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SOLVING OPTIMAL REACTIVE POWER PLANNING PROBLEM UTILIZING NATURE INSPIRED COMPUTING TECHNIQUES

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ABSTRACT

This paper presents the application of recent nature inspired computing (NIC) techniques in solving the Optimal Reactive Power Dispatch (ORPD) problem. As been known, ORPD is a well-known nonlinear optimization problem in power system operation and planning. In order to obtain the best combination of control variables such as generator voltages, tap changing transformers' ratios and the amount of reactive compensation devices, optimization approach need to be done so that the loss minimization as objective function can be achieved. In this paper, four NIC techniques namely Cuckoo Search Algorithm (CSA), Grey Wolf Optimizer (GWO), Gravitational Search Algorithm (GSA) and Firefly Algorithm (FA) have been applied into ORPD problem. The quality of each technique in obtaining the combination of control variables is tested on IEEE 57- bus system.

Keywords: loss minimization, nature inspired computing techniques, optimal reactive power dispatch.

INTRODUCTION

Power system is one of the most complex systems invented by human. It is a complex network consists of generation, transmission and distribution to supply the electricity to load demand. In power system operation research, Optimal Reactive Power Dispatch (ORPD) emerged as one of the active researches due to its significant impact to the security and economic operation issues. ORPD can be categorized as a sub problem of Optimal Power Flow (OPF) calculations which includes continuous and discrete control variables such as generator voltages, reactive compensation elements and transformer tap setting.

In order to solve ORPD, a lot of techniques have been proposed especially based on the Nature Inspired Computation (NIC) techniques such as Particle Swarm Optimisation (PSO) [1, 2], Artificial Bee Colony Algorithm (ABC) [3], Grey Wolf Optimizer (GWO) [4], Genetic Algorithm (GA) [5], Harmony Search Algorithm (HSA) [6], Gravitational Search Algorithm (GSA) [7], Firefly Algorithm (FA) [8] and many more. It can be said that all these techniques have their own merits and demerits in solving the OPD problem.

This paper proposes a comparative study of NIC techniques in solving ORPD problem. Four NIC techniques viz. Cuckoo Search Algorithm (CSA), GWO, GSA and FA are utilized to solve ORPD and the performance of each technique will be demonstrated and presented.

ORPD PROBLEM

This paper focuses on the loss minimization by ORPD which is depicted as follows:

Minimize $f(x,u)$

$$\text{s.t} \quad \begin{aligned} g(x,u) &= 0 \\ h(x,u) &\le 0 \end{aligned} \tag{1}$$

where $g(x, u) = 0$ is the equality constraint, $h(x, u) \le 0$ is the inequality constraint, x is the vector of dependent variables, u is the vector of control variables and the function of $f(x, u)$ is the objective function which is expressed as follows:

$$\min f(x,u) = P_{Loss}(x,u) = \sum_{L=1}^{NL} P_L \tag{2}$$

where P_L is the real power loss at line-L and NL is the total of transmission lines. The equality constraint is the power balanced equation of load flow, as expressed as follows [9]:

$$P_{Gi} - P_{Di} = V_i \sum_{j \in N_i} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) \tag{3}$$

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

where P_{Gi} is the real power generation at bus i, P_{Di} is the real demand at bus i, Q_{Gi} is the reactive power generation at bus i, Q_{Di} is the reactive demand at bus i, V_i is the voltage magnitude of ith bus, G_{ij} and B_{ij} are the conductance and susceptance of the transmission line i-j, and θ_{ij} is the angle difference of i-jth transmission line.

The inequality constraints in solving ORPD can be represented in terms of operating constraints, as follow:

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

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad i = 1, \ldots, N_G \tag{5}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i = 1, \ldots, N_G \tag{6}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad i = 1, \ldots, N_G \tag{7}$$

where N_G is the number of generators.

- Transformer tap setting are bounded by their lower and upper limits, as follows:

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad i = 1, \ldots, N_T \tag{8}$$

where N_T is the of transformers.

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

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \qquad i = 1, \ldots, N_C \tag{9}$$

where N_C is the number of the shunt compensators.

It this paper, a different approach has been done in evaluating the objective function where the load flow program (MATPOWER software package) [10] has been used to calculate the total transmission loss. This is to ensure the accurate result of total transmission loss generation and no violation of the constraints.

NIC TECHNIQUE #1: CSA

CSA is one of the recent nature-inspired meta-heuristics techniques proposed by [11] in 2009. The technique is based on the parasitic behavior of Cuckoo birds in reproduction strategy. The introduction of Levy flight that integrates with the Cuckoo's behavior make this algorithm superior compared to other swarm intelligence techniques such as PSO, GA and others [11].

In general, CSA consists of two main operations: i) a direct search based on Levy flights and ii) a random search by the probability for a host bird to discover an alien egg in its nest. In this technique, each nest represents a solution and a population of nest is utilized to search the best solution of the optimization problem. The steps of the CSA can be summarized as follows:

Initialization

Similar with other meta-heuristics algorithms, the initialization process includes a set of population, X in random as following:

$$X_{i,j} \sim U(low_j, up_j) \text{ for } i=1,2..,N \text{ and } j=1,2..,,D \tag{10}$$

where N, D and U are the population size, the dimension of variables to be optimized and uniform distribution, respectively.

Generation of new solution via Levy flights

The new candidate for solution is calculated based on the previous best nest using Levy flights. In this algorithm, the optimal path is obtained as follows [11]:

$$X_{i,new} = Xbest_i + \alpha \times randn_1 \times \Delta X_{i,new} \tag{11}$$

where $\alpha > 0$ is the updated step size and $randn_1$ is a normal distributed stochastic number. $\Delta X_{i,new}$ is obtained from the expression below:

$$\Delta X_{i,new} = \left[\frac{randn_2}{\left|randn_3\right|^{1/\beta}} \right] \times \sigma_x(\beta) / \sigma_y(\beta) \times \left(Xbest_i - Gbest \right) \tag{12}$$

where $randn_2$ and $randn_3$ are two normally distributed stochastic variables. $\sigma_x(\beta)$ and $\sigma_y(\beta)$ are standard deviation expressed as follow:

$$\sigma_x(\beta) = \left[\Gamma(1+\beta) \times \frac{\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{\pi\beta}{2}\right)} \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)} \right]^{\frac{1}{\beta}} \tag{13}$$

$$\sigma_y(\beta) = 1 \tag{14}$$

where β is the distribution factor and $\Gamma(.)$ is the gamma distribution function.

Discovery of alien egg and perform randomization

In this stage, the action of alien egg discovery in a nest of a host bird with the probability of p_a will create a new solution similar to the Levy flight, as shown in the following expression:

$$X_{i,disc} = Xbest_i + K \times \Delta X_{i,disc} \tag{15}$$

where K is the updated coefficient determined based on the probability of a host bird to discover an alien egg in its nest, as follows:

$$K = \begin{cases} 1 & if \quad rand() < p_a \\ 0 & otherwise \end{cases} \tag{16}$$

The increment of $\Delta X_{i,disc}$ as shown in the following expression:

$$\Delta X_{i,disc} = rand() \times \left[randp_1(Xbest_i) - randp2(Xbest_i) \right] \tag{17}$$

where rand() is the distributed random number between [0,1], $randp_1$ and $randp_2$ are the random perturbation for position of nests in $Xbest_i$.

NIC # 2: GWO

Grey Wolf Optimizer (GWO) was first introduced by [12]. As a new NIC 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, Grey 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 grey 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 grey wolves is depicted in Figure-1. The steps of GWO which is social hierarchy, tracking, encircling and attacking prey are presented in the next sub-section.

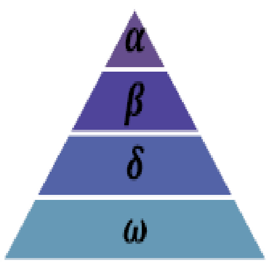

Figure-1. Hierarchy of grey wolves [12].

NIC TECHNIQE #3: GSA

Gravitational Search Algorithm (GSA) is one of the recent NIC techniques where the technique is based on the Newton's Law of gravity and Law of the motion proposed by Rashedi *et al.* in 2009 [13]. GSA has been applied in numerous research fields due to the advantages of memory-less algorithm, adaptive learning rate and said to be faster convergence compared to other techniques. In GSA, agents are considered as objects and their performance are measured by their masses. The attractions among agents are based on gravity force and this force causes global movement of all objects towards the object with heavier masses. The heavier masses represent the corresponding of food solutions and move slower compared to lighter one which is guarantees the exploitation of the algorithm.

There are four specifications of each mass agent viz. position, inertial mass, active gravitational mass and finally passive gravitational mass. The solution of the problem is defined as the position of the mass and the objective function are based on the gravitational and inertial masses. The optimum solution is obtained when the masses attracted by the heaviest mass. In general, the GSA obeys the Newtonian laws of gravity and motion. The general steps of GSA are presented in Figure-2.

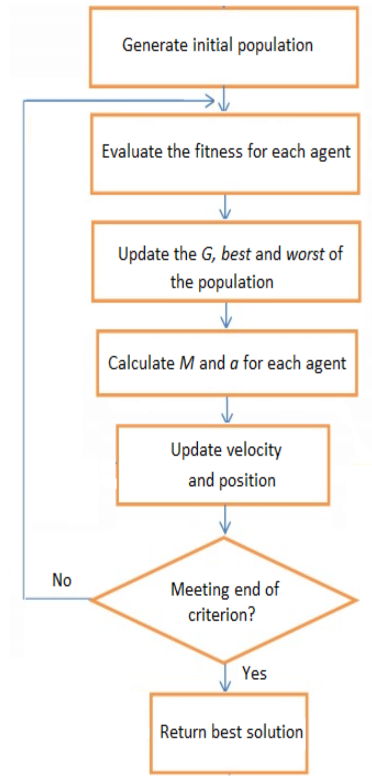

Figure-2. General steps of GSA.

NIC # 4: FA

Firefly Algorithm (FA) is invented by Yang *et al.* [11] for solving optimization problem. The development of FA is based on flashing behavior of fireflies. There are about two thousand firefly species where the flashes often unique for a particular species. The flashing light is produced by a process of bioluminescence where the exact functions of such signaling systems are still on debating. Nevertheless, two fundamental functions of such flashes are to attract mating partners (communication) and to attract potential prey.

For simplicity, the following three ideal rules are introduced in FA development [11]: i) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex, ii) attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one and iii) the brightness of a firefly is affected by the landscape of the objective function. For maximization problem, the brightness can simply be proportional to the value of the objective or fitness function. The basic steps of the FA can be summarized as the pseudo code which is depicted in Figure-3 [11].

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Lévy-Flight Firefly Algorithm
begin
  Objective function f(x),     x = (x_1, ..., x_d)^T
  Generate initial population of fireflies x_i (i = 1, 2, ..., n)
  Light intensity I_i at x_i is determined by f(x_i)
  Define light absorption coefficient γ
  while (t < MaxGeneration)
  for i = 1 : n all n fireflies
    for j = 1 : i all n fireflies
        if (I_j > I_i)
        Move firefly i towards j in d-dimension via Lévy flights
        end if
        Attractiveness varies with distance r via exp[−γr]
        Evaluate new solutions and update light intensity
    end for j
  end for i
  Rank the fireflies and find the current best
  end while
  Postprocess results and visualization
end
```

Figure-3. Pseudo code of the FA.

SOLVING ORPD PROBLEM

This section discusses the implementation of four NIC techniques which have been discussed in the last section into solving the ORPD problem. The implementation of the NIC techniques includes the finding of the optimal values of control variables which is the aim is to minimize the objective function while fulfilling all the constraints mentioned previously. Initially, the number of candidate of solution and the maximum iteration are set. The vector of population can be expressed as follows:

$$X = \begin{bmatrix} x_1^1 & \cdots & x_n^1 \\ \vdots & \ddots & \vdots \\ x_1^p & \cdots & x_n^p \end{bmatrix} \tag{18}$$

where n is the number of control variables and p is the number of population.

In order to find the objective function (evaluation process), each initial solution is mapped into the load flow data and load flow program is executed to obtain the loss. As been pointed out at the beginning of the section in this paper, the objective function is the total transmission losses minimization generated by the load flow program and the best so far result is stored and recorded. The steps of the in solving the ORPD by all NIC techniques is depicted in Figure-4.

From this figure, it can be seen that it is started by generating the random solution using the (18) and then all NIC techniques follow the similar steps in obtaining the optimal combination of variables that are consists of the voltage magnitude of generators, transformer tap setting as well as reactive compensation elements in order to achieve the minimum loss in the system.

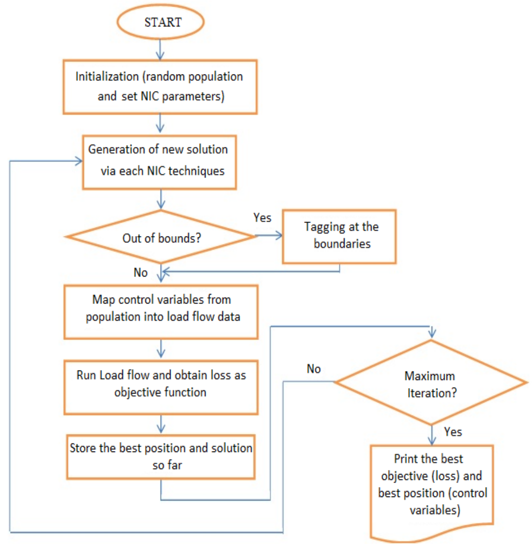

Figure-4. General flow for ORPD solution using NIC techniques: CSA, GWO, GSA and FA

RESULTS AND DISCUSSION

All four NIC techniques have been tested and implemented on IEEE-57 bus system. This system consists of 7 generators, 15 transformers and 3 reactive elements which is sum of 25 control variables. The system is depicted in Figure-5.

The setting for minimum and maximum boundaries for transformer's tap setting, reactive compensation devices and generators voltages are tabulated in Table-1. For this case study, real and reactive power demands are set to 1250.8 MW and 336.4 MVar respectively.

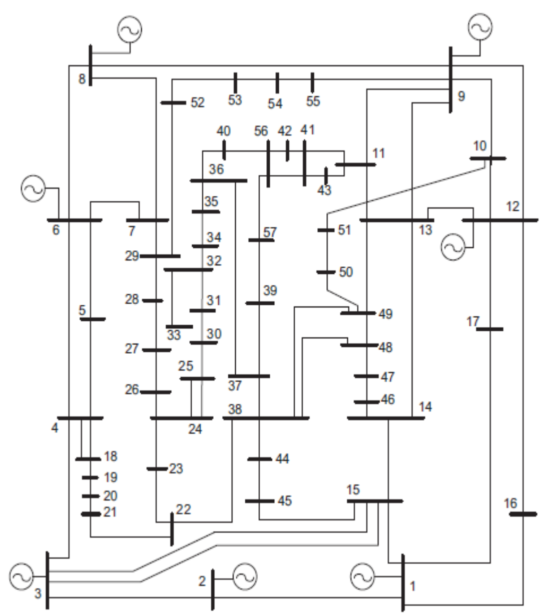

Figure-5. IEEE-57 bus system [6].

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Table-1. Limit setting for control variables.

Variables	Lower limit	Upper limit
Voltages	0.94 p.u	1.06 p.u
Tap setting	0.9 p.u	1.1 p.u
Q_{c18}	0 Mvar	10MVar
Q_{c25}	0 Mvar	5.9MVar
Q_{c53}	0 Mvar	6.3MVar

In this paper, the population size of all NIC techniques are set to 30 and the maximum iteration is set to 300. The details parameter setting for each NIC techniques is set as follows:
CSA: the parameter for alien eggs discovery, *pa* is set to 0.35
GWO: no parameter need to be set.
GSA: the parameter *RNorm* is set to 2
FA: parameters α = 0.5, βmin =0.2 and γ = 1.

The best results obtained by all NIC techniques are tabulated in Table-2. From this table, it can be noted that the optimise results of control variables obtained by CSA produces the lowest power loss among all techniques which is 24.2619 MW. It is about 2%, 0.95% and 0.81% of power loss reduction compared to GWO, GSA and FA respectively. It also can be noted that the results obtained by all NIC techniques are not violate the lower and upper limits of the variables depicted in Table-1.

Table-2. Results of control variables after optimization by CSA, GWO, GSA and FA.

Variables	CSA	GWO	GSA	FA
V_{G1}	1.0600	1.0600	1.0600	1.0600
V_{G2}	1.0582	1.0562	1.0582	1.0572
V_{G3}	1.0466	1.0370	1.0462	1.0428
V_{G6}	1.0409	1.0202	1.0391	1.0366
V_{G8}	1.0587	1.0449	1.0600	1.0541
V_{G9}	1.0417	1.0294	1.0432	1.0355
V_{G12}	1.0377	1.0319	1.0379	1.0320
T_{4-18}	0.9440	0.9847	0.9054	0.9312
T_{4-18}	1.0182	0.9326	0.9978	0.9901
T_{21-20}	1.0207	0.9576	1.0021	0.9845
T_{24-26}	1.0110	0.9968	1.0180	1.0112
T_{7-29}	0.9744	0.9636	0.9712	0.9683
T_{34-32}	0.9721	0.9812	0.9692	0.9657
T_{11-41}	0.9015	1.0621	0.9683	0.9762
T_{15-45}	0.9723	0.9755	0.9717	0.9653
T_{14-46}	0.9537	0.9639	0.9530	0.9524
T_{10-51}	0.9664	0.9723	0.9691	0.9671
T_{13-49}	0.9269	0.9248	0.9242	0.9291
T_{11-43}	0.9645	0.9554	1.0387	1.0020
T_{40-56}	0.9943	1.1000	1.0497	1.0224
T_{39-57}	0.9737	0.9976	1.0668	1.0232
T_{9-55}	0.9750	0.9845	0.9807	0.9687
Q_{C18}	9.2807	1.8917	0.1863	4.1934
Q_{C25}	5.8943	5.2489	4.0488	4.2297
Q_{C53}	6.2885	5.1513	4.8099	5.9252
Loss	**24.2619**	**24.7523**	**24.4922**	**24.4587**

To show the performance of all NIC techniques, the convergence performance for the best result obtained of these techniques are plotted and exhibit in **Figure-6**. It can be seen that CSA and FA produce fast convergence compared to the other two techniques: GSA and GWO. However, it can be noted that CSA finally converged to the minimum of the total loss compared to the other methods. It is also worth to highlight that CSA and GSA has only one control parameter compared to FA which has 3 control parameters. On the other hand, for GWO, no parameters need to be preset. This will make GWO, CSA and GSA superior in term of simplicity of tuning the parameter in order to obtain good results compared to FA. Nevertheless, in this paper, CSA gives the best results followed by FA, GSA and lastly GWO.

Figure-7 shows the performance of CSA, GWO, GSA and FA for 30 free running of simulations. It can be seen that the results obtained by CSA is consistent and the best compared to GWO, GSA and FA. Thus, it can be said that in this comparison studies for solving ORPD problem, CSA emerged as a robust and superior technique compared to the GWO, GSA and FA.

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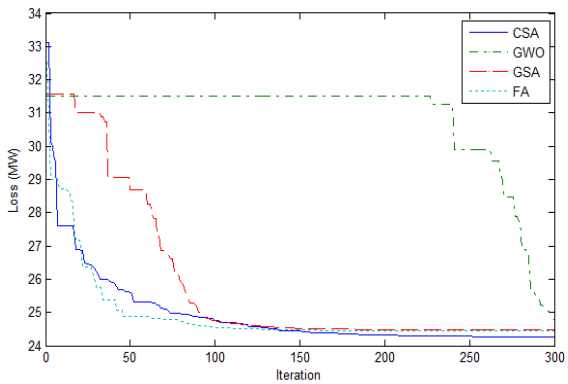

Figure-6. Convergence of characteristic for the best results of CSA, GWO, GSA and FA.

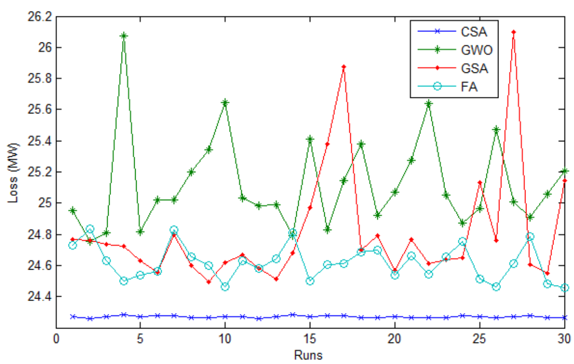

Figure-7. Performance of CSA, GWO, GSA and FA for 30 free running of simulations

CONCLUSIONS

This paper has proposed comparative study of recent NIC techniques: Cuckoo Search Algorithm, Grey Wolf Optimizer, Gravitational Search Algorithm and Firefly Algorithm in solving the ORPD problem. The effectiveness of all NIC techniques was evaluated using IEEE-57 bus system. From the simulation studies that have been conducted, it shows that CSA emerged as the best technique compared to others in terms of obtaining the minimum power loss and produce the consistent results.

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