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Solving Multi-Objective Optimal Power Flow Using Modified GA and PSO Based on Hybrid Algorithm

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Abstract- *The Optimal Power Flow (OPF) is one of the most important issues in the power systems. Due to the complexity and discontinuity of some parameters of power systems, the classic mathematical methods are not proper for this problem. In this paper, the objective function of OPF is formulated to minimize the power losses of transmission grid and the cost of energy generation and improve the voltage stability and voltage profile, considering environmental issues. Therefore, the OPF problem is a nonlinear optimization problem consisting of continuous and discontinuous variables. To solve it, Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and a new hybrid algorithm combining modified Particle Swarm Optimization (PSO) and Genetic algorithm (GA) methods are proposed. In this method, each of the algorithms is performed in its procedure and generates the primary population; then, the populations are ordered and from among them, populations with the highest propriety function are selected. The first population that guesses will enter the two algorithms' procedures for generating the new population. Note that the inputs of the two algorithms are the same; then, generates a new population. Now, there are three groups of populations: one created by modified GA, one created by modified PSO, and the other is the first initial population, and then sorted with the described sorting method.*

Keywords: Optimal power flow, Multi-objective, Genetic algorithm, Particle swarm optimization

1. INTRODUCTION

The study of power flow, which is often known as the load flow, is one of the important parts of analyzing power systems. Studying this issue is essential for the design of power systems, economical programming, power system control, and programming future developments. The problem consists of determining the amplitude and phase angle of voltages in all buses and active and reactive power flows in all lines. The optimal power flow problem, which was proposed by Carpentier about 50 years ago, is one of the major issues in power-system operation [1-3]. This problem can be divided into two sub-problems, optimal reactive and active power dispatch [4-6].

According to the literature, mathematical algorithms such as Newton approach, non-linear programming, interior point, and Jacobian matrix were used for optimal reactive power dispatch (ORPD) in early studies [7-9]. These algorithms optimize the objective function by linearizing it. optimum, it is a non-linear and multi-modal optimization problem. Hence, it is difficult to find the global optimum using mathematical algorithms. Furthermore, there are disadvantages in these algorithms, such as insecure convergence and algorithm complexity (non-linear programming), piecewise quadratic cost approximation (quadratic programming), convergence characteristics (Newton approach), piecewise linear cost approximation (linear programming), termination and optimality criteria (interior point) [10, 11]. For these reasons, researchers have developed heuristic-based algorithms for solving the ORPD problem [12]. In this paper, attention is paid to optimization of the reactive power, minimizing power losses [13-16] and generation cost [15-25], and improving voltage stability and profile, considering environmental issues [25-29]. This objective is achievable by capacitors' placement and determining the values of the capacitor banks, finding the best taps for the tap changers, and determining the best value of the generator buses' voltages. However, in finding these parameters, it should be noted that the constraints of the transmission system should be preserved. In most algorithms, after an initial guess, methods can be directly entered into the process of the algorithm and after doing the Protocol, finally it will be checked whether the results in the interval are allowed or not.

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In this paper, the reverse process is done, so that when we are forming the initial population, we examine each set of entries, whether or not they are allowed to be in the limited area. If confirmed, again it is going to enter a process of other reviews that examine a set of input whether or not it meets the demand of the existing constraints on the grid. For example, the amount of generated power equals to the consumed one [11, 15, 16, 29].

After reviewing the constraints and limitations, it is entered into the process of algorithm. Then, the initial population of the algorithm, once in a parallel and at other times in a separate way, will be fed once to the genetic algorithm and once to PSO. Each of the algorithms based on produce a new generation based on their process. We have 3 sets of answers, one primary and two secondary collection sets per algorithm (Genetic and PSO). These 3 sets will enter the selection process and after selection, the set will be compiled as a primary input in the process of the proposed algorithm.

2. MULTI-OBJECTIVES OPTIMAL SOLUTION

In some applications, multiple functions can be optimized simultaneously and thus the problem takes the form of a multi-objectives function. The formulation of the problem is as follows [5, 12 and 25]:

$$\min\{F(x,u)=\begin{matrix} f_1(x,u) \\ f_2(x,u) \\ \vdots \\ f_n(x,u) \end{matrix}\}; n=1,2,...,N_{obj} \quad (1)$$

$$S.t.\begin{cases} h(x,u)\le 0 \\ g(x,u)=0 \end{cases} \quad (2)$$

where “u” is the vector for the control or independent variables consisting of real power outputs except at the slack bus, generators’ voltages, transformer taps, and injected reactive powers by parallel elements, and it can be expressed as follows:

$$u=(P_G,V_G,T,Q_{sh}) \quad (3)$$

In addition, x is the vector for the state variables or dependent on the load system, consisting of the buses’ voltages, generators’ reactive power, and real power in the slack bus, and expressed as:

$$x=(P_{G_{ref}},V,\delta,Q_G) \quad (4)$$

g(x,u) is the symbol for equality constraints, which expresses the load flow equations of the system. By regulating u as the control variable in each level and solving the nonlinear load flow equations, the corresponding amounts of x are calculated. h(x,u) shows inequality constraints and consists of the following items [24, 25, 29].

2.1 Equality Constraints

$$P_{G_i}-P_{D_i}=\sum_{j=1}^{N_{Buses}} V_iV_jY_{ij}Cos(\theta_i-\delta_i+\delta_j) \quad (5)$$

$$Q_{G_i}-Q_{D_i}=\sum_{j=1}^{N_{Buses}} V_iV_jY_{ij}Sin(\theta_i-\delta_i+\delta_j)$$

(6)

$$\sum_{i=1}^{Ng} P_{Gi}=P_D+P_{Loss} \quad (7)$$

$$\sum_{i=1}^{Ng} Q_{Gi}=Q_D+Q_{Loss} \quad (8)$$

2.2 Inequality Constraints

A) Capacity constraint of the units which consists of up and down constrains of voltage magnitude and active and reactive power. The output power of each generator should not be more than its nominal amount and also not less than the amount that is necessary for the stability of the steam boiler. Therefore, generation is limited by maximum and minimum values [15, 16]:

$$V_{G_i}^{\min}\le V_{G_i}\le V_{G_i}^{\max}, i=1,2,...,N_G \quad (9)$$

$$P_{G_i}^{\min}\le P_{G_i}\le P_{G_i}^{\max}, i=1,2,...,N_G \quad (10)$$

$$Q_{G_i}^{\min}\le Q_{G_i}\le Q_{G_i}^{\max}, i=1,2,...,N_G \quad (11)$$

B) Constraint for the compensation power of parallel elements:

$$Q_{sh_i}^{\min}\le Q_{sh_i}\le Q_{sh_i}^{\max}, i=1,2,...,N_G \quad (12)$$

C) Transformer taps’ constraint:

$$V_i^{\min}\le V_i\le V_i^{\max}, i=1,2,...,N_G \quad (13)$$

D) Operational constraints, which consists of the acceptable range for voltage and the amount of loading:

$$V_i^{\min}\le V_i\le V_i^{\max}, i=1,2,...,N_G \quad (14)$$

$$\begin{cases} P_{L_i}\le P_{L_i}^{\max} \\ Q_{L_i}\le Q_{L_i}^{\max} \end{cases} \quad (15)$$

3. PROBLEM OBJECTIVES

3.1. Generation Cost Minimization

The primary objective is to minimize the total generation cost by considering the operational constraints of generation resources. Economic load flow determines the amount of power plants' generation for decreasing the costs. Its formulation is also proposed as an optimization problem for minimizing the total fuel cost of all power plants which supply loads and losses. Thus, the cost can be expressed as [13-16], [5]:

$$optimum value = \sum_{i}^{Ng} Fi(Pi) = a_i + b_i P_i^2 + c_i P_i \quad (16)$$

where Fi(Pi) is the cost of the ith power plant, Ng is the number of generators, and Pi is the generated power of ith power plant. ai, bi and ci are the coefficients of the cost of the ith generator.

3.2. Minimizing Environmental Pollutions

For analyzing and optimizing greenhouse emission, the following objective function is used, in which α_i, β_i and γ_i are dependent on SO_x pollution, and ξ_i and λ_i are dependent on NO_x emission [25-29]:

$$E_{pi} = \sum_{i}^{Ng} \alpha_i + \beta_i P_i^2 + \xi_i e^{(\lambda_i P_i)} \quad (17)$$

3.3. Minimizing Active Losses

One of the objectives of active power optimal power flow is minimizing active power losses in the transmission grid. The amount of losses in transmission grid can be calculated as [13, 15, 16]:

$$P_{Loss} = \sum_{k=1}^{N_L} g_k [V_i^2 + V_j^2 - 2V_i V_j Cos(\delta_i - \delta_j)] \quad (18)$$

V_i and V_j are the voltages at the beginning and the end of line, θ_{ij} is the phase angle difference between the *i*th and *j*th buses, and g_{ij} is the conductivity of the branch between the *i*th and *j*th buses.

3.4. Measuring stability index

There are many indices for analyzing voltage improvement in power systems, including the analysis of P-V curve, Q-V curve, and L-index. In this paper, the L-index is used to analyze voltage stability. To do so, an n-bus system is divided into two groups of generation and load buses. The buses 1 to g are the generation buses, and the buses g+1 to l are the load buses [30-33]. According to the admittance matrix, the following equation can be written:

$$\begin{bmatrix} I_g \\ I_l \end{bmatrix} = \begin{bmatrix} Y_{gg} & Y_{gl} \\ Y_{lg} & Y_{ll} \end{bmatrix} \begin{bmatrix} V_g \\ V_l \end{bmatrix} \quad (19)$$

The L-index for the load buses is obtained by:

$$L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ij} \frac{V_i}{V_j} \right|, j = N_g + 1, ..., n \quad (20)$$

F_{ig} can be calculated according to the admittance matrix in the following form:

$$[F_{ij}] = -[Y_{LL}]^{-1}[Y_{LG}] \quad (21)$$

The L-index is a number between 0 and 1; when it is near 1, it shows instability and voltage collapse, and when near 0, it shows increase in voltage stability [19].

$$L = \max(L_j), j \in \alpha_j \quad (22)$$

3.5. Voltage Profile Index

In power grids, one important goal is to minimize voltage profile deviation from the nominal value. In the calculations, v_i^{ref} is considered as 1 pu[17]. The amount of voltage profile deviation is calculated as follows:

$$\Delta V_L = \sum_{i=1}^{N_{pq}} \left| v_i - v_i^{ref} \right| \quad (23)$$

4. MULTI-OBJECTIVE NON-DOMINANT ORDERING OF TYPE II (NSGA-II):

This algorithm has been formed by adding two necessary operators from one-objective GA to a multi-objective algorithm, and gives a group of the best answers known as the Pareto front, instead of finding the best answer. These two operators are as follows [24], [34-37]:

(1) The operator, which indicates a superiority factor (level), based on the non-dominant ordering of population members.

(2) The operator, which preserves the diversity of the answers with the same level. Before discussing the algorithm completely, the concepts of dominance, non-dominant ordering, and preserving diversity in the answers should be discussed.

4.1. Concept of Dominance

In a problem of minimizing with more than one objective function, it is said that x has dominance over y, if and only if y is not better than x in any aspect and x is better than y at least from one aspect. This concept is expressed in mathematics as [24], [34-37]:

$$X \leq Y (X dom Y) \leftrightarrow \forall i : X_i \leq Y_i \cap \exists i_0 : X_{i_0} \prec Y_{i_0} \quad (24)$$

4.2. Concept of Non-Dominant Ordering

When the issue is about a single-objective algorithm, the criterion for the dominance of answers over each other is simple and obvious. The reason is that only one objective function is determined, and in the case that the problem is about minimizing, the answer which has the lowest amount of objective function is desired and has dominance over other answers [35-39]. However, when a multi-objective algorithm is applied for solving a problem, it means that there are at least two objective functions; therefore, we cannot easily decide on some of the answers. In most of the cases, there are points which do not have any dominance over each other, and so two by two comparisons are not possible between them. Therefore, for finding the best answers, they have to be ordered by a standard. In this algorithm a rank is dedicated, which is done based on their defeat against others. At the end of the algorithm, the best points which have the 1st rank will be selected as the answer set or the Pareto front points [24]. In addition to the fitness value, a new parameter known as the crowding distance is calculated for each individual [37]. The crowding distance is a measure of how close an individual is to its neighbors. In other words, the crowding distance di of point i is a measure of the objective space around i that is not occupied by any other solution in the population. Here, this quantity of di is simply calculated by estimating the perimeter of the cuboid (Fig.1) formed by using the nearest neighbors in the objective space as the vertices according to Equation 31 [37-39].

$$\begin{cases} d_i^1 = \dfrac{\left|f_1^{back} - f_1^{next}\right|}{f_1^{\min} - f_1^{\max}} \\ d_i^2 = \dfrac{\left|f_2^{back} - f_2^{next}\right|}{f_2^{\min} - f_2^{\max}} \\ \vdots \\ d_i^j = \dfrac{\left|f_j^{back} - f_j^{next}\right|}{f_j^{\min} - f_j^{\max}} \end{cases} \Rightarrow D = d_i^1 + d_i^2 + \ldots + d_i^j \quad (25)$$

where N_{obj} is the number of objectives, f_G^{back} is the Gth objective of the back individual, and f_G^{next} is the Gth objective of the next individual after sorting the population according to crowding distance (CD) fitness. [24], [34-37].

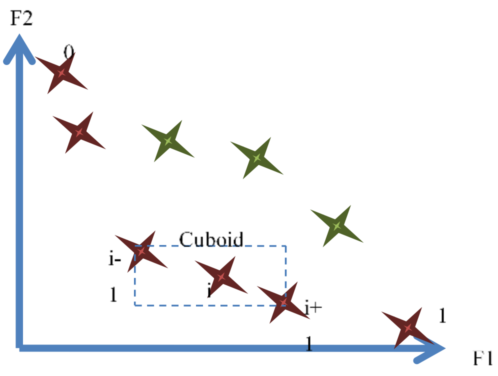

Fig. 1. Behavior of crowding distance

5. A HYBRID METHOD BASED ON MODIFIED GA AND PSO ALGORITHMS

5.1. Modified GA

To begin with, let us define the mathematical model for a constrained optimization problem (COP):

$$\begin{aligned} &\min \ f(\vec{X}) \\ &\text{S.t.} \\ &g_k(\vec{X}) \le 0, \qquad k=1,2,\ldots,K \\ &h_e(\vec{X}) = 0, \qquad e=1,2,\ldots,E \\ &\underline{L}_j \le x_j \le \overline{U}_j, \quad j=1,2,\ldots,D \end{aligned} \quad (26)$$

where, $\vec{X} \in R^D$, D is the number of decision variables, $f(\vec{X})$ the objective function, $g_k(\vec{X})$ the kth inequality constraints, $h_e(\vec{X})$ the eth equality constraint, and each xj has a lower limit $\underline{L}_j$ and an upper limit $\overline{U}_j$. In this paper, we deal with real-valued encoding. We propose a multi-parent crossover (MPC) with the following steps:

(1) Based on a selection rule, store the individuals that will be used for crossover into a selection pool.

(2) Any duplication in the selected three individuals is removed by replacing the unwanted individual with a random individual from the selection pool.

(3) Rank these three individuals from the best ($\vec{x}_1$) to the worst ($\vec{x}_3$), based on their fitness functions and/or constraint violations.

(4) Generate a random number β that follows a normal distribution with mean value μ and standard deviation σ.

(5) Generate three offsprings (oi).

$$\vec{o}_1 = \vec{x}_1 + \beta \times (\vec{x}_2 - \vec{x}_3) \quad (27)$$

$$\vec{o}_2 = \vec{x}_2 + \beta \times (\vec{x}_3 - \vec{x}_1) \quad (28)$$

$$\vec{o}_3 = \vec{x}_3 + \beta \times (\vec{x}_1 - \vec{x}_2)$$

$$f(\vec{x}_1) \le f(\vec{x}_2) \le f(\vec{x}_3) \quad (29)$$

The idea behind MPC comes from the heuristic crossover [5], in which one offspring ($\vec{y}$) is generated from a given pair of parents ($\vec{x}_1, \vec{x}_2$), such that $\vec{y} = (\vec{x}) + r$ and $(\vec{x}_1 - \vec{x}_2)$, where r is a random number between 0 and 1. In our case, the difference vectors in the above equations are not in the same order. The order in Eq. (28) is set differently from that in Eqs. (27) and (29). In fact, Eqs. (27) and (29) are designed to move toward better fitness, while Eq. (29) is to diversify the population.

5.2. Modified PSO

The equation of SPSO-TVAC for velocity updating can be expressed as:

$$\omega = (\omega_{max} - \omega_{min}).\frac{(k_{max} - k)}{k_{max}} + \omega_{min} \tag{30}$$

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, where 4.1 \le \varphi \le 4.2 \tag{31}$$

$$\begin{aligned} V_i(t+1) = C\{ & \omega v_i(t) + ((c_{1f} - c_{1i})\frac{k}{k_{max}} \\ & + c_{1i}).r_1(t)[pbest_i(t) - x_i(t)] \\ & + ((c_{2f} - c_{2i})\frac{k}{k_{max}} + c_{2i}).r_2(t)[leader_i(t) - x_i(t)]\} \end{aligned} \tag{32}$$

where

$$c_{1i} = 2.7;\ c_{1f} = 0.3;\ c_{2i} = 0.4;\ c_{2f} = 2.6;$$
$$c_1 = ((c_{1f} - c_{1i}) \times (k/k_{max})) + c_{1i};$$
$$c_2 = ((c_{2f} - c_{2i}) \times (k/k_{max})) + c_{2i};$$
$$v_{max}(j) = \left(\max\left(X\ (:, j)\right)\right) \times penalty\ \ factor$$

```
if particle_velocity(i,j)==0
   if rand<0.5
      V(i,j)=rand×vmax(j)
   else
      V(i,j)=-rand×vmax(j)
   end
end
X(i,j) = X(i,j) +V(i,j)                (33)
```

where i and j are the size of population and dimension of problem, respectively. The penalty factor for this study is 0.1.

5.3. Hybrid PSO and GA

We now proceed to present the embedding of the constraint handling methods in GA-PSO. The population size of this hybrid GA-PSO approach is set at 21N+1 when solving an N-dimensional problem. The initial population is randomly generated in the problem search. The hybrid GA-PSO algorithm embedded with constraint handling method is described as follows:

1. Initialization: Generate a population of size 21N+1.

Repeat.

2. Constraint handling methods

2.1 The Gradient repair method: Repair particles that violate the constraints by directing the infeasible solution toward the feasible region. Leave unrepairable solutions as they are.

2.2 Constraint fitness priority-based ranking method: Evaluate the constraint fitness and the objective fitness of each particle, and rank them.

3. Simplex method: Apply GA operator to the top N+1 particles and update the (N+1)*th* particle.

4. PSO method: Apply PSO operator for updating the remaining 20N particles with worst fitness.

4.1 Selection: From the population, select the global best particle and the neighborhood best particles.

4.2 Velocity update: Apply velocity updates to the 20N particles with worst fitness according to Equations (32) and (33), until some termination condition is met.

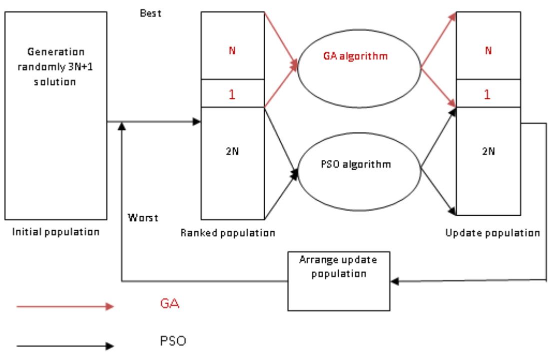

Fig. 2. GA and PSO combination (GAPSO)

6. SIMULATION RESULTS AND VALIDATION

In this paper, MATLAB R2012b is utilized for simulation studies. The GAPSO is applied to problems for IEEE 30 Buses system with six generating's. The input data for 6 generating unit's system are given in [5] with 283.4 MW load demand. The population number is 100, and 200 iterations are considered. As mentioned before, this paper considers five objectives, including cost, emission, power loss, voltage deviation, and voltage stability. It is obvious that showing all of the objectives, which needs five dimensions, is not possible. Hence, 3D diagrams are depicted as Figs. 3 to 5. These figures show 3D curves of the first Pareto front (3 functions in each). Table 1 shows the best data of the fronts of this problem. As can be seen, in each of the answer sets, the corresponding objective has the best result. In addition, the results obtained by the NR classic mathematical calculations which are obtained by

Matpower4.1 for 100 iterations can be observed in Table 1. The first column of the table consists of input variables which are generators' output power (Pi), generators' bus voltage (Vi), tap changers' position at ith bus (ti), and capacitor bank injected reactive power at ith bus (Qci). The second is formed by N.R algorithm outputs. The next five columns show suggested algorithms that combine parallel GA and PSO algorithm. Each of these columns considers one objective. For example, the last column gives the variables which bring about the best Voltage Stability. The last five rows are objectives. As can be observed, one population gives the best cost, and the others give the best emission, best power loss, minimum voltage deviation, and best voltage stability.

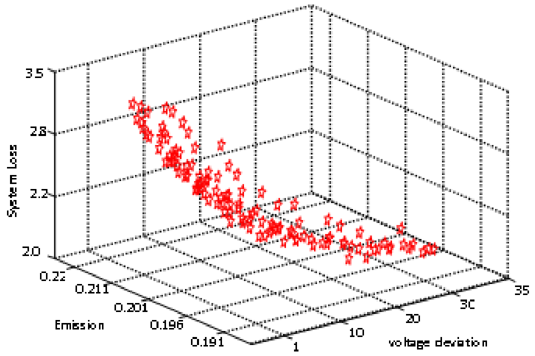

Fig. 3. Pareto-optimal front of the proposed approach for IEEE 30 bus test system with following objective functions; power loss, voltage deviation and emission

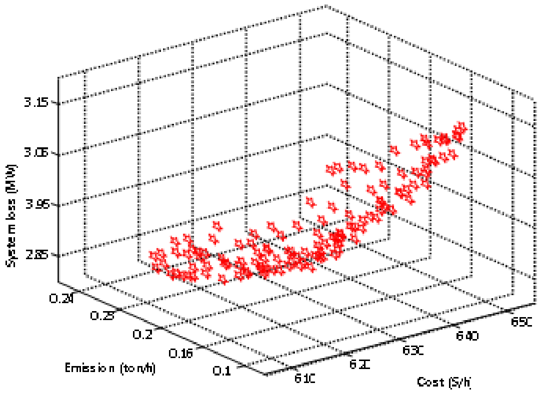

Fig. 4. Pareto-optimal front of the proposed approach for IEEE 30 bus test system with following objective functions; power loss, cost and emission

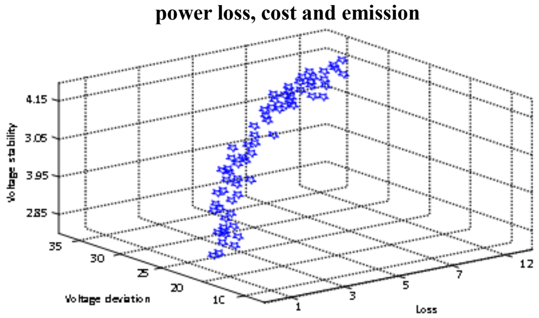

Fig. 5. Pareto-optimal front of the proposed approach for IEEE 30 bus test system with following objective functions; power loss, voltage deviation and voltage stability

Table 1. Best data of the first fronts for each objective

Input	Best Of Each Objective					
	NR	GAPSO Best Cost	GAPSO Best Emission	GAPSO Best Ploss	GAPSO Best Voltage Deviation	GAPSO Best Voltage Stability
P1	88.2869	16.4694	38.5145	15.8729	19.6784	21.6149
P2	60.0000	30.7436	53.3291	28.9501	31.4396	39.6307
P5	30.0000	65.5221	50.2601	79.2701	55.1499	58.8454
P8	25.0000	90.6066	48.5381	84.7852	72.5709	68.1840
P11	35.0000	46.5143	50.6662	43.9962	46.5495	52.6867
P13	50.0000	35.9986	53.5017	32.4169	60.9604	44.6273
V1	1.0600	1.0297	0.9610	0.9961	1.0061	1.0288
V2	1.0430	1.0368	1.0001	0.9935	0.9992	1.0237
V5	1.0100	1.0304	0.9613	1.0007	1.0079	1.0233
V8	1.0100	1.0331	1.0520	1.0057	0.9930	1.0213
V11	1.0820	1.0005	0.9995	1.0069	0.9905	1.0124
V13	1.0710	1.0560	1.0385	1.0084	0.9964	1.0282
t11	0.9780	0.9940	1.0487	0.9660	0.9823	1.0074
t12	0.9690	0.9964	1.0148	0.9989	1.0219	1.0074
t15	0.9320	0.9881	1.0555	1.0229	1.0302	0.9998
t36	0.9680	1.0148	0.9276	0.9791	0.9750	1.0106
Qc10	19.0000	19.4844	25.9500	10.5917	9.3980	10.8618
Qc12	0	16.7997	27.0077	12.4329	15.6894	13.5311
Qc15	0	9.9261	19.1218	11.6964	8.0923	11.1643
Qc17	0	22.6864	14.3163	11.0609	7.3943	7.0875
Qc20	0	14.4964	44.7819	8.5252	16.4303	8.8249
Qc21	0	18.1723	34.6229	7.1265	8.3005	10.3383
Qc23	4.3000	11.4407	6.5645	7.0472	2.9900	7.7017
Qc24	0	9.4263	42.1849	7.7096	8.3809	8.8331
Qc29	0	11.6961	33.8784	5.3612	6.1078	5.4421
Cost($/h)	721.969	607.4217	659.5751	609.5551	618.9147	614.8426
Emission (Ton/h)	0.3046	0.2002	0.1858	0.202632	0.1936	0.1908
PL(MW)	4.9895	2.4574	11.4131	1.894354	2.9544	2.1890
Voltage Deviation	0.7207	1.6186	3.0172	0.325077	0.0823	0.6051
Voltage Stability	0.1122	0.0385	0.1726	0.025545	0.0270	0.0156

Most of the multi-objective problems are solved by assigning a weight to each objective function and using the sum of the functions as an independent target function, which is known as the weighed sum method. This classic method has two main shortcomings. First, it is not able to search the whole problem space, and second, it is not a smart method independently. Finally, the related target functions corresponding to this method should be normalized before being added to each other. In order to demonstrate the superior performance of the proposed algorithm over previously presented ones, a comparative study is performed. In Table 2, the results of the proposed algorithm are compared with those of the previous studies. It is obvious that the quality of answers has increased noticeably. For instance, as can be seen in “proposed (best cost-$/h)” row, in addition to the cost, power loss and emission have the best results compared to most of references. Moreover, according to “Proposed (best voltage stability)” row, when the proposed method reaches the best Voltage Stability, two other objectives including voltage deviation and emission give the best results compared to the references.

Table 2. Comparison with previous works

Method	Objective				
	Cost($/h)	Emission (Ton/h)	Power loss(MW)	Voltage Stability	Voltage Deviation
HBMO[25](Honey Bee Mating Optimization)	612.6193	0.2014	2.9524	-	-
NPGA[40](Niched Pareto Genetic Algorithm)	617.79	0.2004	2.4102	-	-
NSGA[41]	617.80	0.2002	2.3498	-	-
MOPSO[42](Multi-Objective Particle Swarm Optimization)	615	0.2021	2.4905	-	-
MODE[43](Multi-Objective Differential Evolution Algorithm)	613.27	0.2026	2.6573	-	-
EA[44](Evolution Algorithm)	-	-	5.1065	-	0.1477
PSO[45](Particle Swarm Optimization)	-	-	5.0938	-	0.1393
EGA-DQLF[46]	-	-	-	0.10402	-
FAPSO[47](Fuzzy Adaptive Particle Swarm Optimization)	-	-	-	0.1238	-
OSAMGSA[48](Opposition-Based Self-Adaptive Modified Gravitational Search Algorithm)	-	-	5.0713	0.1036	0.1126
N.R.	721.9696	0.3046	4.9895	0.7207	0.1122
GAPSO (Best Cost-$/h)	607.4217	0.20024	2.457403	1.618625	0.038478
GAPSO (Best Emission-Ton/h)	659.57508	0.18583	11.41312	3.01717	0.17264
GAPSO (Best Power loss)	609.5551	0.2026	1.8943	0.3250	0.02554
GAPSO (Best Voltage Stability)	618.9147	0.193633	2.954446	0.082328	0.02702
GAPSO (Best Voltage Deviation)	614.8426	0.190784	2.188952	0.605099	0.01556

Based on the abovementioned descriptions, the intelligent algorithm in multi-objective does not give a unique response [49-50]. It is mean that they give group answers. In Table 2 the best response is given, and we can see improvement in answers. For example, in the classical method, economical cost is 721.969 and the best solution by difference algorithm is 612.61, and by GAPSO method we can reach 607.42, and this is the best response in comparison with other systems. Emission is 0.3046 by the classical method, the best answer by meta-heuristic algorithm is 0.2002, and we can reach 0.18583 by GAPSO method. To assess the validity of the GAPSO (GA&PSO) approach, the studies of ED were compared with many optimization methods such as GA, TS, PSO, and ACO, implemented in MATLAB. In each case study, 100 independent runs are carried out for each optimization method. In addition, 100 different initial trial solutions are used for each method. The proposed GAPSO is applied to ED problems with 13 generating units. The input data for 13 generating unit’s system are given in [51], Table 3 with 2520MW load demand. The global solutions for these systems are not discovered yet. The best local solutions reported until now for 13 generating units are 24169.92 $/h [52], respectively.

Table 3. Best result obtained by proposed GA-PSO for 13-unit system

Unit	Pi(min) MW	Pi(max)MW	Pi(GAPSO) MW
1	0	680	679.82
2	0	360	360.00
3	0	360	359.93
4	60	180	152.15
5	60	180	166.23
6	60	180	152.52
7	60	180	153.41
8	60	180	145.69
9	60	180	160.22
10	40	120	40.00
11	40	120	40.05
12	55	120	55.01
13	55	120	55.95
	Total power output	(MW)	2521.05
	Total generation cost	($/h)	24060.45

Table 4. Convergence results for 13-unit system

Method	Best cost
Proposed GAPSO	24060.45
GAACO[15]	24161.00
PGA[16]	24167.00
Chen [52]	24169.92
Wang [53]	24169.89
GA	24186.02
PSO	24171.70
ACO	24174.39
TS	24180.31
Load demand : 2520 MW	

After performing 100 trials, the best results for P_i s in the 13 units system are shown in Table 4 in order to find the best answer. As can be seen, 24169.92 $/h is obtained by GAPSO.

7. CONCLUSIONS

This paper proposes a new hybrid optimization algorithm based on modified PSO and GA algorithms, namely GAPSO, which is applied to IEEE 30-bus test system with six thermal generating units and a modified test system with 13 generating units. In this problem, variable inputs are the primary population which is generated proposed hybrid optimization algorithm. To enhance the performance, after processing the populations, the chosen population enters GA and the PSO algorithms, and the second populations (the children) are produced. Then, the populations are set in the grid and the rest of necessary parameters are achieved using N.R method for applying the propriety functions. Based on the propriety functions, the populations are ordered first by the crowding distance and then by the non-dominant ordering based on the propriety functions, and after that the best ones are selected. Results demonstrate that the proposed GA-PSO technique is able to provide efficient performance in OPF problem. As a result, to overcome the limitations of PSO, hybrid algorithms with GA are proposed. The basis for this is that such a hybrid approach is expected to have merits of PSO with those of GA. One advantage of PSO over GA is its algorithmic simplicity. Another clear difference between PSO and GA is the ability to control convergence. Crossover and mutation rates can subtly affect the convergence of GA, but these cannot be analogous to the level of control achieved through manipulating inertia weight. Unlike standard PSO, PSO-GA is more reliable in giving better quality solutions with reasonable computational time, since the hybrid strategy avoids premature convergence of the search process to local optima and provides better exploration of the search process.

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