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MULTIOBJECTIVE OPTIMIZATION ALGORITHM FOR SECURE ECONOMICAL/EMISSION DISPATCH PROBLEMS

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ABSTRACT

This paper proposes a dynamic search based optimization algorithm for solving dual security constrained economic load dispatch problem in modern power systems. The proposed research paper presents a multi-objective Dynamic Random Neighborhood PSO "DRN-PSO", which uses random neighborhood of every particle every time we need to know the experience we got in the swarm. This helps the diversity of the swarm to be preserved in order to discourage premature convergence. Moreover, the proposed algorithm uses dynamically adjusted Inertia weight to balance global exploration and local exploitation. Simulations were conducted on IEEE 30-bus test systems and compared to other optimization techniques that reported in the literature. The obtained results demonstrate the superiority of the proposed DRN-PSO compared to other optimization techniques that is reported in the literature. Additional economic benefits with secure settings are fulfilled, while preserving all system constraints within their permissible limits. The proposed algorithm improves the economic issue as well as enhancing the power system operation in the technical point of view with acceptable levels of emissions. So, it can be considered as a promising alternative algorithm for solving problems in practical large scale power systems.

KEYWORDS: Constrained economic load dispatch, dynamic random neighborhood, environmental emission multiobjective, Particle swarm optimization,

1. INTRODUCTION

Developing the search-based optimization algorithms for power system problems has become in the focus of power system developer due to the dramatic variation in fuel costs and the increased concerns of environmental impacts. Economic

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load dispatch “CELD” problem is considered as a challenge for researchers due to its high nonlinear constraints. The problem of economic dispatch of electric power generation aims at meeting the load demand at minimum operating cost while satisfying constraints of all units.

This is done by obtaining the optimum scheduling of the committed generating unit outputs [1, 2].

The CELD problems have non-convex objective functions with nonlinear constraints [3]. These nonlinearities increase even more in real life applications. This is because of the opening of the steam admission valves resulting in a sharp increase in losses [4]. Generally, non-convexities arise from valve points or combined cycle units, zones of prohibited operation of unit, and nonlinear power-flow equality constraints [5].

As a result of these characteristics, difficulty increases in trying to avoid getting trapped in local optimum in case of using any mathematical algorithms [3]. Reduction of the overall fuel cost used to be the main objective of electric power systems ignoring the amount of emission produced in the system.

However, due to the importance of the environmental impacts, the amount of the emission produced must be taken into consideration as well as fuel cost. [6-9].

Recently, the dramatic growing of fuel costs and the increased concerns of environmental issues of power generating units present early alarms for the necessity of continuous improvement of optimization methodologies for solving CELD problems efficiently. From power system operation point of view, it is necessary to minimize both emission impacts and generation costs simultaneously. The CELD problem may be formulated as multiobjective constrained nonlinear problem. The optimization technique needed to solve the CELD problem must take into consideration: the characteristics, types, models of available generation units, both of operation and maintenance costs, the technical and operational constraints, equipment capabilities and transmission line limits, and the reliability of the units for operational points [10-11].

Different optimization techniques have been reported in the literature pertaining to the CELD problem. Lambda iteration and gradient methods were used as alternatives to solve the Economic Load Dispatch “ELD” problems [12]. However, due to the existence of nonlinearities in generators, previous methods aren’t suitable in power systems. Other optimization methods including nonlinear and dynamic programming were also applied to the same problem. However, these methods suffer from non-differential and non-convex objective function, resulting in getting stuck in local optima [10, 12]. Meanwhile, convex CELD problems are efficiently solved through traditional local search algorithms such as lambda iteration “which ignores network constraints” [1] and linear programming [2].

Particle swarm optimization “PSO” is a population-based optimization technique that mimics social behavior of bird flocking. There are many variants of PSO including parameter tuning, hybridizing and these variants are tested and compared against many optimization techniques [13-14].

Nowadays, PSO and its variants were widely used in several power system applications including but not limited to optimal power flow [15], unit commitment problem [16] and state estimation [17].

This paper is concerned with solving the CELD problem considering the emission minimization as well as operating cost as multiobjective problem. The considered problem is solved using DRN-PSO algorithm and the obtained results are compared to those reported in the literature. The tested case study is the standard IEEE 30 bus test system. The rest of the paper is organized as follow: section 2 presents the related work, section 3 demonstrates the problem formulation, section 4 presents the proposed algorithm, and finally section 5 describes the tested case studies with a comparative analysis to previous work reported.

2. PSO BACK GROUND AND RELATED WORK

2.1 Traditional PSO Algorithm

The particle in PSO is considered to be a candidate solution and it is generated randomly in the search space. Each particle is wandering in the search space in compromise to its best location and the swarm global best position. Each particle is treated as a point in an n-dimensional space. The ith particle is represented as $x_i = (x_{i1}, x_{i2}, \dots, x_{in})$. The best previous position of the ith particle is recorded and represented as $p_i = (p_{i1}, p_{i2}, \dots, p_{in})$. The index of the best particle among all the particles in the population is represented by the subscript g. The rate of the position change "velocity" for particle i is represented by $v_i = (v_{i1}, v_{i2}, \dots, v_{in})$[18]. The particles are manipulated according to the following equations [14]:

$$\mathrm{v_{id}} = \mathrm{w_i v_{id}} + \mathrm{c_1 rand(\ \ )(p_{id}\text{-}x_{id})} + \mathrm{c_2 rand(\ \ )(p_{gd}\text{-}x_{id})} \tag{1}$$

$$x_{id} = x_{id} + v_{id} \tag{2}$$

where d is the dimension $(1 \le d \le n)$, c_1 and c_2 are positive constants, $rand(\ \ )$ is a random function in the range $[0,1]$, and w is the inertia weight.

A parameter named $\boldsymbol{Vmax}$ is defined to make sure that the velocity of the particle is not exceeding a certain threshold [14, 19].

2.2 Variants of PSO Algorithm

Convergence speed as well as preserving the diversity are the two main criteria that have as impact on PSO performance [20]. Figure 1 illustrates the four different variants of PSO.

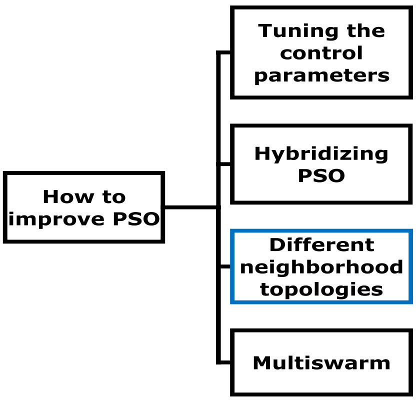

Fig. 1. Different methods to improve PSO performance.

The neighborhoods topologies are used to guarantee the convergence [21]. The premature problems are solved by making a choice on neighborhoods' topologies.

If the current global best particle is a fake point, a wrong direction will be created and the search ends up in a local optima [22].

Kennedy and Mendes searched for a better population topology for PSO and they concluded that wide neighborhood is the best choice for simple optimization problem and vice versa [20, 23, 24]. Moreover, ref. [25] and [26] recommended that time varying topology is the best choice. Also, ref. [22] presented three network topologies to improve the performance of PSO. While, Kennedy proposed four neighborhood structures namely, circle, wheel, star, and random and concluded that neighborhood structure with fewer connections performs better on highly multimodal problems [23, 27].

3. PROBLEM FORMULATION

The non-linear CELD problem of finding the optimal combination of power generation, which minimizes the total fuel cost function of each generator while satisfying the total required demand, can be mathematically stated as a quadratic function. Generally, the generation production costs are represented by quadratic functions with superimposed sine components that represent the rippling effects produced by the steam admission valve opening. The total $/h fuel cost considers the non-smooth valve point effects can be modeled as [2, 5, 6, 28]:

$$min \quad F_t = \sum_{i=1}^{NG} f_i(PG_i) = \sum_{i=1}^{NG}\left(a_i + b_i PG_i + c_i {PG_i}^2\right) + \left|d_i \, sin\left[e_i[PG_i - PG_i^{min}]\right]\right| \qquad (3)$$

Where, F_t: is the non-linear objective function defining the total power generation cost of the system. a_i, b_i and $c_i$are the coefficients of power generation cost function and d_i, and e_i are the coefficients of non-smooth operation of valves. NG is the number of generation buses. The main objective is to minimize value of F_t.

The second objective aims at minimizing the emission effects. The atmospheric pollutants such as sulpher oxides and nitrogen oxides caused by fossil fueled thermal units can be modeled separately [28]. However, for comparison:

$$min \quad E_t = \sum_{i=1}^{NG} g_i(PG_i) = \sum_{i=1}^{NG} 10^{-2}\left(\alpha_i + \beta_i PG_i + \gamma_i {PG_i}^2\right) + |\zeta_i \, exp[\lambda_i PG_i]| \qquad (4)$$

Where, αi, βi, γi, ξi and λi are the coefficients of power generation emissions. The previous objective functions are subjected to the following constraints:

As The generators real and reactive power outputs should be equal to the total load demand and transmission line losses, this constraint can be expressed as:

$$\sum_{i=1}^{NB} P_{Gi} = \sum_{j=1}^{NL} P_{Dj} + P_{Loss} \tag{5}$$

Where, P_{Gi} is the power generation at bus i, P_{Dj} is the load demand at load bus j, NL is the number of load buses and P_{Loss} is the total power losses in the system.

The generation hard constraints include generator voltages, real power outputs, these constraints are defined as hard constraints as they are restricted by their physical lower and upper limits. The generation constraints can be simulated as:

$$\begin{gathered} P_{Gi\,min} \leq P_{Gi} \leq P_{Gi\,max} \\ Q_{Gi\,min} \leq Q_{Gi} \leq Q_{Gi\,max} \\ V_{i\,min} \leq V_i \leq V_{i\,max} \end{gathered} \tag{6}$$

Where $P_{Gi\,\mathrm{min}}$: minimum power generated, and $P_{Gi\,\mathrm{max}}$: maximum power generated.

Mathematically, the security CELD problem formulation involves large number of constraints. For typical power systems, the large amount of lines has a rather small possibility of becoming congested. The CELD problem should consider only the small amount of lines in congestion condition that the power flows in these transmission lines are violated or near to their upper security limits. The critical lines term is identified for the congested lines. In this work, it considers only the critical lines that are binding in the optimal solution [29]. The line flow of the jth line is expressed in terms of the control variables P_{Gi}, by utilizing the generalized generation distribution factors “GGDF” [15] and is given below.

$$T_j\,(P_G) = \sum_{i=1}^{n} \left(D_{ji}\, P_{Gi}\right) \tag{7}$$

Where, $\boldsymbol{D_{ji}}$ is the generalized GGDF for line j, due to generator i and $\boldsymbol{T_j\,(P_G)}$ is the real power flow.

Using Eq. (7), the power system operator is allowed to ramp the power generation and transmission lines constraints corresponding to the amount of reserve that is able to prepare sufficient preventive control actions as [10]. For secure operation, the transmission line loading $\boldsymbol{S_l}$ is restricted by its upper limit as:

$$S_l \leq S_{l\,max},\ l = 1,2,\dots,n_L \tag{8}$$

Where $\boldsymbol{n_L}$ is the number of transmission line.

3.1. Ramp rate limit Constraints

The power generated by the generator i is limited by the amount of the ramp rate limits [30]. Additional generation hard constraints are restricted by their physical ramp rate limits. The ramp rate constraints can be simulated as:

$$DRG_i^{\ min} \leq PG_i - PG_i^{\ (0)} \leq URG_i^{\ max} \tag{9}$$

Where, $URG_i^{\ max}$ and $DRG_i^{\ min}$ are the maximum and minimum of ramp rate for power generation at bus i respectively and $PG_i^{\ (0)}$ is the initial value. These rates are considered around 10 % around the initial generation outputs(PG_i).

4. PROPOSED MULTI-OBJECTIVE DYNAMIC RANDOM NEIGHBORHOOD PSO "DRN-PSO"

4.1 Proposed Algorithm

The proposed algorithm DRN-PSO has many features incorporated to the simple PSO that prevent the algorithm from getting stuck in local optima, converge faster, and be able to cover all the search space. Usually, most of PSO algorithms assign certain number of particles and neighborhood size which have impacts on PSO convergence speed [31]. DRN-PSO presents new form of dynamic random neighborhood which enables each particle to change its neighborhood during searching for the optimal solution. This feature helps in increasing the swarm diversity. When using DRN-PSO, it is possible for the magnitude of the velocities to become very large. Therefore, a constraint on velocity $Vmax$ is being used to avoid exceeding a certain threshold [32]. However, performance can suffer if $Vmax$ is inappropriately set. This paper tries to control the growth of velocities by a dynamically adjusted inertia factor. Initially the values of the velocity vectors are randomly generated with the range, $[Vmin\,Vmax]$, where $Vmax$ is the maximum value of velocity that can be assigned to any particle and $Vmin = -Vmax$. The proposed algorithm is detailed next:

Step 1: Load System Data

Load IEEE 30 bus system data; Fuel cost parameters $(\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}, \boldsymbol{d}, \boldsymbol{e})$ for each generator, generator power limits, generator emission coefficients $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\zeta}, \boldsymbol{\lambda})$, and power flow coefficient

Step 2: Setting Initial Swarm

Number of particles; $No.of\ Particles = 20$
Number of neighbors: $NoOfNeighbors = 5$
Number of Dimension: $DimNum = 6$
Number of cycles: $CycNum = 20$
Maximum Inertia Weight; $wmax = 0.9$
Minimum Inertia Weight;$wmin = 0.4$
$pbest$ — the best solution achieved so far by that particle.
$gbest$ — The best value obtained so far by any particle in the neighborhood of that particle
Initialize particles with random position “candidate solutions” in the range of generator power ranges, and Initialize particle with zero velocity

if < stopping criteria not met > do

Step 3: Fitness function

For each individual $x \in N$: calculate fitness $f(x)$; “Fuel cost and/or emission minimization”

Step 4: Constraint handling

If any one of the $\boldsymbol{pg}$ is outside the range, i.e. constraint violation then punish it, If the power flow in any transmission line is exceeded the secure limit then punish it, and Check power balance if violated then punish it

Step 5: Update pbest

For each particle;
Set $pbest$ as the best position of particle x;
$If\ \boldsymbol{f}(\boldsymbol{x}) < f(\boldsymbol{pbest})\ then\ \boldsymbol{pbest} = \boldsymbol{x}$

Step 6: Update gbest; best neighbor for each particle

Every particle is assigned randomly a neighborhood that is consisted of $\boldsymbol{NoOfNeighbors} = \mathbf{5}$ particles, after evaluating each particle fitness in the neighborhood, the best fitness in the neighborhood of each particle is assigned to $\boldsymbol{gbest}$

Step 7: Update velocity and position

For each particle;
Choose the best value of Inertia Weight; w
$W = Wmax - ((Wmax - Wmin)/\ CycNum) \times i$
For every dimension

$Vmax(:,j) = 0.005 * (Xmax(:,j) - Xmin(:,j))$;

$Vmin(:,j) = -Vmax(:,j)$;

$$v(:,j) = \min(\max((W * v(:,j) + \underbrace{1.4 * rand * (pi(:,j) - x(:,j))}_{Personal\ Influence} + \underbrace{1.4 * rand * (pg(j) - x(:,j))}_{Social\ Influence}), Vmin(:,j)), Vmax(:,j);$$

End
$x = min(max((x + v), Xmin), Xmax)$;
End
Go to Step 3

Otherwise
Print out the generator power along with the considered objective function,
Exit

4.2 Handling of Constraints

The proposed DRN-PSO deals efficiently with the inequality constraints. The equality constraints are treated as close to inequality constraints as given below:

$$\sum P_g - \sum Load - Losses > \epsilon \tag{10}$$

Where, ϵ refers to the convergence degree

4.3 Handling of Conflicting Objectives

The CELD problem has two objective functions fuel cost minimization and emission minimization. These two objectives are conflicted in nature. The mathematical formulation of multiobjective CELD problem minimizes objective functions Eqs. (3-4) while satisfying system operating constraints.

Different conflicting objectives are transformed to one objective by using different multiplication weight factors. These factors reflect the importance of the objective function [33].

The combined CELD problem can be formulated as follows:

$$F = W_1 \times F_1(F) + W_2 \times F_2(Et) \tag{11}$$

Where, F refers to the combined objective function involves fuel cost and emission; w_1 and w_2 is the weighing factors of the two objective functions.

5. CASE STUDY

5.1 Test Systems

In order to validate and to show the effectiveness of the proposed approach for solving the CELD problems using a DRN-PSO, the proposed approach is tested with the standard IEEE 30 bus test system whose single line diagram is shown in Fig. 2 [34]. The test system constitutes 41 lines and six generators located at buses 25-30.

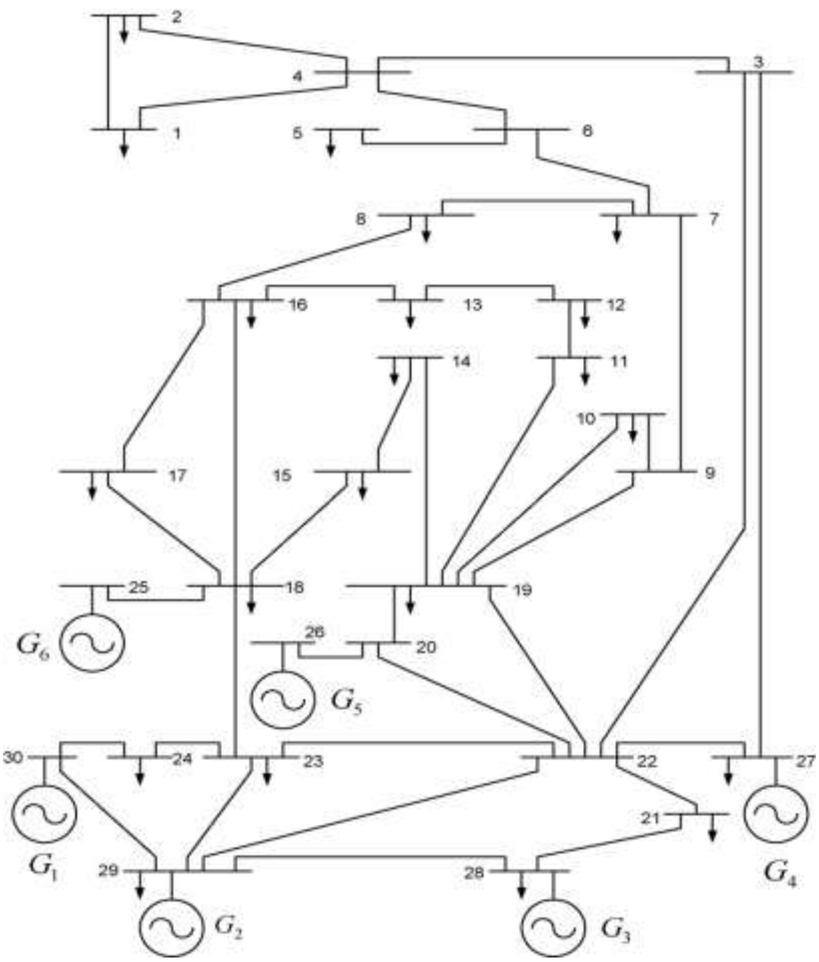

Fig. 2. Single-line diagram of IEEE 30-bus test system [34].

Tables 1 and 2 show the cost and emission coefficients of the six- generator of the studied system with their minimum and maximum limits of power, respectively. The upper and down ramp rate are considered with$\pm$ 10 %.

Table 1. Generation limits and cost coefficients.

Generator	Min MW	Max MW	a ($/MW^2)	B ($/MW)	C $	d $	E MW^{-1}
G_1	0.05	0.5	10	200	100	32.4	0.047
G_2	0.05	0.6	10	150	120	32.4	0.047
G_3	0.05	1	20	180	40	32.4	0.047
G_4	0.05	1.2	10	100	60	23.4	0.063
G_5	0.05	1	20	180	40	24	0.063
G_6	0.05	0.6	10	150	100	24	0.063

Table 2. Generator emission coefficients.

Coefficient	G_1	G_2	G_3	G_4	G_5	G_6
α	4.091	2.543	4.258	5.326	4.258	6.131
β	-5.554	-6.047	-5.094	-3.550	-5.094	-5.555
γ	6.490	5.638	4.586	3.380	4.586	5.151
ξ	2.0E-4	5.0E-4	1.0E-6	2.0E-3	1.0E-6	1.0E-5
λ	2.857	3.333	8.000	2.000	8.000	6.667

5.2 Studied Cases

To assess the efficiency of the proposed DRN-PSO, it has been applied to CELD problems where the objective functions can be either smooth or non-smooth. The studied cases can be classified under the following three categories:

- Case 1:Minimization of the fuel costs only.
- Case 2: Minimization of the generation emissions only.

Two additional joint fuel cost and emission minimization simultaneously are considered as:

- Case 3: both objectives are optimized simultaneously with equal priority.
- Case 4: both objectives are optimized simultaneously using weighted sum approach.

The proposed optimization approach is compared with the results obtained with multi-objective evolutionary algorithms like non-dominated sorting genetic algorithm “NSGA” [35-36], niched Pareto genetic algorithm “NPGA” [35-36], strength Pareto evolutionary algorithm “SPEA” [35-36], and multiobjective fuzzy based on particle swarm optimization algorithm [37], Modified Shuffled Frog Leaping Algorithm “MSFLA” [38] and an improved real coded genetic algorithm “RCGA” [39].

5.3 Results & Discussion

All calculations are done using Matlab 7.12.0.635 “R2011a” on processor core i5 dell Inspiron N5010.

5.3.1 Case 1: Fuel cost minimization

Table 3 shows the CELD solution solved through the proposed DRN-PSO algorithm compared to real coded genetic algorithm “RCGA” [39] for Case 1. The proposed method gets different load dispatch settings for the studied cases. From Table 3, the fuel cost is 591.1517 $/hr while the pollutant emission is 0.215 ton/hr. Compared to RCGA, the fuel cost is improved with total reduction of 24.3965 $/hr.

Also, Table 3 presents the evaluation of the proposed algorithm in terms of mean, best and worst values for 100 runs and the related standard deviation for each case using both optimization methods. Figure 3 illustrates the best fuel cost against run number. The proposed DRN-PSO algorithm improves the convergence characteristics for case 1 as can be noticed from swarm 10 and 15, Fig. 4.

Table 3. Best Fuel costs-based CELD solution of Case 1.

Variable	RCGA [39]	Proposed Algorithm DRN-PSO
PG_1(per unit)	0.1727	0.1764
PG_2(per unit)	0.3966	0.2852
PG_3(per unit)	0.5679	0.4691
PG_4(per unit)	1.1079	0.8981
PG_5(per unit)	0.2194	0.6350
PG_6(per unit)	0.3949	0.3029
Mean (Fuel cost) $/hr	623.3722	602.2351
Best (Fuel cost) $/hr	615.5482	591.1517
Worst (Fuel cost) $/hr	634.9026	619.1436
Standard-deviation	5.7289	6.0778
Emission at best fuel costs ton/hr	0.2285	0.215
Run time	0.29364	0.11086

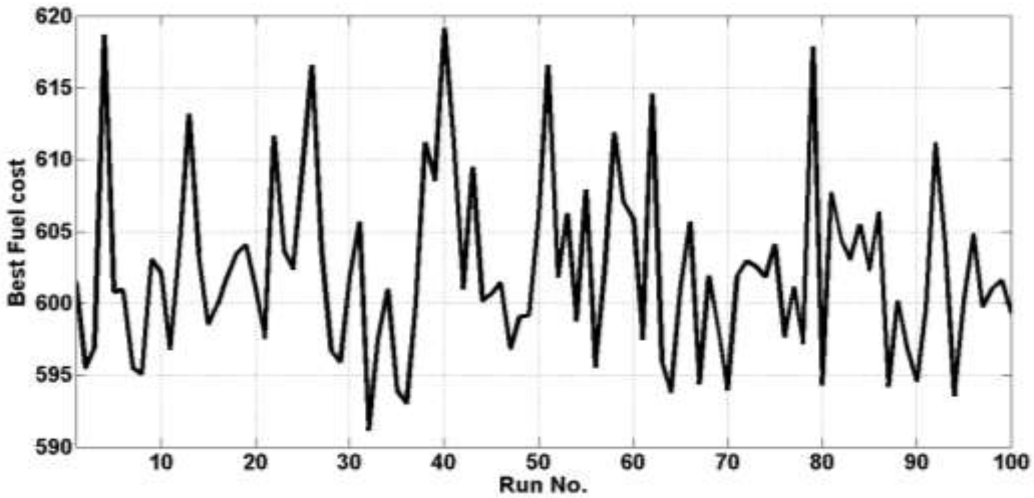

Fig. 3. Best fuel cost against run number for Case 1.

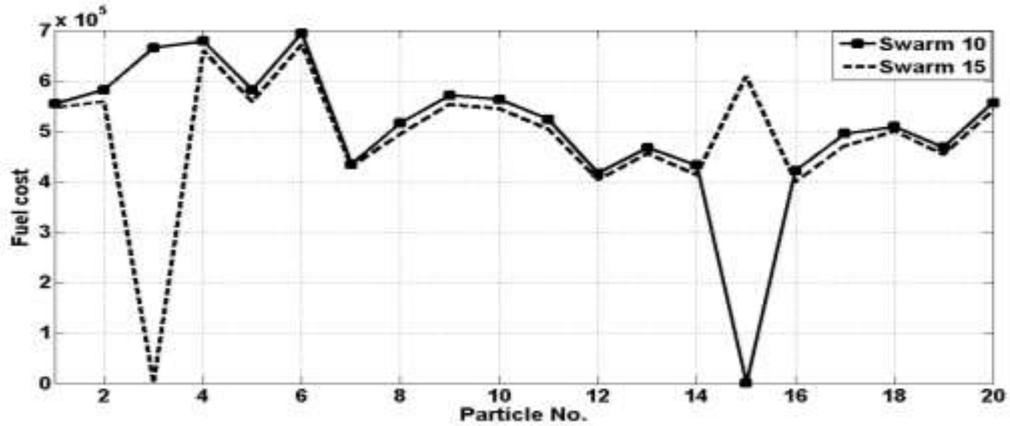

Fig. 4. Swarm 10 against swarm 15 for case 1.

5.3.2 Case 2: Emission minimization

Case 2 considers the emission minimization only as a single objective. Table 4 shows that the fuel costs are decreased to 643.8616 \$/hr while the pollutant emission is 0.1949 ton/hr. In terms of the control variable settings, different security levels are obtained, especially from generators 1, 2 and 3. It is obvious that the obtained fuel costs for Case 2 using the proposed DRN-PSO algorithm are competitive compared to that obtained using RCGA. The convergence characteristics of case 2 are shown in Figs. 5, 6. These figures show the robust performance with fast convergence to the optimal solution at acceptable levels of standard deviations in the range of 0.0036.

Table 4. Best emission CELD solution for Case 2.

Variables	RCGA [39]	Proposed approach
P_{g_1}(per unit)	0.3969	0.3850
P_{g_2}(per unit)	0.4566	0.4396
P_{g_3}(per unit)	0.6015	0.6230
P_{g_4}(per unit)	0.3853	0.4218
P_{g_5}(per unit)	0.5366	0.4702
P_{g_6}(per unit)	0.5064	0.5200
Mean (Emission) ton/hr	0.2018	0.2016
Best (Emission)	0.1932	0.1949
Worst (Emission)	0.2194	0.2128
Standard-deviation	0.0056	0.0036
Fuel costs $/hr	691.3766	643.8616
Run time	0.0502	0.1062

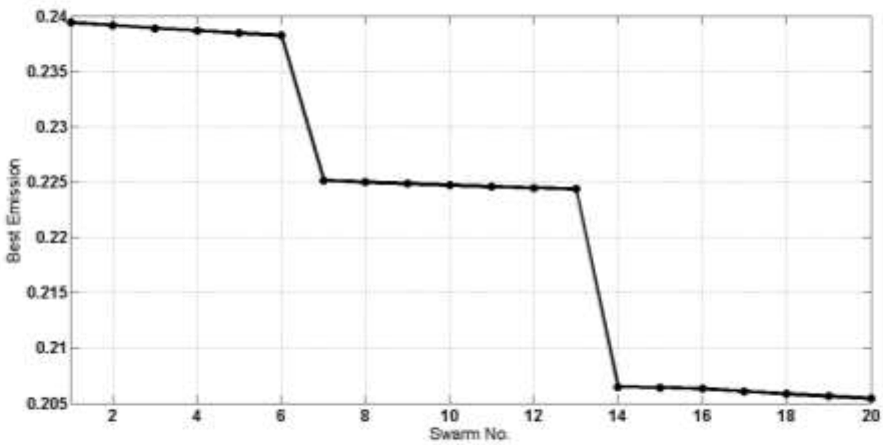

Fig. 5. Best particle in each swarm Case 2.

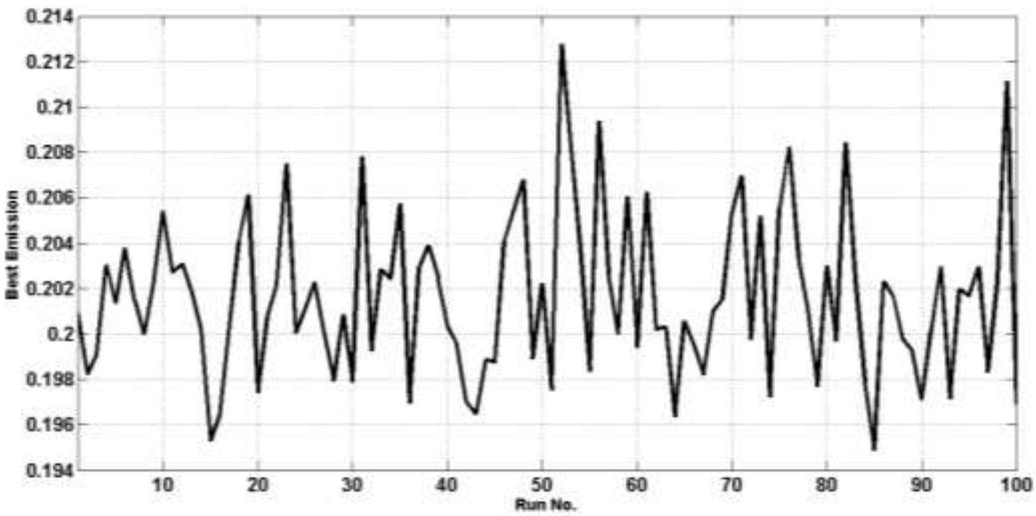

Fig. 6. Best particle against run number for Case 2.

5.3.3 Comparative studies for single objective categories

Table 5 summarizes the comparison results between the proposed DRN-PSO against several optimization techniques for cases 1 and 2 of CELD problem. The use of the proposed method leads to responsible economical solutions of 591.1517 $/hr and 643.8616 $/hr for cases 1 and 2, respectively. The corresponding emission levels are 0.215 and 0.1949 ton/hr. Previous results prove that the use of the proposed DRN-PSO algorithm leads to more economical compromised solutions compared to others at acceptable levels of emissions.

Table 5. Comparison of different methods for compromised solutions for Cases 1and 2

Algorithm	Case 1		Run time (s)/(f.e.)	Case 2		Run time (s)/(f.e.)
	Cost ($/h)	Emission (Ton/h)		Cost ($/h)	Emission (Ton/h)	
NSGA [35]	600.3100	0.2238	0.727 s	633.8300	0.1946	0.727 s
NPGA [35]	600.2200	0.2206	0.750 s	636.0400	0.1943	0.750 s
SPEA [35]	600.3400	0.2241	0.671 s	640.4200	0.1942	0.671 s
FCPSO [37]	600.1300	0.2223	20000 f.e.	638.3577	0.1942	20000 f.e.
MSFLA [38]	600.1114	0.22215	1.02 s	638.2425	0.1942	1.02 s
RCGA [39]	611.6935	0.2285	0.29364 s	648.5301	0.1932	0.0502 s
Proposed Approach	591.1517	0.215	• 0.11086 s • 20000 f.e.	643.8616	0.1949	• 0.1062 s • 20000 f.e.

* f.e. means fitness evaluations. * s is for seconds.

5.3.4 Comparative studies for multiobjective problem

5.3.4.1 Case 3: using equal weighting factors

Returning back to Eq. (11) and using equal weighting factors is a multiobjective case that need to be tested.

Table 6 shows the compromised solution using the proposed multiobjective version of DRN-PSO method for case 3. The obtained results are compared to other optimization algorithms. The performance of multiobjective version of the proposed DRN-PSO model is shown in Figs. 7-9. It is proven that, the proposed method has good convergence characteristics with robust solution.

Table 6. Comparison of different methods for the best compromise solution.

Algorithm	Emission (Ton/h)	Cost ($/h)	Run time
SPEA [35]	0.2004	610.3	0.671
NSGA [35]	0.2041	606.03	0.727
NPGA [35]	0.2015	608.90	0.750
MSFLA [38]	0.2006	610.0783	1.02
RCGA [39]	0.2159	578.8774	0.1291
Proposed approach for Case 3	0.2119	614.8176	0.1124

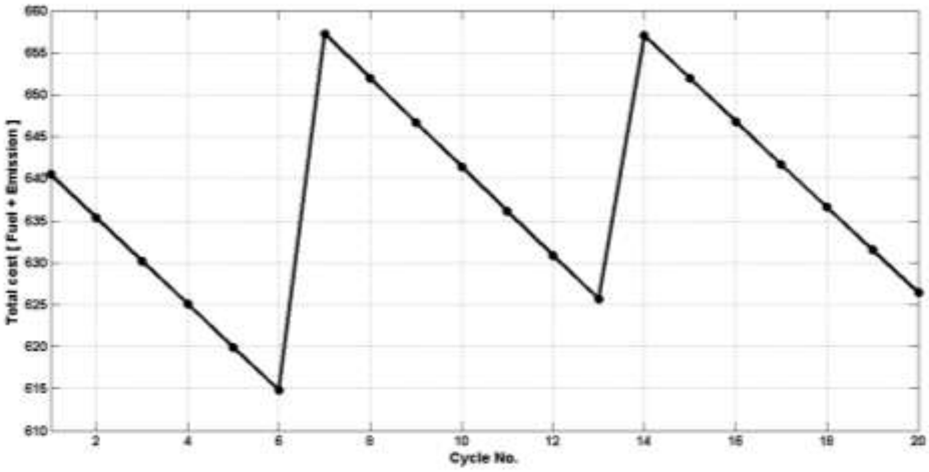

Fig. 7. Best particle against swarm number for case 3.

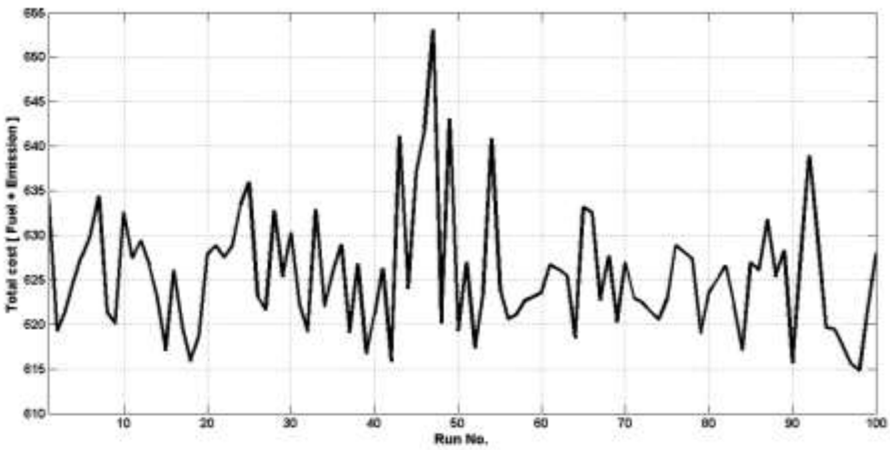

Fig. 8. Best point along all runs.

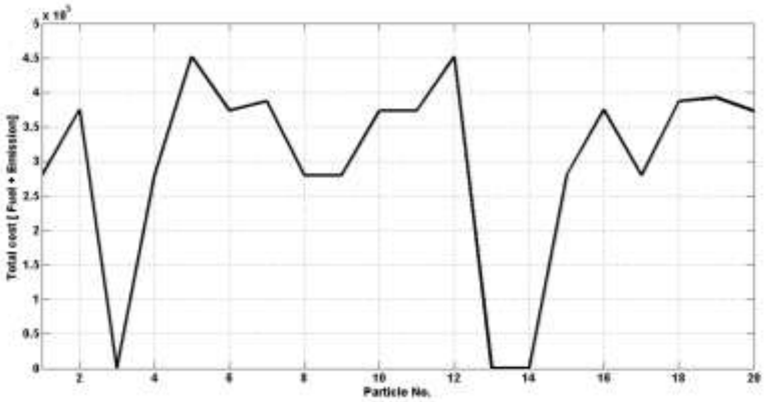

Fig. 9. Final swarm for Case 3.

5.3.4.2 Case 4: using weighted sum approach for different weighting factors

Table 7 shows the compromised CELD solution solved by the proposed DRN-PSO compared to RCGA for Case 4 using different weighting factors "in the range from 10%-90%", respectively. This table shows that the best compromise solution is 588.8579 \$/hr at pollutant emission level of 0.2235 ton/hr. The average value of run time is 0.1124. It is proven that: the obtained results are competitive compared to those obtained by RCGA as shown in Table 7. Thus, the proposed DRN-PSO method can be considered as an efficient promising method to solve non-linear optimization problems. The joint solutions of CELD problem for Case 4 prove the well distribution solutions which are successively obtained using the proposed DRN-PSO method.

Table 7. Joint CELD solution Case 4 for different weighting factors using DRN-PSO compared to RCGA.

Weighting factors		RCGA [39]		Proposed DRN-PSO	
w_1	w_2	Fuel Cost	Emission	Fuel Cost	Emission
0.9	0.1	589.9724	0.2245	589.5156	0.2207
0.8	0.2	590.2386	0.2225	591.2503	0.2200
0.7	0.3	589.6692	0.2160	591.2831	0.2159
0.6	0.4	590.0404	0.2207	589.7860	0.2334
0.5	0.5	590.0163	0.2155	588.8579	0.2235
0.4	0.6	590.9255	0.2147	589.9727	0.2175
0.3	0.7	592.1758	0.2197	592.0996	0.2286
0.2	0.8	590.6076	0.2191	593.0636	0.2245
0.1	0.9	591.0886	0.2226	593.0959	0.2184

6. CONCLUSIONS

This paper is concerned with nonlinear constrained economic dispatch problem to enhance the operation of power plants and to help for building up effective generating management plans. This paper investigated a new improved search algorithm based on the particle swarm optimization known as single / multi-objective PSO called Dynamic Random Neighborhood PSO “DRN-PSO” for non-smooth constrained economic dispatch problems. Experiments were conducted on IEEE 30-bus and compared to other optimization techniques reported in the literature. The obtained results demonstrate the superiority of the proposed DRN-PSO compared to other optimization techniques reported in the literature. The proposed algorithm improves the economic issue as well as enhancing the power system operation in the technical point of view at acceptable levels of emissions. So, it can be considered as a promising alternative algorithm for solving problems in practical large scale power systems. The proposed DRN-PSO algorithm has some merits over other algorithms reported such as simplicity of the approach, low number of adjustable parameters, time requirements are significantly low making the algorithm either comparable or better than other mentioned methods. Robustness of the proposed algorithm is proven with less variation of swarms.

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خوارزم متعدد الاهداف الأمثل لحل مشكلة التوزيع الاقتصادى/ الانبعاثى الامن

يقترح البحث خوارزم فرد السرب الديناميكى (DRN–PSO) لإيجاد التوزيع الامثل للاحمال على وحدات التوليد مع اعتبار دالة متعددة الاهداف تشمل تخفيض تكاليف الانتاج وتخفيض الملوثات البيئية مـع الاخذ فى الاعتبـار قيـود التاميـن ويستخدم البحث الخوارزم المقترح معادلـة الوزن الديناميكية لتحقيق التـوازن فـى التنقيب عـن الحلـول الأفضل حيث أجريت المحاكاة العدديـة على نظـام اختبار IEEE 30–bus وبالمقارنة مع غيرها من تقنيات التحسين السابقة أظهرت النتائج التى تم الحصول عليها تفوق الخوارزم المقترح على نظيراته الأخرى بالإضـافة الى المنافع الاقتصـادية فى وجود إعدادات آمنة، مع الحفاظ على كل من قيود النظام ضمن الحدود المسموح بها. الخوارزم المقترح يحسن مشكلة اقتصـادية فضـلا عن تعزيز مستوى الطاقة وبمستويات مقبولة من الانبعاثات، لذلك فإنه يمكن اعتبار الخوارزم المقترح بديل واعد من أجل حل المشاكل فى أنظمة الطاقة على نطاق واسع.