Applied Soft Computing 32 (2015) 286–292

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Using the gray wolf optimizer for solving optimal reactive power dispatch problem

Mohd Herwan Sulaiman[a,*], Zuriani Mustaffa[b], Mohd Rusllim Mohamed[a], Omar Aliman[a]

[a] Faculty of Electrical & Electronics Engineering, Universiti Malaysia Pahang (UMP), 26600 Pekan, Pahang, Malaysia
[b] Faculty of Computer Systems & Software Engineering, Universiti Malaysia Pahang (UMP), 26300 Gambang, Pahang, Malaysia

ARTICLE INFO

Article history:
Received 29 May 2014
Received in revised form
26 November 2014
Accepted 20 March 2015
Available online 8 April 2015

Keywords:
Gray wolf optimizer
Loss minimization
Voltage deviation minimization
Meta-heuristic technique
Optimal reactive power dispatch

ABSTRACT

This paper presents the use of a new meta-heuristic technique namely gray wolf optimizer (GWO) which is inspired from gray wolves' leadership and hunting behaviors to solve optimal reactive power dispatch (ORPD) problem. ORPD problem is a well-known nonlinear optimization problem in power system. GWO is utilized to find the best combination of control variables such as generator voltages, tap changing transformers' ratios as well as the amount of reactive compensation devices so that the loss and voltage deviation minimizations can be achieved. In this paper, two case studies of IEEE 30-bus system and IEEE 118-bus system are used to show the effectiveness of GWO technique compared to other techniques available in literature. The results of this research show that GWO is able to achieve less power loss and voltage deviation than those determined by other techniques.

1. Introduction

Electrical power system is such a complex network which mainly consists of generation, transmission and distribution network to supply the electricity to variety of load demands. It is expected to operate at minimum consumption of resources, thus giving maximum security and reliability. In recent developments on power system research, optimal reactive power dispatch (ORPD) has received an ever-increasing interest, in particularly from the electric utilities due to its significant influence on the security and economic operation issues. ORPD can be categorized as a sub problem of the optimal power flow (OPF) calculations. ORPD is one of the important nonlinear problems in power system which includes continuous and discrete control variables which satisfying both equality and inequality constraints. In order to determine minimum loss in a system, several main variables need to be controlled and set accordingly such as the voltage of generator buses, the value of shunt reactive elements and transformer tap setting.

Years back from [1–4], the ORPD problems had been discussed and later been solved by applying numbers of classical methods or techniques such as linear and non-linear programming, quadratic programming as well as Newton method of solutions. Compare to classical methods, recent development in meta-heuristic application techniques have given vast choices which producing better results in solving ORPD problem. As a summary, meta-heuristic techniques can be broken down into three categories which are based on swarm intelligence (SI), evolutionary computation (EC) and physics-based [5]. For SI, particle swarm optimization (PSO) [6,7] and artificial bee colony (ABC) [8] together with the variants of honey bee mating optimization (HBO) [9] have been applied in solving ORPD. Refs. [10–15] are the techniques that have been used to solve ORPD fall under EC category while harmony search algorithm (HSA) [16] and improved HSA [17] as well as gravitational search algorithm (GSA) [18,19] are the techniques based on the physics approach. There are also efforts to solve ORPD using hybrid techniques such as hybrid differential evolution with ant system [20] and hybrid of modified imperialist competitive algorithm with invasive weed optimization (MICA-IWO) [21].

This paper proposes the use of a new meta-heuristic technique based on the SI approach called gray wolf optimizer (GWO) in order to solve ORPD problem. This technique has been proposed by [5] which mimic the hunting behavior of gray wolves. The organization of this paper is as follows: Section 2 discusses the problem formulation of ORPD while brief description of GWO technique is presented in Section 3. It is followed by ORPD implementation in solving ORPD problem in Section 4. Section 5 presents the simulation results and discussion. Finally, Section 6 states the conclusion of this paper.

* Corresponding author. Tel.: +60 9 4246140; fax: +60 9 4246111.
E-mail addresses: herwan@ump.edu.my, mherwan@ieee.org (M.H. Sulaiman).

http://dx.doi.org/10.1016/j.asoc.2015.03.041
1568-4946/

2. ORPD problem formulation

The basis of formulating ORPD problem can be first described as follows:

Minimize $f(x, u)$

$$\text{s.t} \begin{matrix} g(x,u)=0 \\ h(x,u)\leq 0 \end{matrix} \tag{1}$$

where the function of $f(x, u)$ is the objective function, $g(x, u) = 0$ is the equality constraint, $h(x, u) \leq 0$ is the inequality constraint, x is the vector of dependent variables and u is the vector of control variables. In this paper, the objective function to be minimized is the total transmission loss, F_1 and voltage deviation at load buses, F_2 expressed as follow [16]:

$$F_1 = P_{\text{Loss}}(x,u) = \sum_{L=1}^{Nl} P_{\text{Loss}} \tag{2}$$

$$F_2 = VD(x,u) = \sum_{i=1}^{Nd} \left| V_i - V_i^{sp} \right| \tag{3}$$

where Nl is the number of transmission lines, V_i is the voltage at load bus-i, V_i^{sp} is the specified value which is usually set to 1.0 p.u and Nd is the number of load buses.

The equality constraint equations suggested in [16] are still valid to give the power balanced of load flow, as follows:

$$P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \tag{4}$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j \in N_i} V_j (B_{ij} \cos \theta_{ij} - G_{ij} \sin \theta_{ij}) \tag{5}$$

On the other hand, the inequality constraints can be represented in terms of operating constraints, as follow:

- Generator constraints: Real and reactive power generation as well as generation bus voltages are restricted by their upper and lower limits, as follow:

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad i = 1, \ldots, N_G \tag{6}$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad i = 1, \ldots, N_G \tag{7}$$

$$V_{Gi}^{\min} \leq V_{Gi} \leq V_{Gi}^{\max} \quad i = 1, \ldots, N_G \tag{8}$$

where N_G is the number of generators.

- Transformer tap setting is restricted by their lower and upper limits, as follows:

$$T_i^{\min} \leq T_i \leq T_i^{\max} \quad i = 1, \ldots, N_T \tag{9}$$

where N_T is the of transformers.

- Reactive compensators (Shunt VARs) are restricted by their limits as follows:

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max} \quad i = 1, \ldots, N_C \tag{10}$$

where N_C is the number of the shunt compensators.

It is vital to highlight that in this paper, a different approach has been taken in order to obtain the objective function. To ensure the accurate result of total transmission loss and no violation of the constraints can be achieved smoothly, load flow program by MATPOWER software package [22] is used to assist the analysis.

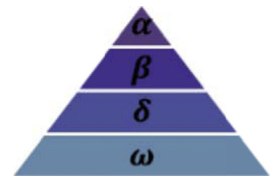

Fig. 1. Hierarchy of gray wolves [5].

3. Gray wolf optimizer (GWO)

gray wolf optimizer (GWO) was first introduced by [5]. As a new swarm intelligence (SI) technique, the GWO has been proven to be competitive with the other remarkable optimization algorithm which includes gravitational search algorithm (GSA), differential evolution (DE) and many others. In nature, gray wolf (*Canis lupus*) belongs to Canidae family. It is considered as a top level of predators and residing at the top in the food chain. They live in a pack which consists of 5–12 wolves on average. In the group, strict dominant hierarchy is practised where the pack is leads by the alphas, followed by the beta which is the subordinate wolves that responsible to assist the alpha in decision making.

The beta reinforces the alpha's commands throughout the pack and gives feedback to the alpha. Meanwhile, the lowest ranking of gray wolves is called omega which commonly plays the role of scapegoat. They also are the last wolves that allowed eating the prey. If a wolf is not alpha, beta and omega, he or she is called a delta. The role of delta wolves are as scouts, sentinels, elders, hunters and caretakers. The hierarchy of gray wolves is depicted in Fig. 1. The steps of GWO which are social hierarchy, tracking, encircling and attacking prey are presented in the next sub-section.

3.1. Mathematical modeling

As to model the GWO algorithm, the fittest solution can be described as the alpha (α) followed by the second and third best solutions as beta (β) and delta (δ), respectively. Meanwhile, the rest of the candidate solutions are considered as omega (ω). GWO has set the hunting (optimization) is guided by α, β and δ while the ω wolves just following them.

When the wolves do hunting, they tend to encircle their prey. The following equations depicted the encircling behavior [5]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \tag{11}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{12}$$

where t is the current iteration, $\vec{X}$ is the position vector of gray wolf, $\vec{X}_p$ is the position of the prey and $\vec{A}$ and $\vec{C}$ are coefficient vectors calculated using the following expressions [5]:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{13}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{14}$$

where r_1 and r_2 are random vectors between 0 and 1 and $\vec{a}$ is set to decreased from 2 to 0 over the course of iterations.

The three best solutions so far are saved and then the other search agents (omega wolves) update their positions according to the current best position. These situations are expressed in the following expressions:

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right|, \quad \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right|, \quad \vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \tag{15}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{X}_\alpha), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{X}_\beta), \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{X}_\delta) \tag{16}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{17}$$