown in Saxena et al. (2012). The lowest values of standard deviations are observed, when the parameters are optimized by GWO. It basically means that in each run of optimization, GWO exhibits precision in computing the parameters. The standard deviation in the values of integral gains for area 1 by J1 and J2 are minimum for GWO (0.012654 and 0.0200); for GA, these values are 0.97 and 0.268; similarly, for GSA, 0.024 and 0.07 and for PSO, 0.02 and 0.08. It can be concluded that regulator setting integral gain observes least variation in numerical values when the parameter is optimized through GWO (J1). The values of standard deviation in objective functions J1 and J2 are lowest for GWO process and highest for GA. The values of standard deviation in objective functions J1 for GA, PSO, GSA, and GWO are 1.76, 0.38, 0.0212, and 0.000978 and for the J2 are 0.013, 0.011, 0.000419, and 0.0000078. It has been observed that the values obtained by GWO are precise and the optimization processes are reliable.
enough for obtaining the regulator design. However, high values of standard deviations in parameters of regulator and in the objective functions (1.76, Table 4) show that the optimization process loses its relevance when it is handled by GA. Figure 11 shows the convergence characteristics of all the optimization algorithms. It can be observed from the figure that GA converges prematurely at 235th iteration; it converges to local minima for the ITAE objective function. The value of the function at this instance is 11.035. In a similar manner, the value of objective function when treated with
PSO is 6.60 and shows the convergence at 256th iteration. Authors found that the optimization process handled by GSA is difficult to converge and time taking; on the other hand, GWO handled the optimization process in a pace and the convergence is faster. It is also worth mentioning here that for this optimization process and for similar run of iterations, the time taken by GA, PSO, and GSA is much more than GWO. This shows the faster convergence of GWO for ITAE functions. It has also been observed that the optimization process by J2 (ISE) is more time-consuming and less accurate.

Table 5 shows the optimization performance of algorithms in terms of average, best, and poor values of objective function J1. For real problems like AGC, the time for evaluation of regulator parameter through optimization process is a critical issue to be addressed. Moreover, the efficacy of the obtained results through dynamic responses is also a major parameter for regulator design. The following section summarizes the major contributions and findings of this work in a conclusive manner.

6. Conclusion

This paper presents an application of recently introduced algorithm, GWO, to find optimal parameters of the AGC regulator. The GWO regulator is employed on a test system of two thermal units connected with a weak tie line of limited capacity for AGC. Following are the major findings of the work:

1. Comparison of the application of two objective functions, namely ISE and ITAE, in optimization process for finding the regulator parameters, under different contingencies, is investigated. Results reveal that ITAE is a better choice to optimize the regulator parameters.

2. Eigenvalue analysis is performed to test the effectiveness of the proposed approach and to compare the results of the proposed approach with the recently published approaches. It is observed that the damping obtained from GWO regulator is more positive as compared with other algorithms.

3. Convergence characteristics of the algorithms are exhibited to monitor the health of algorithms and their flow. It is empirical to judge that GA has a major problem of premature convergence and the time taken by the optimization process is much more in comparison with PSO, GSA, and GWO. GWO shows promising results in terms of overshoot, settling time
obtained from the frequency responses of both areas under different loading cases, standard deviations in regulator’s parameter values, ISE and ITAE values, and optimization performance.

(4) Damping performance is evaluated with different contingencies, load changes, and step disturbances in both areas. PI controller setting obtained through GWO exhibits better dynamic performance and overall low settling time.

Application of other new meta-heuristic algorithms in AGC regulator design on different models of power system considering different renewable energy power sources lays in future scope.

Nomenclature

\( I \) subscript referred to area \( i \) (1,2)

\( \Delta f_i \) frequency deviation in area \( i \) (Hz)

\( \Delta P_{gi} \) incremental generation of area \( i \) (p.u.)

\( \Delta P_{Li} \) incremental load change in area \( i \) (p.u.)

\( ACE_i \) area control error of area \( i \)

\( B_i \) frequency bias parameter of area \( i \)

\( R_i \) speed regulation of the governor of area \( i \) (Hz/p.u.MW)

\( T_{gi} \) time constant of governor of area \( i \) (s)

\( T_{ti} \) time constant of turbine of area \( i \) (s)

\( K_{wi} \) gain of generator and load of area \( i \)

\( T_{wi} \) time constant of generator and load of area \( i \) (s)

\( \Delta P_{tie} \) incremental change in tie line (p.u.)

\( T_{12} \) synchronizing coefficient

\( T \) simulation time (s)

\( \alpha \) alpha wolf

\( \beta \) beta wolf

\( \delta \) delta wolves

\( \omega \) omega wolves

\( t \) current iteration

\( \vec{X}_p \) position vector of the prey

\( \vec{X} \) position vector grey wolf

Supplementary material
Supplementary material for this article can be accessed here http://dx.doi.org/10.1080/23311916.2016.1151612.

Funding
The authors received no direct funding for this research.

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Citation information
Cite this article as: Grey wolf optimizer based regulator design for automatic generation control of interconnected power system, Esha Gupta & Akash Saxena, Cogent Engineering (2016), 3: 1151612.

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