Improved Group Search Optimization Algorithm for Multi-Objective Optimal Reactive Power Dispatch

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ABSTRACT:
This paper utilizes the improved group search optimization algorithm for optimal reactive power dispatch (ORPD). The ORPD problem is a non-linear, non-convex optimization problem which has various decision variables such as compensation capacitor proportions, voltage of generators and the tap position of tap changing transformers. In this paper the multi-objective ORPD considering loss, voltage deviation and the security index is studied. Due to complicating objectives and also physical and operating constraints, an efficient optimization algorithm is needed. This paper solves the mentioned problem using the group search optimization algorithm (GSO). GSO is one of the novel presented optimization algorithms based on group living and especially searching behavior of animals. In order to improve the algorithm efficiencies, the improved group search optimization algorithm (IGSO) is used. Accordingly, the algorithm would obtain better results due to its ability to find better solutions. Moreover, the penalty factor approach is used in order to solve the multi-objective case.

KEYWORDS: Optimal reactive power dispatch, multi-objective optimization, group search optimization, voltage deviation.

1. INTRODUCTION

The electric power network is known as a hard to manage system due to its large scale and redundant connections established between the components. In order to control such a system efficiently, extensive functions should be implemented [1]. The power flow concept, as a mathematical approach has a significant role in achieving the efficient operation of the power system. The optimal power flow (OPF) could be divided into two main groups including the optimal real power dispatch and the optimal reactive power dispatch [2]. OPF mainly tries to optimize a determined objective as well as considering the physical and operational constraints of the system [3]. In this regard, the ORPD attempts to optimize objectives such as loss or voltage profile by determining optimum proportions for reactive power recourses and other variables [4]. Hence, the ORPD problem would be a non-linear non-convex problem which leads the authors to implement the optimization procedures by heuristic approaches. Within past few years, many researchers interested in OPRD concept due to its appropriate efficiency. Consequently various objectives have been considered for the ORPD problem in the literature. The most well-known objective for reactive power dispatch problem is the transmission loss. In [5], various types of ant colony algorithms are proposed to solve ORPD problem considering the total active loss as the objective. On the other hand, an improved hybrid evolutionary programming technique is used as optimization procedure in [6]. As it was mentioned, the ORPD efficiency is obvious to system operators and also researchers. Consequently studies tend to consider the multi-objective concept for the ORPD problem. In [7], the seeker optimization algorithm is proposed in order to minimize the active power loss in transmission network. On the other hand, minimizing the voltage and reactive power deviations are also considered and penalty factor solution is implemented to adjust the proportions. The outlined problem is also implemented by adaptive genetic algorithm in [8]. Moreover, in [9] a multi agent based particle swarm optimization (PSO) algorithm attempts to minimize the same objectives. In [10] the multi-objective ORPD problem considering loss and voltage deviation is optimized by PSO algorithm. In [11] the strength pareto evolutionary algorithm tries to optimize the active power loss and voltage stability index, simultaneously. The multi-objective based VAR dispatch considering total loss, voltage deviation and also voltage stability is also studied in the literature implementing various algorithms such as gravitational search algorithm (GSA) in [12], harmony search algorithm in [13], fuzzy adaptive PSO algorithm in [14], quasi-oppositional teaching learning based optimization algorithm in [15], opposition based gravitational search algorithm in [16] and the opposition-based self-adaptive modified gravitational search algorithm in [17].

Besides the system loss and stability aspects, the security of power systems is an important issue which should be considered by the system operators. As it was mentioned, various functions are considered as the objectives of ORPD problem. However, the security index is rarely, got investigated. Consequently, the security index besides the combination of mentioned objectives could be considered as the ORPD problem fitness function.

Within past few years, a new evolutionary algorithm known as group search optimization (GSO) algorithm is introduced and implemented for various problems. GSO is known as a fast, robust and easy to implement algorithm [18].The main problem with the GSO algorithm is its getting stuck in local optimal instead of reaching the global one, especially in limited iterations. This weakness could be handled by implementing some modifications. According to the literature, the modified, hybrid, improved and adaptive versions of GSO reached better results in comparison to other algorithms [19], [20], [21] and [22].

In this paper, the improved group search optimization (IGSO) algorithm is implemented to solve the multi-objective ORPD problem. The multi-objective ORPD problem is formed by considering the real transmission loss, voltage deviation and security index as the objectives, simultaneously. The security index incorporates bus voltage violations and transmission lines overloads after the most critical N-1 contingency condition. The proposed method is implement to the IEEE-30 bus test system and the obtained results are compared with the ones available in the literature.

2. PROBLEM FORMULATION

2.1. Active power loss

Power system loss is one of the most important concerns due to its considerable effect on power generation, power transmission and etc. In this paper, active power loss is considered as an objective function as follows:

$$F_{loss} = \sum_{k=1}^{nl} g_k [V_{1,k}^2 - V_{2,k}^2 - 2V_{1,k}V_{2,k}\cos(\theta_{1,k} - \theta_{2,k})] \tag{1}$$

where F_{loss} is the total power loss, *nl* is the number of transmission lines, g_k is conductance of the k^{th} line, $V_{1,k}, V_{2,k}$ are voltage amplitude of two ending buses 1 and 2 of the arbitrary branch k and $\theta_{1,k}, \theta_{2,k}$ are voltage angles of the same buses.

2.2. Voltage deviation

Voltage deviation is another important function in power systems. Electrical equipment are designed to operate efficiently at their nominal voltages. Any deviation from these rated values would result in equipment failure, efficiency decrease and consequently, reduction of electrical equipment life time. Minimizing the voltage deviation would optimize the voltage profile of the power system. In this paper the mentioned function is defined as follows and considered as an optimization objective:

$$F_{voltage\,deviation} = \sum_{j=1}^{N_L} | V_j - V_j^{ref} | \tag{2}$$

Where $F_{voltage\,deviation}$ is the total voltage deviation. N_L is the number of load buses, V_j is the voltage amplitude of the j^{th} bus. V_j^{ref} is the reference value of the voltage magnitude of j^{th} load bus which is usually set to one p.u.

2.3. Security index

Security of an electrical network has been always a key factor in the efficient operation of the system. Probable faults which disrupts the system security, would lead to detrimental consequences.

In this regard, authors suggest a practical index in order to evaluate the system security.

In this paper, the security index is observed under (N-1) contingency. In other words, for each system by single line outage, some parameters such as voltages of buses may exceed their limits or some of the lines could experience overloading. As these overvoltages or overloadings increase, the system security will decrease. Minimizing the mentioned deviations would lead to a more reliable system.

In order to guarantee the system security, the worst case contingency is considered to be implemented in fitness function. In this paper, the security index is defined as follows:

$$SI = w_l \sum_{l=1}^{nl} \left(\frac{S_l}{S_{l\max}} \right) + w_v \sum_{i=1}^{nb} \Delta V_i \tag{3}$$

Where, *SI* is the security index. S_l and S_{lmax} are the complex power and the apparent complex power rate of line *l*, respectively. *nl* is the number of transmission lines and *nb* is the number of system buses.

Additionally, w_l, w_v are represented as weighting coefficients. Also ΔV_i is defined as follows:

$$\Delta V_i = \begin{cases} \dfrac{V_{ref\min} - V_i}{V_{ref}} & V_i < V_{ref\min} \\ 0 & V_{ref\min} < V_i < V_{ref\max} \\ \dfrac{V_i - V_{ref\max}}{V_{ref}} & V_{ref\max} < V_i \end{cases} \quad (4)$$

where, V_i is the voltage magnitude related to bus *i*. $V_{ref\min}$ and $V_{ref\max}$ are upper and lower limits of voltage magnitude, respectively and V_{ref} is considered one pu for each bus.

As it was mentioned, the security index is computed for the most critical contingency scenario. In this paper, the most critical scenario is introduced as a line outage by which the system faces the most unbalances. In other words, the line outage which leads to the most system line overloads and voltage deviations, is considered as the critical scenario and the security index would be computed in this state of the system.

2.4. Multi objective approach

In this paper the multi objective case is performed using the penalty factor solution. The penalty factor solution, mainly, stands on giving appropriate weights to the under studied objectives. Eq. (5) presents the multi objective reactive power, voltage deviation and security index formula as follows:

$$Min \quad Z = h_1 * L + h_2 * D + h_3 * SI \quad (5)$$

Where, L is total transmission loss, D is the voltage deviation parameter, SI is the amount of security index and Z is the multi objective function. On the other hand, h_1, h_2 and h_3 are the loss, voltage deviation and security index penalty factors, respectively.

Problem objectives are coordinated by these penalty factors. When $h_2=0$ and $h_3=0$ the problem is pure transmission loss optimization and so on. As it is obvious, a trade-off value should be determined for these penalty factors in the multi-objective case. In this regard, h_1 is gotten the amount of 1, h_2 is considered 50 and h_3 is set on the amount of 10 for the mentioned case.

2.5. Constraints

As an optimization problem, the ORPD problem should be considered with respect to the set of physical and operational constraints. At the following, the equality and non-equality constraints are presented.

The power flow equations, as the main equality constraint, present the physics of the power systems. The general form of power balance equations are as follows:

$$P_i(V,\theta) + P_{d\,i} - P_{g\,i} = 0 \quad (6)$$

$$Q_i(V,\theta) + Q_{d\,i} - Q_{g\,i} = 0 \quad (7)$$

Where, P_i and Q_i are injected active and reactive powers corresponding to bus *i*, respectively. P_{di} represents the active power and Q_{di} stands for reactive power of load related to bus *i*. P_{gi} and Q_{gi} are generated active and reactive powers corresponding to the same bus, respectively.

The non-equality constraints of the power flow problem indicate the limits on physical devices. The following non-equality equations summarize the non-equality constraints of this problem:

$$P_{gi\min} \le P_{gi} \le P_{gi\max} \qquad i = 1, 2, \ldots, N_{gen} \quad (8)$$

$$Q_{gi\min} \le Q_{gi} \le Q_{gi\max} \qquad i = 1, 2, \ldots, N_{gen} \quad (9)$$

$$V_{i\min} \le V_i \le V_{i\max} \qquad i = 1, 2, \ldots, N_L \quad (10)$$

$$Q_{ci\min} \le Q_{ci} \le Q_{ci\max} \qquad i = 1, 2, \ldots, N_{Cap} \quad (11)$$

$$T_{i\min} \le T_i \le T_{i\max} \qquad i = 1, 2, \ldots, N_{Tran} \quad (12)$$

$$|P_{ij}| \le P_{ij}^{\max} \quad (13)$$

Where, $P_{gi\max}$, $P_{gi\min}$, $Q_{gi\max}$ and $Q_{gi\min}$ are the maximum, minimum active power and the maximum, minimum reactive power of the i^{th} generation unit, respectively. N_L indicates the number of load buses. Finally, $V_{i\max}$ and $V_{i\min}$ represent the maximum and minimum limits of voltages amplitude, respectively.

3. OPTIMIZATION ALGORITHM

In this section, firstly the brief explanation of the GSO algorithm is provided. Afterwards, the ameliorative procedure of the mentioned algorithm is proposed.

3.1. Basic group search optimization algorithm

The GSO algorithm is a novel heuristic optimization algorithm which is basically inspired by animal group-living theory especially their searching behavior. The mentioned algorithm is mainly based on producer-scrounger (PS) model which uses "producing" (finding) or "joining" strategies particularly. The population of the GSO algorithm is known as a group and each individual in population is called a member. The GSO member is defined by its current position and head angle in each iteration. In an *n*-dimensional search space, the i^{th} member at the k^{th} iteration has a current position $X_i^k \in R^n$ and a head angle $\varphi_i^k = (\varphi_{i1}^k, \ldots, \varphi_{i(n-1)}^k) \in R^{n-1}$ and also a search direction $D_i^k(\varphi_i^k)$ which is calculated via a polar to Cartesian coordinate transformation as follows:

$$D_i^k(\varphi_i^k) = (d_{i1}^k, ..., d_{in}^k) \in R^n$$

$$d_{ij}^k = \begin{cases} \prod_{q=1}^{n-1} \cos(\varphi_{iq}^k) & j = 1 \\ \sin(\varphi_{i(j-1)}^k) \prod_{q=j}^{n-1} \cos(\varphi_{iq}^k) & j = 2, ..., n-1 \\ \sin(\varphi_{i(n-1)}^k) & j = n \end{cases} \quad (14)$$

Where, R is the set of real numbers and φ_{in} is polar angle of i^{th} member relative to the n^{th} dimension.

The GSO group is basically divided into three types known as producer, scroungers and rangers. The producer finds the opportunities, while scroungers join to the opportunities and rangers perform random walks. At each iteration, a group member which has the best fitness value, is chosen as the producer. The producer is able to perform some searches around its current position to find better states. It uses its scanning ability called vision to perform such searches. In GSO algorithm, the producer scans three points around by certain distances and head angles. At the k^{th} iteration, the producer behaves as follows:

1- The producer scans at zero degree and checks three points, one point at zero degree, one point at right hand side and one point at the left hand side. The scanned positions are defined as following equations.

$$X_z = X_p^k + r_1 l_{\max} D_p^k(\varphi^k) \quad (15)$$

$$X_r = X_p^k + r_1 l_{\max} D_p^k(\varphi^k + r_2\theta_{\max} / 2) \quad (16)$$

$$X_l = X_p^k + r_1 l_{\max} D_p^k(\varphi^k - r_2\theta_{\max} / 2) \quad (17)$$

Where, X_p is position of the producer, $r_1 \in R^1$ is a normally distributed random number with mean 0 and standard deviation 1 and $r_2 \in R^{n-1}$ is a uniformly distributed random number in the range of (0, 1), $l_{\max}$ is maximum pursuit distance and $\theta_{\max}$ is maximum pursuit angle.

2- The producer will then find the best point. If the best point has a better value in comparison with its current position, producer will fly to that point. If not, it will stay in its current position and turn its head using (18).

$$\varphi^{k+1} = \varphi^k + r_2 a_{\max} \quad (18)$$

Where, $a_{\max} \in R^1$ is the maximum turning angle.

3- If the producer cannot find a better area after a iterations, it will turn its head back to zero degree as follows:

$$\varphi^{k+a} = \varphi^k \quad (19)$$

Where, 'a' is a constant value.

At each iteration, some of group members are selected as scroungers. The scroungers will keep searching for opportunities as they get close to the current position of the producer. At the k^{th} iteration, the i^{th} scrounger can be modeled as a randomly walks toward the producer, using (20).

$$X_i^{k+1} = X_i^k + r_3 \circ (X_p^k - X_i^k) \quad (20)$$

Where, X_i^k is position of i^{th} scrounger at k^{th} iteration and $r_3 \in R^n$ is a uniform random sequence in the range of (0, 1). Operator "∘" is the Hadamard product, which calculates the entry wise product of the two vectors.

Rangers are the third type of members which play an essential role during the GSO searching and finding procedure. Rangers are dispersed from their current positions and randomly move at search area. At the k^{th} iteration, a ranger performs a random head angle φ_i using (14), then chooses a random distance and moves to the new point using (21) and (22), respectively.

$$l_i = a\, r_1\, l_{\max} \quad (21)$$

$$X_i^{k+1} = X_i^k + l_i D_i^k(\varphi^{k+1}) \quad (22)$$

3.2. Improved group search optimization algorithm

The IGSO algorithm is obtained by applying some modifications on the conventional GSO. The results of recent studies have shown that the conventional GSO would mostly get stuck in local optimum especially in limited iterations. However, the IGSO would be able to overcome this problem efficiently. As it was described, at each iteration, a member with the best position is chosen as the producer and it is more probable to find better opportunities in the vicinity of producer's current position. Hence, candidate points close to the current optimum are chosen as new positions for the producer. Therefore, scroungers could walk toward the candidate points and searching process would be done utilizing multi-producers. Fig. 1, depicts the candidate points and scroungers path [21]. In this paper, it is assumed that if the fitness value does not change after 50 iterations, multi-producer searching process would be done. According to the comprehensive simulation studies, it seems that 50 is the best value for this study. If it sets to greater number, the optimizing procedure lasts unreasonably. On the other hand, if it sets to a lower number, searching process of ranger members is disrupted. The candidate points are modeled as follows [21].

$$\left| X_p^{iter} - X_p^{iter-50} \right| \le \varepsilon \quad (23)$$

$$X_{p\ test}^{r} = X_p^{iter} + r_4 \left(\frac{X_{\max} - X_p}{X_{\max}}\right)\left(\frac{iter\max - iter}{iter}\right) \quad (24)$$

$$X_{p\ test}^{l} = X_p^{iter} - r_4 \left(\frac{X_{\max} - X_p}{X_{\max}}\right)\left(\frac{iter\max - iter}{iter}\right) \quad (25)$$

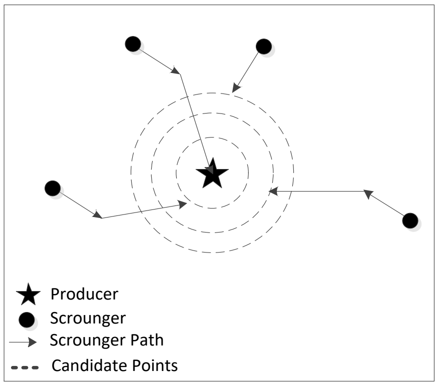

Fig. 1. Candidate points and scroungers path [21]

Where $r_4 \in R^1$ is a uniformly distributed random number in the range of (0, 1). $X_{\max}$ is the maximum value of that variable, *iter max* is maximum number of iterations and ε is a threshold value.

As mentioned, the candidate points near to the current producer are generated using (23)-(25). Afterwards, the candidate points are tested in the same way as explained for the primary producer using equations (15)-(17). In each step, X_z, X_r and X_l are appointed as producers rank one to three and modeled as follows:

$$X_i^{k+1} = X_i^k + r_5 \circ (X_p^k - X_i^k) \tag{26}$$

$$X_{i'}^{k+1} = X_{i'}^k + r_6 \circ (X_{p1}^k - X_{i'}^k) \tag{27}$$

$$X_{i''}^{k+1} = X_{i''}^k + r_7 \circ (X_{p2}^k - X_{i''}^k) \tag{28}$$

$$X_{i'''}^{k+1} = X_{i'''}^k + r_8 \circ (X_{p3}^k - X_{i'''}^k) \tag{29}$$

Where, X_i^{k+1}, $X_{i'}^{k+1}$, $X_{i''}^{k+1}$ and $X_{i'''}^{k+1}$ are members of various groups of scroungers, respectively. The r_5, r_6, r_7 and r_8 are random numbers in the range of (0, 1).

4. IMPLEMENTATION OF IGSO ALGORITHM FOR REACTIVE POWER DISPATCH PROBLEM

In this section, the implementation process of the proposed algorithm for reactive power dispatch problem is described.

Step 1. *Generating and evaluating initial members*: For the reactive power dispatch problem, the control vector could be defined as follows:

$$X = [V_g,\ Tap,\ Q_c] \tag{30}$$

According to (30), X represents the control vector. In addition, V_g, Tap and Q_c are voltage magnitude of the i^{th} generator, the tap level of the i^{th} transformer, and the reactive power of the i^{th} compensator capacitor, respectively

As it was mentioned, X is considered as IGSO member while V_g, Tap and Q_c would be sub members and are initialized as follows:

$$V_i^k = V_{i_{\min}}^k + r(V_{i_{\max}}^k - V_{i_{\min}}^k) \tag{31}$$

$$tap_i^k = tap_{i_{\min}}^k + r(tap_{i_{\max}}^k - tap_{i_{\min}}^k) \tag{32}$$

$$Qc_i^k = Qc_{i_{\min}}^k + r(Qc_{i_{\max}}^k - Qc_{i_{\min}}^k) \tag{33}$$

According to (31)-(33), the decision variables would be initialized within their feasible zones.

Step 2. *Fitness evaluation:* Equation (1)-(3) are used to calculate the fitness function, which contains the total system loss, the voltage deviation amount and the security index. The mentioned functions would be considered individually or simultaneously as different cases. The fitness function should be minimized while satisfying all constraints. At each iteration, inequality constraints should be checked before calculating the fitness value and if they are not in feasible band, they have to be fixed on their limits.

Step 3. *Producing:* Fitness function should be calculated for all members of IGSO group. A group member, which has the best fitness value, would be chosen as the producer. Producer performs producing using equations (15)-(17).

Step 4. *Scrounging:* 40% of IGSO group members are chosen as scroungers and they perform scrounging using equation (20).

Step 5. *Ranging:* 60% of IGSO group are chosen as rangers to accomplish ranging using (22).

Step 6. *Modification process:* As mentioned, in order to improve the algorithm efficiency, after certain iterations, if the producer cannot find a better state, discussed modifications in section (3.2) are implemented.

Step7. *Search stopping criterion:* The terminating criterion is selected to be the maximum number of iterations. The algorithm will be terminated if the maximum iteration number reaches; otherwise it continues from Step3.

5. CASE STUDIES AND NUMERICAL ANALYSIS

To validate the performance of the proposed method, this method is tested on the IEEE 30-bus test system. The 30-bus IEEE test system has 41 transmission lines, six generators and four transformers $(T_{6-9}, T_{6-10}, T_{4-12}\ and\ T_{27-28})$. The lower and upper voltage magnitudes and transformer tap limits are considered between 0.9 and 1.1 p.u. For the purpose of comparison, the simulations are carried out for four different cases categorized as case (1-4). Moreover, the obtained results are compared with those reported by other approaches according to the literature. The rest of this study is divided into categories as follows:

Case 1: Minimizing the power loss.

Case 2: Minimizing the load voltage deviation.

Case 3: Optimizing the security index.

Case 4: The multi objective approach.

In this paper the number of IGSO group is considered 30 and the maximum iteration number is assumed 400. IGSO based simulations are developed in Matlab 7.6 and it runs on a 2.5 GHz personal computer.

5.1. Minimization of the power loss

As it was mentioned, the transmission loss is one of the most important problems with which the system operators face mostly. Though, achieving the minimum power loss is the goal. In this case, minimizing the real power loss by optimizing the compensator capacitors, transformers taps and the voltage of generator buses is gotten under study. Fig. 2 illustrates the convergence procedure of this case. As it is obvious, the IGSO algorithm achieves better results in comparison with GSO algorithm. Additionally Table 1 indicates the numerical results for mentioned problem. On the other hand, Table 2 compares the results of the proposed algorithm with others such as evolutionary algorithm (EA), particle swarm optimization (PSO) algorithm, coordinated aggregation (CA) particle swarm optimization, gravitational search algorithm (GSA) and opposition-based self-adaptive modified gravitational search algorithm (OSAMGSA**)**. As it is obvious, the IGSO algorithm indicates more capability in optimizing the loss objective. Although, these methods don't have impressive differences in total loss value, but considering the system operation, these differences are significant. It is noteworthy to say that, the difference between these methods is mainly related to capacitive resource proportions.

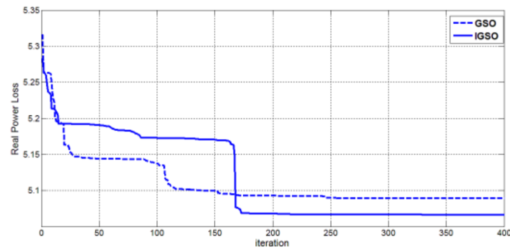

Fig. 2. Convergence procedure for real power loss

Table 1. Numerical Results of Pure Power Loss Optimization

	GSO	**IGSO**
VG1	1.05	1.05
VG2	1.0404	1.0363
VG5	1.014	1.0061
VG8	1.018	1.0156
VG11	1.0455	1.049
VG13	1.05	1.05
T6-9	0.9002	0.984
T6-10	0.9396	0.9434
T4-12	0.9002	0.9499
T27-28	0.9114	0.9008
Qc10	0.2195	0.2541
Qc24	0.1	0.0986
loss(MW)	5.091	**5.066**
Deviation	0.2593	**0.2016**
Security index	0.5319	**0.5598**

5.2. Minimization of the load voltage deviation

According to reliability issues, it is essential for a power system to keep the voltage of load buses in certain ranges with minimum deviations. In this case, minimizing the total voltage deviation is considered as the target.

Table 2. Comparison Results of Pure Power Loss Optimization

	Initial settings	EA [23]	PSO [24]	CA [24]	GSA [17]	OSAMGSA [17]	GSO	**IGSO**
VG1	1.05	1.05	1.0408	0.95	1.05	1.05	1.05	1.05
VG2	1.045	1.044	1.05	0.95	1.0079	1.0107	1.0404	1.0363
VG5	1.01	1.024	0.95	0.95	0.9637	0.95	1.014	1.0061
VG8	1.01	1.026	0.95	0.9622	0.9542	0.9791	1.018	1.0156
VG11	1.05	1.093	1.05	0.9753	0.9661	0.95	1.0455	1.049
VG13	1.05	1.085	1	1.05	1.05	1.05	1.05	1.05
T6-9	0.978	1.078	1.0329	0.9966	1.0988	0.9121	0.9002	0.984
T6-10	0.969	0.906	1.0132	1.05	1.0992	0.9	0.9396	0.9434
T4-12	0.932	1.007	1.0007	1.0006	0.9	0.9263	0.9002	0.9499
T27-28	0.968	0.959	1.0069	1.0073	1.0533	0.9222	0.9114	0.9008
Qc10	0.19	0.19	0.18938	0.25	0.2476	0.27432	0.2195	0.2541
Qc24	0.043	0.043	0.06281	0.06253	0.0852	0.06284	0.1	0.0986
loss(MW)	5.3786	5.1065	5.0938	5.0933	5.0924	5.0713	5.091	**5.066**

Fig. 3 indicates the convergence plots of this case. As it was mentioned, the IGSO algorithm by defining candidate locations for the producer arises its efficiency in achieving better solutions. This fact is specifically shown in Fig. 3. In which the GSO is gotten stuck in a local optimum but the IGSO reaches the global one. On the other hand, Table 3 illustrates the numerical results obtained by the proposed method and Table 4 is related to comparison results which compares the GSO and IGSO solutions with other approaches. Table 4 indicates that the IGSO algorithm gets better results in optimizing the voltage deviation. However, the IGSO approach by searching the wide area, gets capable to find better results.

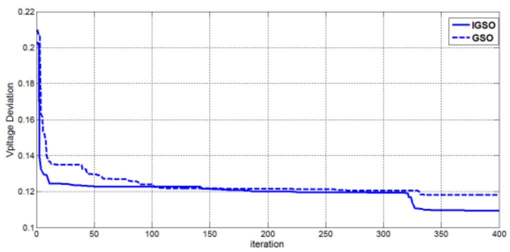

Fig. 3. Convergence procedure for load bus voltage deviation

Table 3. Numerical Results of Pure Voltage Deviation Optimization

	GSO	**IGSO**
VG1	1.0106	1.0112
VG2	1.0046	1.001
VG5	1.0002	1.0001
VG8	1.0147	1.0159
VG11	1.0744	1.0445
VG13	1.0437	1.0444
T6-9	1.0625	1
T6-10	1.0394	09539
T4-12	0.9309	1
T27-28	0.9231	0.9942
Qc10	0.2480	0.294
Qc24	0.0816	0.1
Deviation	0.118	**0.1094**
Loss	6.1707	**5.7734**
Security index	0.8805	**0.8486**

5.3. Minimization of the security index

In this section, the proposed method optimizes the reactive power dispatch problem considering security index. Also, the obtained results are compared with those gotten by the GSO algorithm. Table 5 indicates the numerical results of this case while Fig. 4 indicates the convergence procedure. As it was mentioned, in previous works the security index isn't considered as the objective. Therefore, the GSO and IGSO algorithms are implemented and compared in this case and as it is obvious, the IGSO due to its efficiencies got better results in comparison with GSO algorithm.

Table 4. Comparison Results of Pure Voltage Deviation Optimization

	Initial settings	EA [23]	PSO [24]	CA [24]	GSA [17]	OSAMGSA [17]	GSO	**IGSO**
VG1	1.05	1.037	1.05	1.005	0.9649	0.9714	1.0106	1.0112
VG2	1.045	1.027	1.05	0.95	1.1	1.1	1.0046	1.001
VG5	1.01	1.013	0.95	1.05	1.0022	1.0022	1.0002	1.0001
VG8	1.01	1.008	0.95	1.05	1.0199	1.02	1.0147	1.0159
VG11	1.05	1.03	1.05	1.0021	1.0238	1.0206	1.0744	1.0445
VG13	1.05	1.007	1.0156	1.0279	0.9855	0.9792	1.0437	1.0444
T6-9	0.978	1.054	1.0335	1.0287	1.0059	1.0053	1.0625	1
T6-10	0.969	0.907	0.9532	0.95	0.9396	0.9382	1.0394	09539
T4-12	0.932	0.928	0.9941	0.9929	0.9454	0.932	0.9309	1
T27-28	0.968	0.945	1.0222	1.0248	0.9595	0.9646	0.9231	0.9942
Qc10	0.19	0.19	0.11131	0.00467	0.1694	0.15739	0.2480	0.294
Qc24	0.043	0.043	0.00734	0.00636	0.0436	0.0652	0.0816	0.1
Voltage Deviation	0.4993	0.1477	0.1393	0.1245	0.1133	0.1126	0.118	**0.1094**

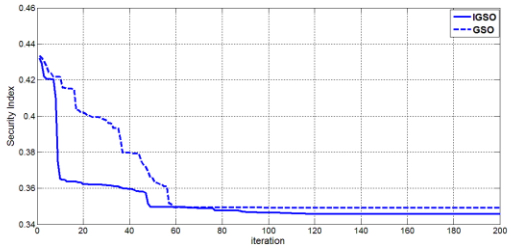

Fig. 4. Convergence procedure for security index optimization

Table 5. Numerical Results of Pure Security Index Optimization

	GSO	**IGSO**
VG1	1.0991	1.0998
VG2	1.0752	1.0737
VG5	1.0587	1.0454
VG8	1.083	1.0794
VG11	1.0776	1.0847
VG13	1.1	1.1
T6-9	1.0916	1.0673
T6-10	1.1	1.0787
T4-12	1.0821	1.0609
T27-28	1.096	1.1
Qc10	0.291	0.2951
Qc24	0.0735	0.0775
Security Index	0.3478	**0.3457**
Loss	5.3528	**5.4475**
Deviation	0.3670	**0.3518**

5.4. Multi objective approach

In this case, the proposed method optimizes the multi objective reactive power dispatch problem. Moreover, the penalty factor solution is considered by giving each objective the appropriate weighting coefficient.

Considering more than one objective would influence the optimization results while in this case, the optimizer tries to optimize all of the objectives simultaneously.

Table 6 illustrates the optimization results obtained by the IGSO which is compared with the GSO algorithm. The total active loss is 5.3102 (MW) in multi-objective approach, which had the amount of 5.066 (MW) in single objective case. This fact is acceptable because of considering several objectives in the multi-objective case. In other words, the multi-objective case tries to optimize all functions instead of one objective. For instant, considering the first case, the optimizer optimizes the active loss. In the considered case, minimizing the value of other objectives isn't consequential. In this regard, the voltage deviation and the security index reach the values of 0.2016 and 0.5598, respectively. The same objectives have the amounts of 0.1292 and 0.5245 in the multi-objective case, respectively. As it was mentioned, it is clear that in the multi-objective case, the target is approaching to an optimal solution considering all functions.

Otherwise, by considering the voltage deviation as the fitness function, the IGSO reaches the 0.1094 as the result. On the other hand the multi- objective case got the answer 0.1292. Although the difference isn't neglectable, the IGSO algorithm gets better results, nevertheless. Moreover, the security index is 0.3457 considering single objective and has the amount of 0.5245 in multi-objective case. However, the multi objective approach has less capability in optimizing the security index. Although, it indicates impressive efficiencies in optimizing the loss and voltage deviation objectives.

Table 6. Numerical Results of Multi Objective Approach

	GSO	**IGSO**
VG1	1.0158	1.0331
VG2	1.0117	1.0126
VG5	1.0003	1
VG8	1.0087	1.0001
VG11	1.0449	1.05
VG13	1.044	1.0446
T6-9	0.9025	1.069
T6-10	1.1	1.05
T4-12	0.9487	0.9919
T27-28	1.0342	0.9036
Qc10	0.3	0.3
Qc24	0.1	0.0999
Loss	5.552	**5.3102**
Voltage Deviation	0.1212	**0.1292**
Security Index	0.5772	**0.5245**

6. CONCLUSION

In this paper, the multi-objective reactive power dispatch is studied considering transmission active loss, voltage deviation and the security index, simultaneously. The penalty factor is used in multi objective case. Also the problem is considered as a single objective by considering mentioned objectives individually as separate cases. The continuous and discrete control variables including reactive power of compensation capacitors, tap position of transformers and the bus voltages were considered simultaneously in order to solve the proposed problem. The IGSO algorithm is implemented for this problem. The obtained results have shown the efficiency of the proposed algorithm in both single objective and multi objective cases. The mentioned algorithm achieves better results in comparison to EA, GA, and PSO techniques

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