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The Optimal Reactive Power Dispatch Using Seeker Optimization Algorithm Based Different Objective Functions

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ABSTRACT

Reactive Power Dispatch is one of the important tasks in the operation and control of power systems. It is a section of optimization problems in power system that minimizes the objective functions by satisfying a set of constraints and using a set of controllable variables. As the Reactive Power Dispatch is a nonlinear problem, it has multiple minima. So the conventional techniques and mathematical programming methods are not suitable to solving these problems. In this paper, the Seeker Optimization Algorithm (SOA) is considered to find a global optimum reactive power dispatch by minimizing the different objective functions. In this work, the objective functions are reducing active power losses, improving voltage deviation and increasing voltage stability. To show efficiency and powerful performance of SOA, it is applied to optimal reactive power dispatch on standard IEEE-30 bus power system. Finally, the obtained results of SOA are compared with Particle Swarm Optimization (PSO) algorithm, Multi Agent Particle Swarm Optimization (MAPSO) and Genetic Algorithm (GA) methods.

KEYWORDS: Reactive Power Dispatch, Seeker Optimization Algorithm, Active Power Loss, Voltage Deviation, Voltage Stability, Optimization Techniques.

I. INTRODUCTION

Optimal Reactive Power Dispatch (ORPD) means controlling regulating equipment to optimize reactive power flow reduce active power and voltage losses and improve voltage quality, to make electric equipments work safely and reliably [1], [2]. It is a sub-problem of the optimal power flow calculation, which adjusts all controllable variables, such as generator voltages, transformer taps, shunt capacitors, shunt inductors, etc, and conducts a given set of physical and operating constraints to minimize transmission losses or other concerned objective functions. It is well-known that the reactive power optimization is a nonlinear and multimodal optimization problem with a mixture of discrete and continuous variables.

Many conventional algorithms and various mathematical programming methods have been proposed to find a global optimum power flow problems. But, these techniques have many limitations in handling nonlinear, discontinuous functions and constraints.

One of the optimization techniques used to optimal reactive power dispatch (ORPD) is Genetic Algorithm (GA) method. The study of genetic algorithms began in 1970[3].These algorithms simulate the natural selection mechanism, where the chromosomes of the engineering problem are the set of its independent variables. The healthiest individual transcends their genes into the next generation so that the new population is better adapted to the environment. Likewise, the independent variables are optimized so that they lead to a better solution of the problem [4]. Nowadays, there are many engineering fields where they are employed.

Kennedy and Eberhart [5] proposed a swarm-intelligence based parallel optimization algorithm, Particle Swarm Optimization (PSO) in 1995. PSO shows a realistic performance on pattern classification, optimization and controller parameters design [6], [14].

One of the common optimization methods is Multi Agent- based Particle Swarm Optimization (MAPSO) that is used to solve the optimization problems. In MAPSO, an agent represents not only a candidate solution to the optimization problem but also a particle to PSO. Firstly, a lattice-like environment is constructed, with each agent fixed on a lattice-point. In order to obtain optimal solution quickly, each agent competes and cooperates with their neighbors, and they can also use knowledge to obtain high-quality optimal solution by self-learning. Making use of evolution mechanism of PSO, it can speed up the transfer of information among agents, and the proposed MAPSO method can realize the purpose of optimizing the value of objective function [13],[12].

Recently, a new population-based heuristic search algorithm is Seeker Optimization Algorithm (SOA). In this purposed method, it regards optimization process as a search of optimal solution by a seeker population. The algorithm herein is the continuation of work previously published in [7].

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In this paper the Seeker Optimization Algorithm (SOA) has employed to optimal reactive power dispatch is applied on standard IEEE-30 bus power system. In this problem, the controllable variables are voltage of generators, transformer taps, sources of reactive power compensation such as capacitors and inductors. Also, the objective functions are reducing active power losses, improving voltage deviation and increasing voltage stability. The main optimization technique originally proposed in this work is the Seeker Optimization Algorithm (SOA). Also, different optimization techniques are applied to these power systems. To show the efficiency of SOA to finding the global optimum reactive power dispatch, the results of SOA are compared with PSO, MAPSO and GA methods.

As to organization of this paper: Section II indicates the formulation problems and cost functions. Section III explains the Seeker Optimization Algorithm (SOA) and implementation of SOA for optimal reactive power dispatch. In Section IV, the SOA, PSO, MAPSO and GA are applied to standard IEEE-30 bus power systems and the results are compared to each other.

II. PROBLEM FORMULATION

In this paper, to obtain the optimal reactive power dispatch (ORPD), three cost functions are considered which include the technical and economic goals. The technical goals are to minimize the load bus voltage deviation from the ideal voltage and to improve the voltage stability margin (VSM) [9]. Hence, the objectives of the optimal reactive power dispatch model in this paper are active power loss (P_{loss}), voltage deviation (ΔV_L) and voltage stability margin (VSM).

A. The Active Power Loss

The active power loss minimization in the transmission network can be defined as follows, [10], [11]:

$$f_1 = P_{loss} = \sum_{k=1}^{N} g_k[(V_i^2 + V_j^2 - 2V_iV_j cos\theta_{ij})] \qquad (1)$$

where the θ_{ij} is the voltage angle difference between bus i and j, V_i and V_j are the voltage of i and j, g_k Conductance of branch k.

B. Voltage Deviations

Treating the bus voltage limits as constraints in often results in all the voltages toward their boundary limits after optimization, which means the power system lacks the required reserves to provide reactive power during contingencies. One of the effective ways to avoid this situation is to choose the deviation of voltage from the desired value as an objective function [10],

$$f_2 = \Delta V_L = \sum_{i=1}^{N_L} |V_i - V_i^*| \qquad (2)$$

where f_2 is the sum of voltage deviations and the N_L is the number of buses in power system. Also the V_i, V_i^* are the actual voltage magnitude and desired voltage magnitude at bus i th.

C. Voltage Stability Margin

Voltage stability problem has a close relationship with the reactive power of the system, and the voltage stability margin is inevitably affected in optimal reactive power flow (ORPF) [9]. Hence, the maximal voltage stability margin should be one of the objectives in ORPF [11], [12], [9]. For example, in two bus power system shown in Fig. 1, voltage stability margin for bus i th can be evaluated as follows [15]:

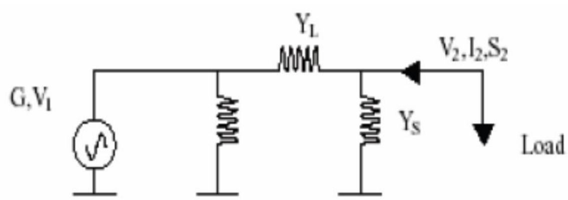

Figure 1. The two bus power system

By using the Kirchhoff Current Low (KCL) in Fig.1:

$$I_2 = \overrightarrow{V_2}\overrightarrow{Y_S} + (\overrightarrow{V_2} - \overrightarrow{V_1})\overrightarrow{Y_L} = \frac{\overrightarrow{S_2}}{\overrightarrow{V_2}} \qquad (3)$$

Simplify the equation (3), the constraint for occurrence of voltage collapse is obtained as follows:

$$\sqrt{\frac{{V_0}^4}{4} + a{V_0}^2 - b^2} = 0 \qquad (4)$$

where

$$\overrightarrow{Y_{22}} = \overrightarrow{Y_S} + \overrightarrow{Y_L} \quad (5)$$

$$\frac{\overrightarrow{S_2}}{\overrightarrow{Y_{22}}} = a + jb \quad (6)$$

$$\overrightarrow{V_0} = -\frac{\overrightarrow{Y_L}}{\overrightarrow{Y_S}+\overrightarrow{Y_L}}\overrightarrow{V_1} \quad (7)$$

In other word, determinant of Jacobian matrix must be zero:

$$J = \begin{bmatrix} 2|V_2| + |V_0|cos\delta & -|V_0||V_2|sin\delta \\ |V_0|sin\delta & |V_0||V_2|cos\delta \end{bmatrix} \quad (8)$$

So, the voltage stability margin obtained as follows:

$$\left|1 + \frac{\overrightarrow{V_0}}{\overrightarrow{V_2}}\right| = \left|\frac{\overrightarrow{S_2}}{V_{22}^2\overrightarrow{Y_{22}}}\right| = \mathrm{L}_2 \quad (9)$$

Finally, it could be extended for a power system. By using the following equations and above results:

$$\mathrm{I}_{\mathrm{bus}} = Y_{bus} \times V_{bus} \quad (10)$$

$$\begin{bmatrix} I_{\mathrm{G}} \\ I_{\mathrm{L}} \end{bmatrix} = \begin{bmatrix} Y_1 & \mathrm{Y}_2 \\ \mathrm{Y}_3 & \mathrm{Y}_4 \end{bmatrix} \begin{bmatrix} \mathrm{V}_{\mathrm{G}} \\ \mathrm{V}_{\mathrm{L}} \end{bmatrix} \quad (11)$$

$$\begin{bmatrix} I_G \\ V_L \end{bmatrix} = \begin{bmatrix} H_1 & H_2 \\ H_3 & H_4 \end{bmatrix} \begin{bmatrix} V_G \\ I_L \end{bmatrix} \quad (12)$$

where $\mathrm{I_L}$, $\mathrm{V_L}$ are current and voltage of load buses and $\mathrm{I_G}$, $\mathrm{V_G}$ are current and voltage of voltage controlled buses respectively. By using equations (11) and (12)

$$H_3 = -{Y_4}^{-1} \times Y_3 \quad (13)$$

So, the voltage of voltage controlled bus *j* th evaluated as follows:

$$V_{0j} = \sum_{i\in G} H_{3ki} V_i \quad (14)$$

where *G* is the number of generator buses. Finally the voltage stability margin of each bus calculated as follows:

$$\mathrm{L_j} = \left|1 + \frac{\mathrm{V_{0j}}}{\mathrm{V_j}}\right| \quad (15)$$

where the $\mathrm{V_j}$ is the voltage of *j* th bus .In this work, we consider the global voltage stability margin for whole of power system as follows:

$$f_3 = L = \max(L_j) \quad (16)$$

D. Equality and Inequality constraints in Optimal Reactive Power Dispatch Problem

The ORPD has the many equality and inequality constraints to finding the global optimum reactive power dispatch. In this paper, constraints that are considered in ORPD, subjected as follows:

$$P_{Gi} - P_{Di} = V_i \sum_{j\in N_i} V_j \left(G_{ij}cos\theta_{ij} + B_{ij}sin\theta_{ij}\right) \quad (16)$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j\in N_i} V_j \left(B_{ij}cos\theta_{ij} - G_{ij}sin\theta_{ij}\right) \quad (17)$$

$$\mathrm{V}_{\mathrm{G_{i\,min}}} \le \mathrm{V}_{\mathrm{G_i}} \le \mathrm{V}_{\mathrm{G_{i\,max}}} i = 1, \dots N_G \quad (18)$$

$$\mathrm{Q}_{\mathrm{G_{i\,min}}} \le \mathrm{Q}_{\mathrm{G_i}} \le \mathrm{Q}_{\mathrm{G_{i\,max}}} i = 1, \dots N_G \quad (19)$$

$$\mathrm{Q}_{\mathrm{C_{i\,min}}} \le \mathrm{Q}_{\mathrm{C_i}} \le \mathrm{Q}_{\mathrm{C_{i\,max}}} i = 1, \dots N_C \quad (20)$$

$$\mathrm{T}_{\mathrm{i\,min}} \le \mathrm{T}_{\mathrm{i}} \le \mathrm{T}_{\mathrm{i\,max}} i = 1, \dots N_T \quad (21)$$

$$\mathrm{V}_{\mathrm{L_{i\,min}}} \le \mathrm{V}_{\mathrm{L_i}} \le \mathrm{V}_{\mathrm{L_{i\,max}}} i = 1, \dots N_L \quad (22)$$

$$\mathrm{S}_{\mathrm{L_i}} < \mathrm{S}_{\mathrm{L_i}}{}^{\max} \mathrm{i} = 1, \dots \mathrm{N_L} \quad (23)$$

where V_G is the generator voltage (continuous), T_k is the transformer tap (integer), Q_C is the shunt capacitor/inductor (integer), V_L is the load-bus voltage, Q_G is the generator reactive power, θ_{ij} is the voltage angle difference between bus *i* and *j* , P_{Gi} is the injected active power at bus *i*, P_{Di} is the demanded active power at bus *i*, V_i is the voltage at bus *i*, G_{ij} is the transfer conductance between bus *i* and *j*, G_{ij} is the transfer susceptance between bus *i* and *j*, Q_{Gi} is the injected reactive power at bus *i* , Q_{Di} is the demanded reactive power at bus *i* , N_i is the set of numbers of buses adjacent to bus (including bus *i*), N_C is the set of numbers of possible reactive power source installation buses, N_G is the set of numbers of generator buses, N_T is the set of numbers of transformer branches, N_L is the number of load buses, S_l is the power flow in branch l, the superscripts "min" and "max" in above constraints denote the corresponding lower and upper limits, respectively.

The first two equality constraints in (16) and (17) are the power flow equations. The rest inequality constraints are used for the restrictions of reactive power source installation, reactive generation, transformer tap-setting, and bus voltage and power flow of each branch.

E. Total Cost Function for Optimal Reactive Power Dispatch Problem

In finding the global optimum reactive power dispatch, the control variables are self-constrained, and dependent variables are constrained using penalty terms to the objective function. So, the total cost function is generalized as follows:

$$\min f = f_j + \sum_{i \in N_V^{\lim}} \lambda_{Vi}(V_i - V_i^{\lim}) + \sum_{i \in N_Q^{\lim}} \lambda_{Gi}(Q_{Gi} - Q_{Gi}^{\lim}) \tag{24}$$

where f_j is one of these functions: active power loss, voltage deviation or voltage stability margin. So equation in (24) explains the three different cost functions that is used to ORPD.

III. SEEKER OPTIMIZATION ALGORITHM FOR OPTIMAL REACTIVE POWER DISPATCH

Seeker Optimization Algorithm (SOA) operates on a set of solutions called search population. The individual of this population is called seeker. In order to add a social component for social sharing of information, a neighborhood is defined for each seeker. In the present simulations, the population is randomly categorized into k=3 subpopulations in order to search over several different domains of the search space and all seekers in the same subpopulation constitute a neighborhood. Assume that the optimization problems tobe solved are minimization problems [12].

In the SOA, a search direction $d_{i,j}(t)$ and a step length $\alpha_{i,j}(t)$ are computed separately for each seeker i on each dimension j for each time step t, while $\alpha_{i,j}(t) \geq 0$ and $d_{i,j}(t) \in \{-1,0,1\}$[12].
$d_{i,j}(t) = 1$means that the i th seeker goes towards the positive direction of the coordinate axis on the dimension j.$d_{i,j}(t) = -1$ means the seeker goes towards the negative direction, and $d_{i,j}(t) = 0$ means the seeker stays at the current position. For each seeker i the position update on each dimension is calculated as follows [12]:

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) d_{ij}(t) \qquad 1 \leq i \leq S \qquad 1 \leq j \leq D \tag{25}$$

where S is the population size and D is the size of each seeker. Since the subpopulations are searching using their own information, they are easily to converge to local optimum. In order to avoid this situation, the positions of the worst k-1 seekers of each subpopulation are combined with the best one in each k-1of the other subpopulations as follows [12]:

$$x_{k_n j,worst} = \begin{cases} x_{lj,best} & if\ R_j \leq 0.5 \\ x_{k_n j,worst} & else \end{cases} \tag{26}$$

where

R_j: random real number within [0, 1].

$x_{knj,worst}$: j th dimension of the n th worst position in the k th subpopulation.

$x_{lj,best}$: is the j th dimension of the best position in the l th subpopulation.

And it is true when $\begin{cases} n, k, l = 1,2, \dots, k-1 \\ k \neq l \end{cases}$.

In this way, the good information obtained by each subpopulation is exchanged among the subpopulations and then the diversity of the population is increased. The mechanism of SOA is illustrated in Fig. 2, [12].

a) *Search direction*

The search space may be viewed as a gradient field. A so-called empirical gradient (EG) can be determined by evaluating the response to the position change especially when the objective function is not available in a differentiable form at all, and then the seeker can follow an EG to guide his search. Since the SOA does not involve the magnitude of the EG, search direction can be determined only by the signum function of a better position minus a worse position.

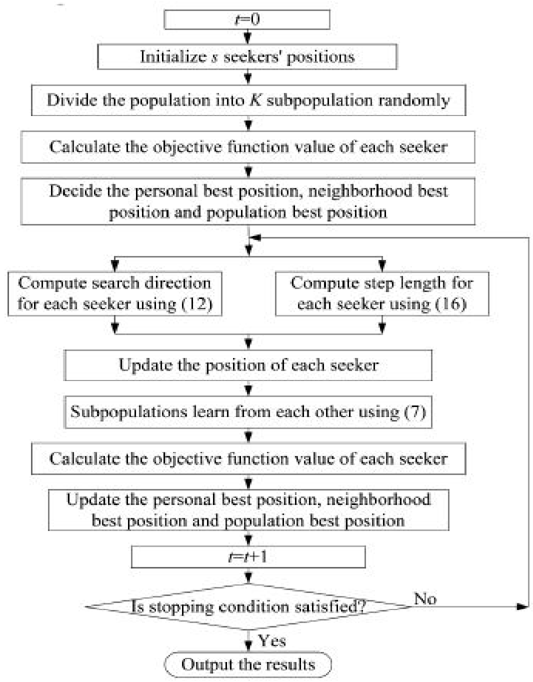

Figure 2.flowchart of SOA

In SOA, each seeker selects his search direction based on several EGs by evaluating the current or historical positions of himself or his neighbors. In this study, the EGs involve egotistic behavior, altruistic behavior and pro-activeness behavior to yield their respective directions as follows [12].

Swarms specialize in mutual cooperation among them in executing their routine needs and roles there are two extreme types of cooperative behavior. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group. Every seeker, as a single sophisticated agent, is uniformly egotistic, believing that he should go toward his historical best position $p_{i,best}(t)$. Then, an EG from $x_i(t)$ to $p_{i,best}(t)$ can be involved where $x_i(t) = [x_{i1}, x_{i2}, \dots, x_{iD}]$ is the position of

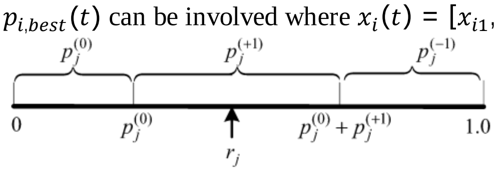

Figure 3.proportional selection rule of search direction

$$\vec{d}_{ij} = \begin{cases} 0 & if\ r_j \le p_j^{(0)} \\ +1 & if\ p_j^{(0)} < r_j \le p_j^{(0)} + p_j^{(+1)} \\ -1 & if\ p_j^{(0)} + p_j^{(+1)} < r_j \le 1 \end{cases} \qquad (27)$$

where r_j is a uniform random number in [0,1] and $p_j^{(m)}(m\epsilon\{0, +1, -1\})$ is the percent of the number of "*m*" from the set [$\vec{d}_{i,ego}(t)$ ، $\vec{d}_{i,alt1}(t)$ ، $\vec{d}_{i,alt2}(t)$ ، $\vec{d}_{i,pro}(t)$] on each dimension of all the four empirical directions, i.e., $p_j^{(m)} = \frac{the\ number\ of\ m}{4}$.

b) Step length

In the continuous search space, there often exists a neighborhood region close to an extremum point. In this region, the fitness values of the input variables are proportional to their distances from the extremum point. It may be assumed that better points are likely to be found in the neighborhood of families of good points, and search should be intensified in regions containing good solutions through focusing search. Hence, from the standpoint on human searching, one may find the near optimal solutions in a narrower neighborhood of the point with lower fitness value and, contrariwise, in a wider neighborhood of the point with higher fitness value [12].

Fuzzy systems arose from the desire to describe complex systems with linguistic descriptions. According to human focusing searching discussed above, the uncertainty reasoning of human searching could be described by natural linguistic variables and a simple control rule as "If *fitness value* is *small* (i.e., the *conditional* part), then *step length* is *short* (i.e., the *action* part)". The understanding and linguistic description of human searching makes fuzzy system a good candidate for simulating human focusing searching behavior [12].

Different optimization problems often have different ranges of fitness values. To design a Fuzzy system to be applicable to a wide range of optimization problems, the fitness values of all the seekers are descendingly sorted and turned into the sequence numbers from 1 to as the inputs of Fuzzy reasoning. The linear membership function is used in the conditional part since the universe of discourse is a given set of numbers, i.e., 1, 2…, *s*. The expression is presented as

$$\mu_i = \mu_{max} - \frac{s - I_i}{s - I}(\mu_{max} - \mu_{min}) \qquad (28)$$

where I_i is the sequence number of $\vec{x_i}(t)$ after sorting the fitness values, μ_{max} is the maximum membership degree value which is equal to or a little less than 1.0. In this study, $\mu_{max} = 0.95$.

In this study, the Bell membership function $\mu(x) = e^{-\frac{x^2}{2\delta^2}}$. is used in the action part (shown in Fig. 4). For the convenience, one dimension is considered. Thus, the membership degree values of the input variables beyond $[-3\delta, 3\delta]$, and $\mu_{min} = 0.0111$, and the elements beyond $[-3\delta, 3\delta]$ in the universe of discourse can be neglected for a linguistic atom. Thus, the minimum value $\mu_{min} = 0.0111$ is set. Moreover, the parameter, $\vec{\delta}$ of the Bell membership function is determined by the following [12]:

$$\vec{\delta} = \omega \,.\, abs(\vec{x}_{best} - \vec{x}_{rand}) \qquad (29)$$

where abs (.)returns an output vector such that each element of the vector is the absolute value of the corresponding element of the input vector. The parameter ω is used to decrease the step length with time step increasing so as to gradually improve the search precision. In the present experiments ω linearly decreased from 0.9 to 0.1 during a run. The $\vec{x}_{best}$ and $\vec{x}_{rand}$ are the best seeker and a randomly selected seeker from the same subpopulation to which the *i* th seeker belongs, respectively. $\vec{x}_{rand}$ is different from $\vec{x}_{best}$, and $\vec{\delta}$ is shared by all the seekers in the same subpopulation.

To introduce the randomicity on each dimension and improve local search capability μ_i is changed into a vector $\vec{\mu_i}$. Then the *action* part of the Fuzzy reasoning gives every dimension j of *step length* by in the following [12]:

$$\mu_{ij} = RAND(\mu_i, 1) \qquad (30)$$

$$\alpha_{ij} = \delta_j \sqrt{-Ln(\mu_{ij})} \qquad (31)$$

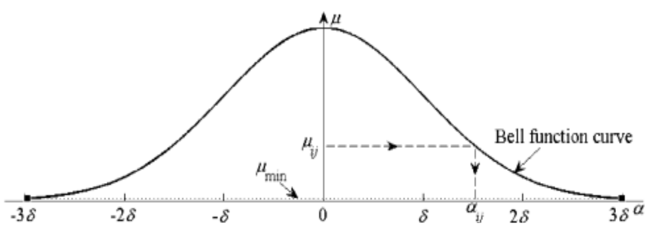

Figure 4. The action part of fuzzy reasoning

IV. CASE STUDIES

To assess the efficiency of suggested method, the SOA is applied to standard IEEE 30 bus with considering the total cost function in equation (24). To verify the obtained results, the GA, PSO and MAPSO are applied to mentioned power system.

By using the total cost function in equation (24) and using the active power loss in transmission network mentioned in (1), the obtained results in 10 trials of different optimization techniques to minimizing the active power loss are shown in Table. I. Fig. 5 illustrates the convergence of different methods to minimizing the active power loss in standard IEEE-30 bus power systems.

TABLEI. The results of different optimization techniques to minimize the active power loss in standard IEEE-30 bus power system

Active Power Loss	GA	PSO	MAPSO	SOA
Best (MW)	4.9382	4.9246	4.8987	4.8974
Worst (MW)	5.1568	5.1077	4.9631	4.9055
Average (MW)	5.0072	4.9776	4.9267	4.8992

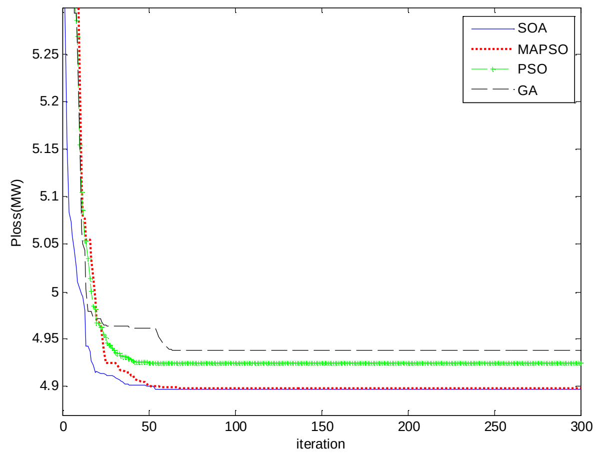

Figure. 5. The convergence of different optimization techniques to minimizing the active power loss

By comparing the results in Table. I, to minimizing the active power loss, although find out that the best results of SOA (i.e. 4.8974 MW) is similar to best obtained result of MAPSO, but the main advantage of SOA is the proximity of average value and best value and the scattering of results in SOA is less than other optimization techniques. Also, by comparing the results in Fig. 5, one can find out that the convergence speed of SOA is more than other methods.

In this case, by using the total cost function in equation (24) and the voltage deviation function mentioned in (2), the results in 10 trials of different optimization methods is obtained and shown in Table. II. Also, The convergence of different methods to minimizing the voltage deviation in standard IEEE-30 bus power system is presented in Fig. 6.

TABLEII. The results of different methods to minimize the voltage deviation

Voltage Deviation	GA	PSO	MAPSO	SOA
Best	0.1504	0.1442	13.01	0.1235
Worst	0.1733	0.1665	0.1526	0.1365
Average	0.1545	0.1501	0.1345	0.1321
Percent Improvement of Voltage Deviation	86.98	87.50	88.72	89.30

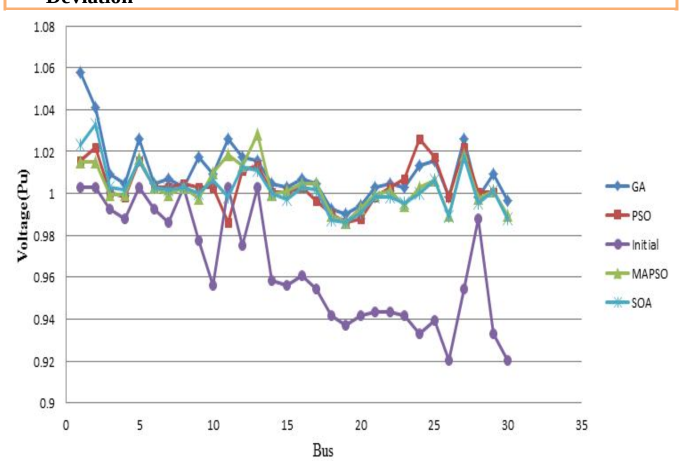

Figure. 6. Voltage profile of standard IEEE-30 bus power system

According to Table. II, by using the SOA to minimizing the voltage deviation, it is reduced to 0.1235. This verifies the advantage of SOA in decreasing of voltage deviation than other optimization techniques.

Finally, by using the total cost function and voltage stability margin function mentioned in (24) and (16), the results of 10 trials to increasing the voltage stability margin of standard IEEE-30 bus power system are obtained and shown in Table.III.

TABLEIII. The results of different optimization method to improving the voltage stability margin

Increasing the Voltage Stability Margin	GA	PSO	MAPSO	SOA
Best	0.1227	0.1217	0.1206	0.1192
Worst	0.1545	0.1328	0.1241	0.1211
Average	0.1343	0.1268	0.1209	0.1204

By using the SOA, L index that mentioned in (16) is improved to the 0.1192. This shows the efficiency of SOA to improve the voltage stability margin due to the correct selecting the search direction and step length. These features cause to not placing the algorithm in local optimum points and obtain the best convergence speed.

V. CONCLUTION

This paper proposed an approach for optimal reactive power dispatch (ORPD). It is well-known that the reactive power optimization is a nonlinear and multimodal optimization problem with a mixture of discrete and continuous variables. So the mathematical methods are not suitable for ORPD. In this paper, the seeker optimization algorithm (SOA) has successfully employed to find a global optimum reactive power dispatch by minimizing the technical and economical objective functions. In this work, the objective functions were reducing active power losses, improving voltage deviation and increasing voltage stability .To show the efficiency and powerful performance of SOA, it has applied on standard IEEE- 30 bus power system. To verify the obtained results, other optimization techniques like PSO, MAPSO and GA were employed. By comparing the results, one can find out that the convergence speed of SOA is more than other methods. Also, it can obtain that the main advantage of SOA is the proximity of average value and best value and the scattering of results in SOA is less than other optimization techniques. Also one can find out the advantage of SOA in decreasing of voltage deviation than other optimization techniques. Also the results show the efficiency of SOA to improve the voltage stability margin due to the correct selecting the search direction and step length. These features cause to not placing the algorithm in local optimum points and obtain the best convergence speed.

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