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Economic load dispatch of wind-solar-thermal system using backtracking search algorithm

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Abstract

Due to rise in the price of fossil fuels and technical advances in the area of renewable energy, integrated systems became more popular now a day. However uncertain nature of wind, solar irradiation due to weather and climate change, integration of renewable power generation system complicates the ELD formulation. The paper presents optimum scheduling of integrated solar-wind-thermal system using backtracking search algorithm (BSA). BSA is a novel population based stochastic search optimization technique, having simple structure and only one control parameter as population size. BSA has two new types of operator's as crossover and mutation for exploration and exploitation of search space of problem desired to be optimized and also satisfies all associated constraints of the objective function.

Keywords: BSA, Photovoltaic cell, Valve point loading effect, Probability density function.

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1. Introduction

Economic load dispatch (ELD) problem is an essential optimization problem in electrical power system. The core aim of ELD problem is to minimize the operating fuel cost while satisfying all associated operating constraints (Wood *et al*., 1984). Finding optimal solution is very difficult as practical ELD problem is highly nonlinear due to presence of various practical operating constraints like valve point loading (VPL) effect, ramp rate limits(RRL) and prohibited operating zones(POZ)(Walter *et al*., 1993; Wang *et al*., 1993; Oreo *et al*., 1996). Conventional methods fail to solve problem with these types of operating constraints. To optimize these types of problems an intelligence scheduling of generating units is required and by this we can achieve minimum operating cost with higher reliability.

Recently, different nature inspired (NI) techniques that follow heuristic approaches have been proved to be effective with promising performance due to their ability to solve complicated problem specially related to power system. These include genetic algorithm (GA) (Walter *et al*., 1993; Oreo *et al*., 1996), evolutionary programming (EP) (Sinha *et al.*, 2003), simulated annealing (SA) (Vishwakarma *et al.*, 2013) , differential evolution (DE) (Noman *et al.*, 2008), particle swarm optimization (PSO) (Selvakumar *et al.*, 2007; Chaturvedi *et al.*, 2008; Park *et al.*, 2010) etc. Recently novel NI techniques as well as improved version has been also proposed for solution of complex constrained ELD problem as bacterial foraging optimisation(BFO) (Panigrahi *et al.*, 2008), biogeography-based optimization(BBO) (Bhattacharya *et al.*, 2010) , group search optimizer(GSO) (Dalvand *et al.*, 2012), ant colony optimization(ACO) (Pothiya *et al.*, 2010), cuckoo search algorithm(CSA)(Basu *et al.*, 2013), krill herd algorithm(KHA)(Mandal *et al.*, 2014) , chemical reaction optimization (CRO)(Roy *et al.*, 2014) , flower pollination Algorithm(FPA) (Dubey *et al.*, 2015), gravitational search algorithm(GSA)(Udgir *et al.*, 2013), hybrid PSO GSA(Dubey *et al.*, 2014; Duman *et al.*, 2015) , invasive weed optimization(IWO) (Barisal *et al.*, 2015) etc. Detail review of NI techniques for solution of ELD can be found in (Dubey *et al*, 2014).

Now a day's renewable energy resources and integrated power generation system has attracted much attention of researchers. Even though initial installation cost of renewable power generating system is higher, but the operating cost of solar and wind generating unit is significantly low. These are the two potential alternate energy resource attract much to match growing electric power demand of electricity as prices of limited fossil resources is increasing day by day. However unpredictable wind velocity of wind and weather dependent solar irradiation, unable to match time varying power demand as a result integrated power generation system creates new operational challenges for optimum generation scheduling. Here maintaining reliability is a big issue for the resulting integrated solar-wind-thermal system problem. Therefore ELD problem needs reformulation to include the operating constrains occurs due to uncertain nature of wind and weather dependent solar irradiation. In this area also from energy conservation point of view more researchers expressed their interest. Considering weather dependent and uncertainty, wind speed is mostly expressed as probability distribution function (pdf))(Hetzer *et al.*, 2008; Reddy *et al.*, 2013; Zhu *et al.*, 2014; Dubey *et al.*, 2015). The wind integrated ELD modeling using pdf can be presented in (Hetzer *et al.*, 2008; Reddy *et al.*, 2013; Zhu *et al.*, 2014; Dubey *et al.*, 2015) and modeling of solar-wind system is presented in(Karaki *et al.*, 1999; Habib *et al.*, 1999; Deshmukh *et al.*, 2008; Reddy *et al.*, 2015). Renewable power integration makes ELD model much complex due to additional constraints and required robust algorithm to solve these types of problems.

In this paper a novel optimization algorithm namely back tracking search (BSA) is applied to solve the ELD problems with/ without solar and wind power integration. BSA utilizes the principles of evolution and natural genetics where the population is updated by mutation, crossover and selection to generate the trial population.

2. Problem formulation of ELD problem with solar and wind integration

The ELD problem with wind integration has complex equality and inequality constraints associated with thermal, and wind power generating units. Due to zero fuel cost of solar power generation, the prime objective becomes minimization of fossil fuel cost of thermal units along with cost of wind power generating units (F_{Total}) . The objective function to be minimized as:

$$F_{Total} = \sum_{i=1}^{m} F_{th}(P_i) + \sum_{j=1}^{n} F_w(P_{wj}) \tag{1}$$

The cost of thermal power generation with VPL effect can be written as:

$$F_{th}(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i \sin(e_i(P_i^{\min} - P_i)) \right| \text{ (\$/hr.)} \tag{2}$$

The cost of thermal power generation with cubic function can be expressed as:

$$F_{th}(P_i) = (a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i) \text{ (\$/hr.)} \tag{3}$$

The cost of wind power output using wind power coefficient 2_j can be expressed as (Hetzer *et al.*, 2008; Dubey *et al.*, 2015):

$$F_w(P_{wj}) = \sum_{j=1}^{n} 2_j \times P_{wj} \tag{4}$$

2.1 Equality constraints

$$P_D = \sum_{i=1}^{m} P_i + P_{pv} + \sum_{j=1}^{n} P_{wj} \tag{5}$$

2.2 Inequality constraints

Generation power should lie within minimum and maximum values.

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{6}$$

$$P_{wj}^{\min} \le P_i \le P_{wj}^{\max} \tag{7}$$

2.3 Modeling of wind power system

The wind velocity is an arbitrary variable and wind power imparts a nonlinear connection to it. The wind speed information from different places is found to take after weibull distribution nearly and it is use for processing wind speed and wind power**.** *pdf* of wind velocity is expressed as (Hetzer *et al.*, 2008; Reddy *et al.*, 2013):

$$pdf(u) = \frac{}{\sim}\left(\frac{v}{\sim}\right)^{-1} \exp\left[-\left(\frac{v}{\sim}\right)\right] \tag{8}$$

The wind power (*Wp*) can be represented as a stochastic variable and calculated from wind speed as (Hetzer *et al.*, 2008).

$$P_{wj} = \begin{cases} 0 & (v < v_{ci} \quad or \quad v \geq v_{co} \\ P_{wj}^{R} & (v_r \leq v < v_{co}) \\ \dfrac{(v - v_{in})P_{wj}^{R}}{v_r - v_{in}} & (v_{ci} \leq v < v_r) \end{cases} \tag{9}$$

Whenever the wind speed is in between the v_r and v_{ci}, the power output of the wind farm is assumed to be a continuous variable, its pdf is given as (8). The total of all wind generator yields is taken as one random variable P_{wj} and the *pdf* is given by

$$pdf\ (P_w) = \frac{\text{¥}\, v_{in}}{P_{wj}^{R}\sim} \left[\frac{(1 + \dfrac{\text{¥} P_{wj}}{P_{wj}^{R}}) v_{in}}{\sim} \right]^{-1} . \exp \left[- \left\{ \frac{\left(1 + \dfrac{\text{¥} P_{wj}}{P_{wj}^{R}}\right) v_{in}}{\sim} \right\} \right] \tag{10}$$

$$\text{Here } \text{¥} = \left(\left(\frac{v_r}{v_{ci}} \right) - 1 \right) \tag{11}$$

To describe the condition that the available power is not ample to satisfy the total power demand, a probabilistic tolerance δ_a is chosen to model the uncertainty of wind power availability. In context to this the power balance constraint in (12) with wind and solar power is modified as expressed below.

$$P_r (\sum_{j=1}^{n} P_w^{j} + \sum_{i=1}^{m} P_i + P_{pv} \leq (P_D) \leq \text{¢}_a \tag{12}$$

A smaller value of δ_a decreases the risk of not enough wind power and increases the thermal generation to ensure the good reserve capacity.

2.4 Modeling for photovoltaic (PV) system

Power output PV generator mainly depends on solar radiation and temperature. The hourly power output of PV generator can be calculated as (Deshmukh *et.al.*, 2008, Habib *et al.*,1999) :

$$P_s = I_T \text{¦} A_{pv} \tag{13}$$

For PV system average solar radiation (I_T) for an inclined surface can be calculated as (Duffie *et al.*,1991) :

$$I_T = I_a R_a + I_b R_b + (I_a + I_b) R_r \tag{14}$$

System efficiency (η) is represented as (Habib *et al.*,1999):

$$\text{¦} = \text{¦}_m \text{¦}_{pce} P_f \tag{15}$$

Where, $\text{¦}_m = \text{¦}_{re} \left[1 - \quad (T_k - T_{re}) \right]$ (16)

3. Backtracking search algorithm

BSA is a metaheuristic technique based on the principles of evolution and natural genetics where the population is updated by mutation, crossover and selection to generate the trial population(Civicioglu *et al.*,2013). The five processes used here are initialization, selection-I, mutation, crossover and selection-II. The mutation and crossover operations in BSA are relatively different from that of GA and DE and are found to produce better population diversity. BSA is a double population algorithm which makes use of random past experiences stored in its memory. Most NI techniques make use of the better or best individuals for generating new solutions but BSA employs the current and previous iteration populations, non-uniform crossover, a random mutation strategy having only one direction individual for each solution and a novel boundary control mechanism. The magnitude of mutation is controlled by a random mutation factor drawn from the normal distribution which randomly controls exploration/exploitation depending on larger/smaller value of the mutation factor. There is only one control parameter *mixrate* which controls the number of elements of individuals which are mutated in each iteration. BSA has various principle steps as initialization, selection-I, mutation, crossover and selection-II and are described as below. Figure 2 shows the flow chart of BSA.

3.1. Initialization

In this process a set of population is randomly generated within the limits of upper bound (ub) and lower bound (lb) as:

$$pop = lb + rand * (ub - lb) \tag{17}$$

rand is any random number between 0 and 1.

3.2. Selection-I

Here a set of historical population is generated. The process of generation of *historicalpop* is same as the pop.

$$historical\ pop = lb + rand * (ub - lb) \tag{18}$$

Then each element of historical population is updated through a simple reasoning as below:

$$if \quad i < j, \quad historical\,pop = pop \quad end \quad i, j \in (0,1) \tag{19}$$

The advantage of generating historical pop is that, it is stored in BSA as a memory and historical pop is not changed until it's get a better fitness value.

After that a permute process is used to change the order of individuals of $historicalpop$:

$$historical\ pop = historical\ pop\ (randperm\ (popsize\ )) \tag{20}$$

3.3. Mutation

In mutation process mutants i.e. trial population matrix are generated as:

$$mutant = pop + M * (historical\ pop - pop) \tag{21}$$

Where M is taken *(3*rndn)* and it controls the amplitude of search- direction matrix *(historicalpop-pop)* and it is based upon standard Brownian walk. Mutants take some advantage from grown experienced or previous generation due to involvement of historical population.

3.4 Crossover

As an initial form of trial population is generated as per (21) and here final form of trial population is generated. There are two algorithms inside crossover process, *first* is for generation of integer valued matrix (B_{map}) and second is for *mixrate* that controls the number of elements and they will further mutate by (*mixrate * rand* D)*. Here *D* is the dimension of the problem.

3.5. Selection-II

It is the final stage of BSA, here all the population sets are put together and compared to get a better fitness value of population. If in selection-II process the updated values have better fitness then the global minimum value of individual of population obtained so far. Then it is updated to global minimizer.

The pseudo code depicted in Figure 1 shows the process applied as selection I, Mutation and crossover in BSA algorithm for optimization.

Algorithm-1

Define mixrate

```
historicalpop=historicalpop (randperm(popsize),:)
Map=zero(popsize,D);
If rand<rand,
 for i=1:popsize
     u=randperm(D);
     map(i,u(1:ceil(mixrate* rand* D)))=0;
 end
 else
  for  i=1:popsize
       map(i, randi(D))=0;
  end
end
mutant=pop+(map*F)*(histiricalpop-pop);
```

Algorithm-2

Boundary control mechanism for trial population

```
for i=1:popsize
    for j=1:D
        k=rand<rand;
       if pop(i,j)<lb(j)
          if k
             pop(i,j)=lb(j)
          else
             pop(i,j)=rand*(ub(j)-lb(j))+lb(j);
          end
       end
     if   pop(i, j)>ub(j),
        else
        pop(i,j)=rand*(ub(j)-lb(j))+lb(j);
     end
   end
end
     T(i,:)=pop(i,:)
end
```

Figure 1. Section I, Mutation and crossover process for BSA algorithm

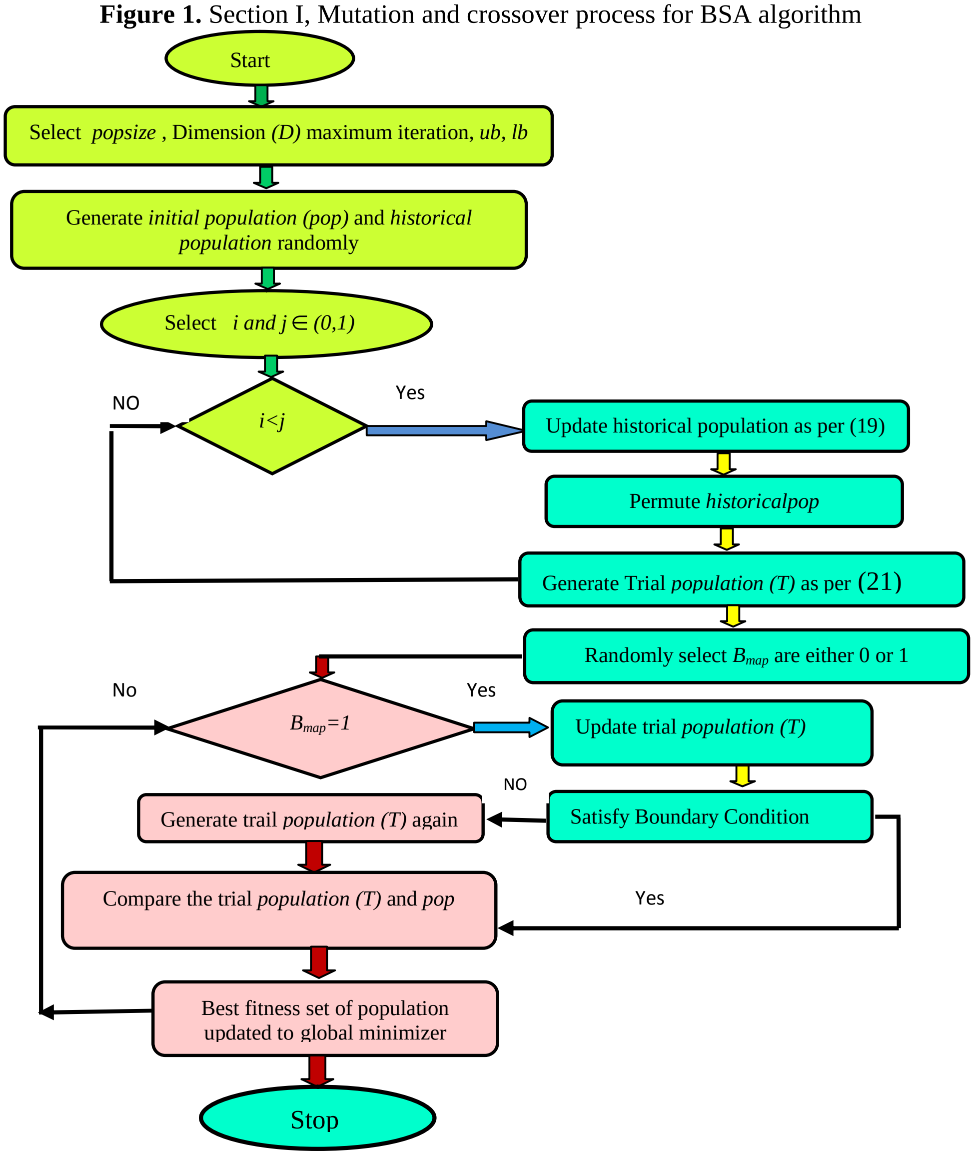

Figure 2. Flow chart of Backtraking search algorithm

4. Implementation of BSA for solar-wind-thermal scheduling

Step-1: Each individual set of population matrix is Initialized as per (22) generated within the limits of maximum and minimum power dispatched

$$pop = P_i^{\min} + rand\,(N, D) * (P_i^{\max} - P_i^{\min}) \tag{22}$$

Step-2: Evaluate the objective function for each set of population generated by (22) with the satisfaction of all constraints (5)-(10).

Step-3: Based on values of objective function identify the best population set which gives minimum values of (1), and keep it unchanged after each iteration without making any modification in it.

Step-4: Now historical population is initialized the using (18).Compute the objective function as per the historical population after that each set of historical population is updated as per (19) for each iteration. After making new set of historical population each set of power dispatched is shuffled as per (20).

Step-5: Initial position of mutant matrix is produced using (21).

Step-6: Trial population set (T) is generated in this step. The algorithm-1 defines the mixrate and algorithm-2 defines the boundary control mechanism. Update the values of T is applicable to individuals of generated matrix. Compute the objective function for T.

Step-7: For population *(pop)* set and trial population *(T)* set the values of objective function is compared. If the set of population has better fitness than the global minimum value then this new set of population is updated to global minimizer.

Step-8: Iteration process is terminated here as if current iteration is greater than or equal to maximum iteration. Store the best power output in an array otherwise repeat step-1 to step-7 in that order.

5. Results and discussion

To demonstrate the efficiency of BSA, it is applied and test on three types of test cases, namely optimal scheduling of thermal system, optimal scheduling of solar-thermal system and optimal scheduling of solar-wind-thermal system. code of all test cases is developed and implemented in MATLAB 9 and programs are executed on 2.10 GHz Intel Pentium Processor with 1.0 GB RAM.

5.1. Description of Test cases

Test Case-1:
In this test case standard 13 generating unit with valve point loading effect (Sinha N. *et al.*, 2003).
Load demand is set at 2520MW and transmission loss is not considered here.

Test Case-2:
In this test case has 26 generating units with cubic fuel cost characteristic (Chandram *et al.*, 2011). The power demand is set at 2900MW and transmission losses are not considered here.

Test Case-3:
It is a composite solar-thermal system having 26 thermal generating units similar to test case 2 and a solar plant of maximum rating 50 MW. The data for radiation and average ambient temperature is adopted as per (Solar Radiation Hand Book, et al.,2008) for city Delhi (India).The other data for PV generator are set at P_f =0.9, A_{pv} =90163.04m^2, β=-4.7e-3, η_{re}=0.105, η_{pce}=0.9 and T_{re} =25ºC.

Test Case-4:
It is an integrated wind-solar-thermal system. Here all power generating unit data are considered similar to test case 3 along with an additional wind farm. The cost coefficient for wind farm considered as kr =1, kp=5, rated power output 155 MW. The other constants are set at v_{ci}=5, v_{co} =45 and v_r=15. The shape and scale factor are considered as 1 and 15 respectively. The whole network adopted for simulation analysis in this test case is shown in Figure 3.

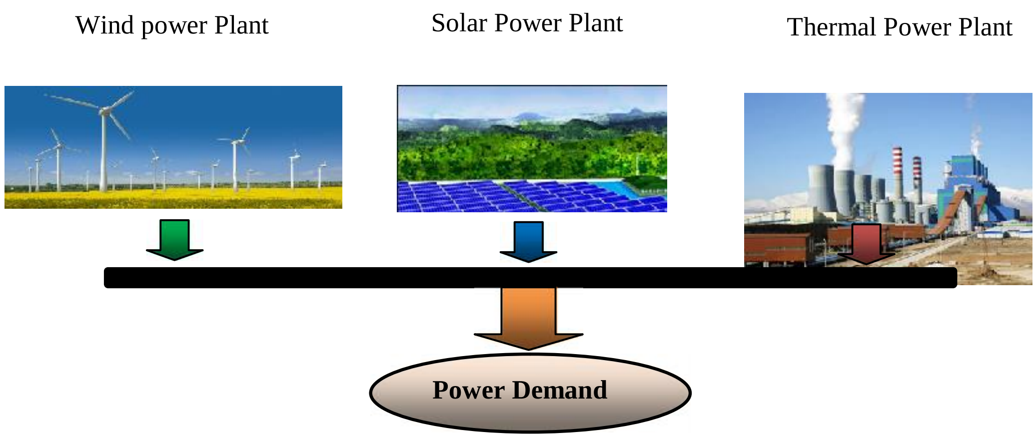

Figure 3. Wind-solar- Thermal system

5.2. Selection of Parameters

BSA belongs to the family of stochastic method; it requires optimal selection of tuning parameter to get global optima solution. In order to explore best tuning parameter BSA, it is applied and tested on test case 1 having 13 power generating unit system with non convex fuel cost characteristic. As BSA have only one control parameter as pop size (NP), twenty-five independent run were conducted with different value of NP. The statistical results obtained by simulation are tabulated in Table.1. Here it is observed that optimum operating cost is obtained with NP=100 with comparatively low standard deviation (SD) of **0.750**, therefore selected for simulation analysis.

Table 1. Effect of pop size (NP)

Pop Size (NP)	Min cost ($/h)	Max cost ($/h)	Ave cost ($/h)	S.D	CPU (s)
50	24165.2809	24166.7871	24165.9115	0.574	**4.07**
100	**24164.0524**	**24166.5831**	**24164.2942**	**0.750**	**5.12**
150	24164.7986	24165.9506	24165.2273	0.4261	**7.65**
200	24164.5755	24165.4754	24164.9175	0.3068	**11.36**

5.3. Optimal dispatch solution Comparison of results

As test case 1 is highly nonlinear multi-model problem due to valve point loading effect, and it is quite difficult to get global best solution. Here the optimum cost obtained by BSA is 24164.0524 $/hr, which is found to be better than recent reported method as Genetic algorithm (GA) (Noman *et al*., 2008), Differential evolution (DE) (Noman *et al*., 2008), Hybrid Chemical reaction Optimization(HCRO) (Roy *et al*., 2014), Chemical Reaction Optimization (CRO) (Roy *et al*., 2014), Iteration PSO with time varying acceleration coefficients (IPSO_TVAC) (Ivatloo *et al*., 2012) and Simulated annealing (SA) (Vishwakarma *et al*., 2012). The Optimal dispatch solution obtained by BSA and statistical comparison of results are presented in table 2 and table 3 respectively. The convergence characteristic obtained by BSA for test case 1 is plotted in Figure 4.
For test case 2, which is comparatively a large system and have cubic fuel cost characteristic, the optimum cost obtained by BSA over twenty-five repeated trails is 43436.5297($/hr) . Here also the results obtained by BSA are found to be comparable with Hybrid PSO-GSA (Dubey *et al.*, 2014) and Equal Embedded Algorithm (EEA) (Chandram *et al.*, 2011) as depicted in Table 4.

Similarly for renewable power integration as in test case 3, the best cost solution obtained by BSA is 42250.8926 ($/hr), where as for wind-solar-thermal test case 4 it is 40608.8435($/hr). Their full dispatch solutions are presented in Table 5. Here it observed that total operating cost reduced by approximately 3% by solar integration and by 6.5% by integration of both wind and solar system as compared to thermal system with cubic fuel cost characteristic as described in test case 2. The smooth and stable convergence characteristic obtained by BSA for thermal system (test case 2), solar thermal system (test case 3) and, integrated wind-solar- thermal system (test case 4) is plotted in Figure 5.

Table 2. Optimal Power Dispatch for 13 unit system test case 1

Unit	GA**	DE**	CRO**	HCRO**	IPSO_TVAC**	SA**	BSA
P_1 (MW)	628.32	628.3185	628.3149	628.3185	628.319	628.3185	628.3185
P_2 (MW)	356.49	299.1993	299.2010	299.1993	299.199	299.1993	299.1993
P_3 (MW)	359.43	299.1993	294.9875	294.9957	295.878	299.1993	294.4848
P_4 (MW)	159.73	159.7331	159.7100	159.7331	159.265	159.7331	159.7331

Table 2 (cont'd). Optimal Power Dispatch for 13 unit system test case 1

Unit	GA**	DE**	CRO**	HCRO**	IPSO_TVAC**	SA**	BSA
P_5 (MW)	109.86	159.7331	159.7335	159.7331	159.733	159.7331	159.7331
P_6 (MW)	159.73	159.7331	159.7330	159.7331	159.733	159.7331	159.7331
P_7 (MW)	159.63	159.7331	159.7332	159.7331	159.733	159.7331	159.7330
P_8 (MW)	159.73	159.7331	159.7330	159.7331	159.733	159.7331	159.7331
P_9 (MW)	159.73	159.7331	159.7332	159.7331	159.733	159.7331	159.7331
P_{10} (MW)	77.31	77.3999	77.3631	77.3999	77.363	77.3999	77.3999
P_{11} (MW)	75.00	77.3999	77.2999	77.3999	77.397	77.3999	77.3999
P_{12} (MW)	60.00	92.3999	92.4154	92.3999	92.397	87.6845	92.3997
P_{13} (MW)	55.00	87.6845	92.0423	91.8882	91.517	92.3999	92.3997
Total cost($/h)	24398.23	24169.9177	24,165.1664	24,164.8260	24,166.8	24169.9176	**24164.0524**

Table 3. Statistical results for 13 unit system test case 1

Methods	CRO**	HCRO**	IPSO_TVAC**	SA**	BSA
Min cost ($/h)	24,165.1664	24,164.8260	24,166.8	24169.9176	24164.0524
Max cost ($/h)	24,169.3642	24,165.3402	24,169.41	N.A	24166.5831
Average cost ($/h)	24,166.9355	24,164.9837	24,167.37	N.A	24164.2942
S.D	0.94	0.93	N.A	N.A	0.75
Ave CPU time(sec)	5.56	5.04	N.A	N.A	5.12

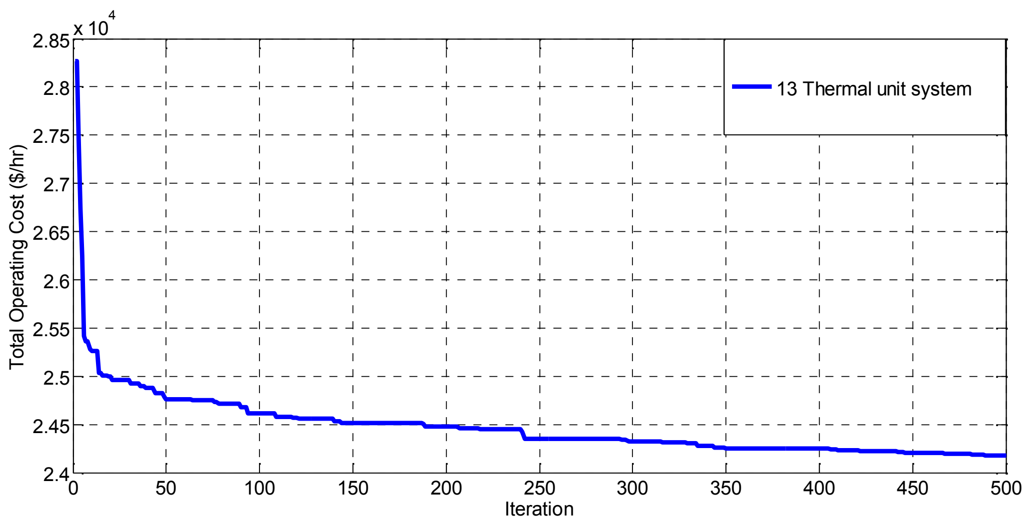

Figure 4. Convergence characteristic of non convex 13 unit system, power demand=2520MW

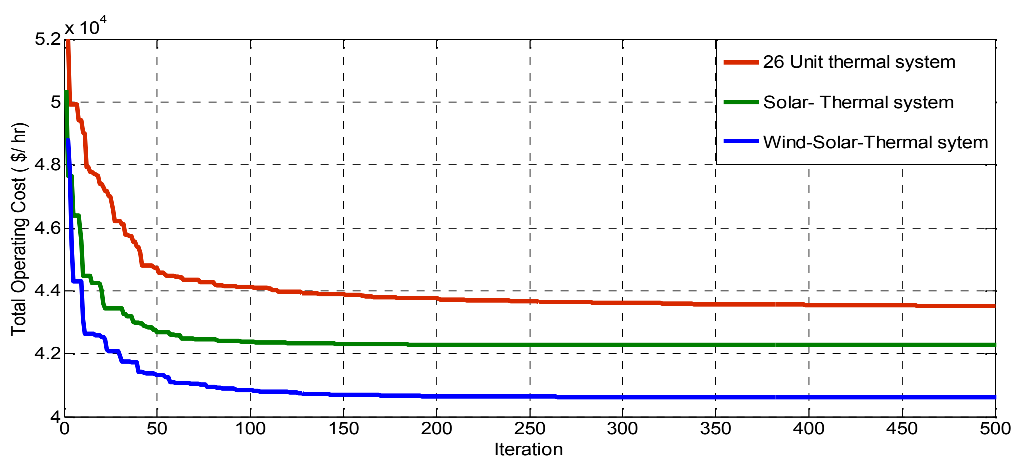

Figure 5. Convergence characteristic of 26 unit system, power demand=2900MW

Table 4. Optimal Power Dispatch for 26 unit system

Unit	EEA*	TVPSOGSA**	BSA	Unit	EEA**	TVPSOGSA**	BSA
P_1 (MW)	2.40000	2.40000	2.40001	P_{14}(MW)	100.00000	100.00000	100.00000
P_2 (MW)	2.40000	2.40000	2.40002	P_{15}(MW)	100.00000	100.00000	100.00000
P_3 (MW)	2.40000	2.40000	2.40000	P_{16}(MW)	100.00000	100.00000	100.00000
P_4 (MW)	2.40000	2.40000	2.40004	P_{17}(MW)	155.00000	155.00000	155.00000
P_5 (MW)	2.40000	2.40000	2.40001	P_{18}(MW)	155.00000	155.00000	155.00000
P_6 (MW)	4.00000	4.000000	4.00003	P_{19}(MW)	155.00000	155.00000	155.00000
P_7 (MW)	4.00000	4.00000	4.00003	P_{20}(MW)	155.00000	155.00000	155.00000
P_8 (MW)	4.00000	4.00000	4.00004	P_{21}(MW)	190.99000	187.86800	190.99900
P_9 (MW)	4.00000	4.00000	4.00002	P_{22}(MW)	166.00000	165.09440	166.00000
P_{10} (MW)	76.000000	76.00000	76.00000	P_{23}(MW)	141.00000	145.03760	141.00100
P_{11} (MW)	76.00000	76.00000	76.00000	P_{24}(MW)	350.00000	350.00000	350.00000
P_{12} (MW)	76.00000	76.00000	76.00000	P_{25}(MW)	400.00000	400.00000	400.00000
P_{13} (MW)	76.00000	76.00000	76.00000	P_{26}(MW)	400.00000	400.00000	400.00000
				Total cost($/h)	43436.5	43436.58355	**43436.5297**

Table 5. Optimal power dispatch solution for renewable integrated system obtained by BSA (Test case 3 and Test case 4)

Unit	Test case 3:Solar Thermal system	Test case 4:wind-Solar- Thermal system
P_1 (MW)	2.40195	12.0000
P_2 (MW)	2.40296	2.4014
P_3 (MW)	2.40235	2.4118
P_4 (MW)	2.40286	2.4012
P_5 (MW)	2.40033	2.4059
P_6 (MW)	4.00003	4.0006
P_7 (MW)	4.00003	4.0000
P_8 (MW)	4.00005	4.0008
P_9 (MW)	4.00005	4.0000
P_{10} (MW)	75.9999	76.0000
P_{11} (MW)	75.9999	75.9999
P_{12} (MW)	75.9999	76.0000
P_{13} (MW)	75.9999	76.0000
P_{14}(MW)	100.0000	99.9988
P_{15}(MW)	99.9999	99.9984
P_{16}(MW)	99.9998	99.9979
P_{17}(MW)	155.0000	155.0000
P_{18}(MW)	155.0000	154.9998
P_{19}(MW)	155.0000	154.9988
P_{20}(MW)	155.0000	155.0000
P_{21}(MW)	175.1190	119.1194
P_{22}(MW)	148.2370	93.2265
P_{23}(MW)	124.6710	71.0914
P_{24}(MW)	350.0000	349.9996
P_{25}(MW)	400.0000	399.9985
P_{26}(MW)	400.0000	399.9980
P_{solar}(MW)	49.9636	49.9521
P_{wind}(MW)	NA	154.9992
Total thermal cost($/h)	42250.8926	40283.6778
Wind over estimation cost($/hr)	NA	325.1642
Wind under estimation cost($/hr)	NA	0.0015
Total operating cost($/hr)	42250.8926	40608.8435

5.4. Computational efficiency and robustness

The computation time for BSA over 25 independent trials is used to authenticate the computational efficiency of applied approach. Form table 3 it is evident that standard deviation for test case 1 is found to be low which approves that BSA is computationally efficient .Also as per statistical results in terms of minimum, maximum, average cost, S.D and average CPU time in table 3 confirms the superiority and robustness of BSA for complex constrained optimization problems related to power system.

The average CPU time associated with different test cases under investigation are depicted in figure 6.which is found to be obvious as per complexity and dimension of test cases.

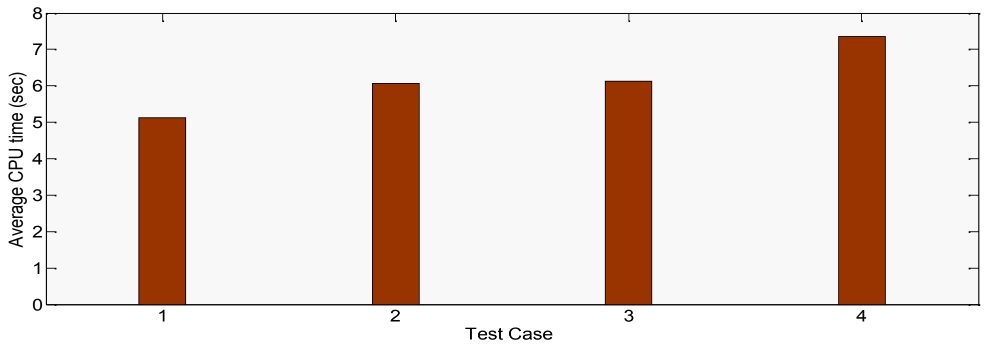

Figure 6. Average CPU time for different test cases

6. Conclusion

The paper presents a novel optimization technique BSA to solve ELD problem with / without integration of solar power. Wind power is model by pdf where as solar photo voltaic system is model by deterministic approach. As BSA is a double population algorithm employs the current and previous iteration populations, non-uniform crossover, a random mutation strategy having only one direction individual for each solution and an efficient boundary control mechanism which helps to attain global best solution. As a results simulation results obtained by BSA is found to be significantly better than individual performances of GA, DE, CRO, IPSO_TVAC, SA and TVPSOGSA. All operating constraints are satisfied as well as BSA compute best dispatch solution in efficient manner irrespective of dimension and complexity of test cases. It can be easily applied and extended for solution of large scale optimization problem related to power system operation and control.

Nomenclature

$F_{th}(P_i)$	Cost associated with power generation of i^{th} thermal unit
$F_w(P_{wj})$	Cost associated with power generation of j^{th} wind farm
F_{Total}	Total operating cost of power generation
a_i, b_i, c_i, d_i & e_i	Cost coefficients of i^{th} generating unit
m	number of thermal power units
n	number of wind farm
P_D	Total Power Demand
$P_i^{\min}, P_i^{\max}$	Minimum and maximum power output limit of i^{th} thermal generating unit
$P_{wj}^{\min}, P_{wj}^{\max}$	Minimum and maximum power output limit of j^{th} wind farm
pdf	Probability density function
α ,β	shape and scale factor
v_r, v_{ci} and v_{co}	rated wind speed, cut-in speed and cut-out speed
I_T	Average solar radiation incident on PV surface
I_a and I_b	normal and diffuse solar radiations
R_a, R_b and R_r	tilt factor for normal, diffused and refracted surface
A_{pv}	Area of Solar Modules
P_s	Average power output of PV generator
η	System efficiency
η_{pce}	Power conditioning efficiency
P_f	Packing factor
η_m	Module efficiency

η_{re}	Reference module efficiency
β	Array efficiency temperature coefficient
T_k	Average cell temperature
T_{re}	Reference temperature for cell efficiency
**	Result from references
NI	Nature Inspired
NA	Not available in literature
S.D	Standard Deviation

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