Optimal Operation of Wind-thermal generation using differential evolution

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Abstract: Numerous optimization paradigms have been developed for power system optimization tasks till date but none has found the level of acceptance which is being received by evolutionary soft computing methods. Traditional methods are found to be inefficient for complex practical problems with equality and inequality constraints therefore the complexity of the task reveals the necessity for development of efficient algorithms to accurately locate the optimum solution. The present paper proposes to solve complex constrained optimization problems using differential evolution (DE) with multiple mutation strategies. The role of control parameters and mutation strategies of DE algorithm in achieving the global best result is critically explored. The depleting reserves of fossil fuel and growing concern about environmental protection dictates the integration of renewable power resources into the power grid. Including wind power with the conventional power has become very popular in recent years due to the rapid development of technology in this field. Modeling of wind-thermal system is required to find the optimal wind generator capacity that can be integrated into the existing system such that all operating constraints are satisfied. The developed algorithm is tested on a standard test system taking into consideration the wind uncertainty and ramp-rate limits of thermal power units. The results clearly demonstrate the effectiveness of the proposed method in finding feasible and efficient globally optimal solutions **Keywords** - Differential evolution, equality and inequality constraints, mutation strategies, wind-thermal economic dispatch.

INTRODUCTION I.

Nature inspired, evolutionary computation is applied to solve various single and multi-objective optimization problems, which cannot be solved using conventional optimization techniques because of high dimensionality, nonconvexity/non-smooth nature of objective function. In general, evolutionary computation techniques are composed of a set of different families of algorithms that iteratively improve a set of tentative solutions to obtain an optimal or a quasi-optimal solution to the problem. Evolutionary optimization techniques are being preferred over traditional methods for solving real-world engineering optimization problems because these methods do not depend on the nature of the problem and are able to model complex constraints with ease. The last decade has seen tremendous growth in the field of heuristic based optimization methods for NP complete problems. Many new nature inspired evolutionary optimization algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony search (ACS), harmony search (HS), bacterial foraging (BF), biogeography based optimization (BBO) etc. were proposed for almost all the fields of engineering, science and management. The major advantages of these methods are i) population based random search mechanism ii) non-dependence on nature of objective function iii) ability to handle complex constraints iv) non-dependence on initial solution and v) simple implementation. The objective of solving the economic dispatch (ED) problem of electrical power systems is to find the optimal allocation of output power among the available generating units such that the system load is met and operating constraints are satisfied[1][2]. Alternate sources of power are continuously being explored to find a sustainable and economic solution to the ever increasing global power needs. A model based on differential evolution is proposed in this paper to include wind energy conversion systems (WECS) into the conventional power network. The most important factor associated with wind energy is that after the preliminary land and capital costs, there are almost no financial requirements in producing electrical power by harnessing wind energy. The wind energy system is environment friendly as compared to conventional fossil fuels. A number of research efforts can be found in literature where wind-thermal cost optimization has been carried out using numerical optimization methods. A model to include the wind energy conversion system (WECS) in the economic dispatch(ED) problem is presented using numerical solutions [3]. Both overestimation and underestimation of available wind power are analyzed. The stochastic nature of wind speed characterization is modeled using Weibull probability density function for a system having two conventional and two wind-powered generators. The economic dispatch problem for power systems which contain wind power generation plants is presented in [4]. The dynamic optimal dispatch takes into account of the coupling effect of system at different time moments, such as the limit on the climbing rate of a generator. Quantum genetic algorithm is adopted in this paper, the calculation of which is to borrow fully the concept and theory of Quantum computing [4]. The transformation of the multi-objective dispatch problem into a single-objective one to compromise different objectives is presented in [5] using, the optimal generation dispatch (OGD) model. Then the OGD is solved by a particle swarm optimization algorithm. The plant growth simulation algorithm (PGSA) is applied to solve the wind-thermal dispatch problem with different constraints like valve point loading effect, ramp rates, power loss and prohibited zones. Problem formulation of wind-thermal dynamic economic dispatch [6] A stochastic optimization method utilising a simulated annealing (SA) approach combined with an efficient constrained dynamic economic dispatch (CDED) is proposed in [7].

This paper proposes a DE based approach for wind-thermal scheduling problem in dynamic environment with complex constraints. A detailed analysis and comparison of the various DE mutation strategies is carried out. The proposed approach is found to be very effective in locating optimal solutions consistently.

II. PROBLEM FORMULATION OF WIND-THERMAL DYNAMIC ECONOMIC DISPATCH

The objective function for wind-thermal economic dispatch includes minimization of the operating cost of thermal as well as wind power at any given time interval consisting of all sub-intervals. After the initial costs, the wind power farm does not consume fuel therefore power companies normally dispatch all wind power first. The objective of economic dispatch for power systems containing wind power farm can be formulated as:

$$MinF_{T} = \min \sum_{t=1}^{T} \sum_{i=1}^{N} F_{it}(P_{git}) + F_{cp}$$
(1)

Where F_T is the total cost for producing power for the N number of conventional generating units over time interval T; The active power output of the ith generator at time t is taken as P_{Git} ; the operating cost of individual thermal unit is expressed using the quadratic cost function as $F_i(P_{Git})$ And for the tth time it can be expressed as: $F_i(P_{Git}) = a_i + b_i P_{Git} + c_i P_{Git}^2$ (2)

Where a_i , b_i and c_i are the fuel cost coefficients of the ith thermal generating unit. In the electricity market, the cost function due to environmental effects of thermal generation can also be included in the optimal wind-thermal system by defining the emission content in terms of additional coefficients based on the emission characteristics. The ecological cost of coal-fired generating units is added to the fuel cost of electricity generation. The environmental cost function F_{cp} can be given as:

$$F_{cp} = \sum_{t=1}^{m} M_{cpi} \times f_{di} \tag{3}$$

Where M_{cpi} is the cost coefficient for modeling environmental effect and f_{di} is the emission amount of the ith thermal generating unit. On the basis of the weight of the harmful pollutant gases discharged from the thermal units, the emission characteristics for each unit can be represented by emission per unit time as:

 $f_{di}(t) = \alpha_i + \beta_i P_{Git} + \gamma_i P_{Git}^2 + \delta_i \exp(\Theta_i \times P_{Git})$

Where α_i , β_i , γ_i , δ_i and θ_i are the emission characteristics coefficients for the ith thermal generating unit, which can be measured.

The objective function specified by (1) is to be minimized subject to the following constraints:

2. 1 Power balance constraint

The total power generated by wind and thermal units at any given time should match the load plus losses at that time [1] [2].

$$\sum_{i=1}^{N} P_{Git} + \sum_{j=1}^{N_{W}} P_{Gjt}^{W} = P_{Dt} + P_{Lt}$$
(5)

Where N_w represents the total wind power plants in the system; P_{Gjt} is the output of active power for the jth wind power plant at time t; P_{Dt} is the load at time t.

2.2 Power losses

The power losses taking place at any particular time t can be expressed using the B-loss coefficient by applying the following expression [1]:

$$P_{Lt} = \sum_{i=1}^{N_T} \sum_{j=1}^{N_T} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_T} P_{Gi} B_{io} + B_{00}$$
(6)

 P_{Lt} is the line loss for the N_C number of generators given by $N+N_W$; The loss parameters B_{ij} , B_{io} and B_{oo} are also called B parameters.

2.3 Unit operating limits constraint

The power outputs of generating units have to lie within the specified minimum and maximum values. This is due to the operating constraints on units.

$$P_{Git}^{min} \le P_{Git} \le P_{Git}^{max} \tag{7}$$

(4)

Where P^{min} and P^{max} are the upper and lower bound respectively for the active power output of the ith conventional unit at time t.

2.4 Ramp-rate limit of generators

 $-\varepsilon_{idown} \leq P_{Git} - P_{Gi(t-1)} \leq \varepsilon_{iup}$

(8)

Where ε_{idown} and ε_{iup} are the ramp down rate and the ramp up rate respectively for the ith conventional unit. These limits are applied because a unit cannot change its output beyond these values between two consecutive time intervals. The ramp-rate limits modify the operating limits of a unit for every time interval depending on the state of the preceding interval.

2.5 Nonconvex cost characteristics due to valve point loading

The valve-point effects cause ripples in the cost curves of thermal units and create discontinuous, nonconvex objective function which has multiple minima. For an accurate modeling of VPL effects, a rectified sinusoidal function [8] is added in the fuel input-power output cost function of the ith unit as given below

$$F_i(P_{Git}) = a_i + b_i P_{Git} + c_i P_{Git}^2 + d_i \sin\left(e_i \left(P_{Git}^{min} - P_{Git}\right)\right)$$
(9)

 d_i and e_i all are the coefficient cost for evaluation for the i^{th} unit; P_{Git} is the minimum power output for the i^{th} unit.

2.6 The Weibull Probability distribution of wind power

The wind power W and wind speed V share a highly nonlinear relation. V is the wind speed (m/sec), which varies randomly with time however the data collected from field have shown that V approximately follows [9] $E_{r}(v) = 1 - \exp\left[-\frac{v}{r}\right]^{k}$

$$F_{v}(v) = 1 - \exp\left[-(\frac{-}{c})^{n}\right]$$
 (v≥0) (10)

Where c and k are referred to as the scale factor and shape factor, respectively. Correspondingly, the probability density function of V is:

$$f_{v}(v) = \frac{\kappa}{c} (\frac{v}{c})^{k-1} \exp\left[-(\frac{v}{c})^{k}\right]$$
(11)

The relation between the input wind power and the output electric power depends on many factors, like the efficiencies of generator, wind rotor, gearbox, and inverter, depending on what kind of turbine is being employed. The generic relation between wind power and wind speed can be given as [9]:

$$W = \begin{cases} 0; & (V < v_{in} \text{ or } V \ge v_{out}) \\ w_r; & (v_r \le V < v_{out}) \\ \frac{(V - v_{in})w_r}{v_r - v_{in}} & (v_{in} \le V < v_r) \end{cases}$$
(12)

Where v_r , v_{in} , v_{out} : Rated, cut-in, and cut-out wind speeds; W is the power generated by the wind generating unit; Wr is the rated power of the wind generating unit; c is the scale factor and k is the shape factor of the Weibull distribution.

III. DIFFERENTIAL EVOLUTION

Researchers the world over are proposing evolutionary methods as alternate approaches for solving power system optimization and other problems, because these methods are nature inspired and hence are more robust and suitable for practical problems having a real world flavor. This section presents an i) in-depth review and comparison of various DE strategies ii) impact of tuning parameters. The DE results are analyzed using reliable performance metrics such as convergence behavior, consistency and solution quality for solving the CHPED problem.DE is a population-based stochastic function minimizer/maximizer based on evolutionary computation. It's simple yet powerful and straightforward features make it very attractive for numerical optimization. DE differs from classic genetic algorithms in the manner of using the vector differential of two randomly chosen parameter vectors; a concept borrowed from the operators of Nelder and Mead's simplex optimization technique. The DE algorithm was first introduced by Storn and Price in 1995 [10] and was successfully applied in the optimization of complex and nonlinear, non-convex and non-differentiable, and functions. Optimization using DE is carried out by three operations known as mutation, crossover and selection.

3.1 Mutation

Mutation is an operation that adds a vector differential to a population vector of individuals according to the chosen variant. Three issues are central to DE, first, the method for selecting the parent population member which is used for creating the mutated population, second, the number of difference vectors that will be used form the mutant vector and third issue is which crossover method is used to create the offspring population. The notation used for these three concepts is known as DE, $/\alpha/\beta/\delta$. Most published work has explored the variant DE / rand / 1 / bin which means, random selection, one difference vector and binomial crossover [Storn

et al]. The best performing variant is found to be problem specific and needs detailed investigation. The donor or mutant vector for each population member is generated for different variants in classic DE as given by

Mutant vector generation using DE/rand/1: MS-I

$$Z_{i}(t+1) = x_{i,r1}(t) + f_{m}[x_{i,r2}(t) - x_{i,r3}(t)]$$
(13)
Mutant vector generation using DE/best/1: MS-II

$$Z_{i}(t+1) = x_{i,best}(t) + f_{m}[x_{i,r2}(t) - x_{i,r3}(t)]$$
(14)
Mutant vector generation using DE/rand-to-best/1: MS-III

$$Z_{i}(t+1) = x_{i}(t) + f_{m}[x_{i,best}(t) - x_{i}(t)] + f_{m}[x_{i}r_{1}(t) - x_{i}r_{2}(t)]$$
(15)
Mutant vector generation using DE/best/2: MS-IV

$$Z_{i}(t+1) = x_{ibest}(t) + f_{m}[x_{i,r1}(t) - x_{i}r_{2}(t)] + f_{m}[x_{i}r_{3}(t) - x_{i}r_{4}(t)]$$
(16)
Mutant vector generation using DE/rand/2 : MS-V

$$Z_{i}(t+1) = x_{ir5}(t) + f_{m}[x_{i,r1}(t) - x_{i}r_{2}(t)] + f_{m}[x_{i}r_{3}(t) - x_{i}r_{4}(t)]$$
(17)

Where i = 1, 2, ..., R is the individual population member's index, t is the iteration count; r1, r2, r3, r4 and r5 and are random integers generated by using the randperm (R) command. These integers should be different and not the same as the integer i.To implement the mutation operation, a parameter called mutation factor, fm in the range [0, 2] is taken which controls the amplification of the difference between two individuals so as to avoid search stagnation.

3.2 Crossover Operation

The crossover operation is performed after the mutation operation is completed for the set of population. Recombination is employed to generate a trial vector Ui by replacing some attributes of the target vector (xi) with the corresponding parameters of the randomly generated donor or mutant vector (Zi) as per the following logic:

$$U_{ij}(t+1) = \begin{cases} Z_{ij}(t+1), \dots, if(rand(j) \le CR) or(j = rand \operatorname{int}(i)) \\ x_{ij}(t), \dots, \dots, if(rand(j) > CR) or(j \neq rand \operatorname{int}(i)) \end{cases}$$
(18)

In the above, rand (j) is the jth assessment of a random number generated in the range 0-1; *CR* is a crossover rate. The effectiveness of a DE algorithm is normally decided by the population size N, the mutation rate f_m and the crossover factor *CR*.

3.3 Selection

Selection is the procedure of producing better progeny. For a continuously evolving population, each member of the trial vector is compared to its parent target vector. If it is found to be better, then it replaces the concerned target vector in the population as expressed below.

$$x_{i}(t+1) = \begin{cases} U_{i}(t+1)....if(u(t+1) < f(x_{i}(t))) \\ x_{i}(t),...otherwise \end{cases}$$
(19)

Selection helps in maintaining a stable convergence.

IV. RESULTS AND ANALYSIS

4.1 Desription of Test Cases

4.1.1 Case 1:- The DE mutation strategies are compared using a model ten thermal generating units system [7]. The system unit data and the load demand are given in Tables 1 and 2. Optimal dispatch is computed for the thermal system alone for the given loads without considering wind and ramp rate limit.

4.1.2 Case 2:- Thermal and wind dispatch is computed taking fixed wind generation of 400 MW without ramp rate limits.

4.1.3 Case 3:- Thermal and wind dispatch is computed taking random distribution for wind power. In this case ramp rate limits are also considered.

Unit	P_{ir}^{min} ,	$P_{i,r}^{max}$,	a_i ,	b_i ,	c_i ,	Ramp
No.	MW	MW	\$	\$/MW	MW^{2}	Rate
						Limit
1	10	60	15	2.2034	0.00510	10
2	20	80	25	1.9161	0.00396	15
3	30	100	40	1.8518	0.00393	20
4	25	120	32	1.6966	0.00382	25
5	50	150	29	1.8015	0.00212	50
6	75	280	72	1.5354	0.00261	80
7	120	320	49	1.2643	0.00289	100
8	125	445	82	1.2163	0.00148	125
9	250	520	105	1.1954	0.00127	130
10	250	550	100	1.1285	0.00135	150

TABLE II.LOAD DEMANDS FOR 24 HOURS

Hour	Loa	d(MW)	Hour		d(MW)
01.1	Case I	Case II,III		Case I	Case II,III
1	2000	2000	13	1200	1390
2	1980	1980	14	1160	1400
3	1940	1940	15	1140	1440
4	1900	1900	16	1160	1418
5	1840	1840	17	1260	1375
6	1870	1870	18	1380	1380
7	1820	1820	19	1560	1560
8	1700	1700	20	1700	1700
9	1510	1510	21	1820	1820
10	1410	1410	22	1900	1900
11	1320	1355	23	1950	1950
12	1260	1370	24	1990	1990

4.2 To find the best strategy and F & CR values

It has been reported that the results obtained using the DE algorithm are highly dependent on i) selected mutation strategy(MS) ii) value of mutation rate iii) value of crossover rate [11]. This observation was found to be true for the wind-thermal optimal power dispatch problem also. Table 3 and Table 4 present the mean and standard deviation obtained out of 50 trials using strategy I and strategy V.

For both these mutation strategies it can be observed that as value of CR is increased the cost and standard deviation both increase. Fig. 1 and Table 4 show that global convergence with consistent zero standard deviation is obtained for strategy 5 for F=0.7 & CR=0.9. Strategy 3 and 4 do not produce very good convergence, however the results are always near global best value. Fig. 2 shows that best results are found with F=0.1. Fig. 3 shows the effect of wind power integration in reducing the operating cost.

Table 5 shows the relationship of cost with wind generation for three cases, without wind, with fixed wind power and with random wind power. The cost is least when a fixed wind power is continuously available.

F	CR=0.1	CR=0.2	CR=0.3	CR=0.5	CR=0.7	CR=0.9
0.1	4245.5618	4245.3554	4243.5223	4245.0187	4254.2811	4255.5376
	(7.9812)	(8.9979)	(8.4924)	(22.5795)	(31.0444)	(36.9009)
0.2	4240.3521	4246.4940	4243.6239	4245.5773	4248.8850	4243.5450
	(9.1937)	(8.3769)	(11.4629)	(20.3567)	(21.0925)	(28.6233)
0.3	4250.8266	4246.980	4242.2202	4246.3093	4246.2946	4248.5935
	(12.3743)	(9.7107)	(12.9055)	(17.9767)	(23.7051)	(22.4571)
0.5	4238.2065	4245.2676	4246.0359	4245.3787	4252.6645	4248.1615
	(10.3236)	(12.3595)	(11.9931)	(19.8149)	(23.5366)	(23.9279)
0.7	4245.0439	4249.4871	4254.3232	4256.5425	4254.1127	4245.8025
	(11.6658)	(13.1986)	(8.9480)	(19.0788)	(26.1179)	(21.1863)
0.9	4251.0841	4251.6762	4254.9534	4265.5998	4259.3879	4258.7923
	(11.2567)	(10.4748)	(14.8966)	(14.2520)	(18.9648)	(23.5657)

TABLE III. EFFECT OF MUTATION FACTOR AND CROSS OVER RATE ON MEAN AND S.D.IN DE (10-UNIT SYSTEM; 50 TRIALS) MS I

F	CR=0.1	CR=0.2	CR=0.3	CR=0.5	CR=0.7	CR=0.9
0.1	4246.0109	4241.2656	4241.0371	4245.326	4238.1201	4240.7255
	(9.4674)	(7.1350)	(9.4932)	(10.4868)	(11.9217)	(11.0542)
0.2	4244.5245	4242.8636	4252.0133	4244.2131	4237.2133	4236.6224
	(8.4043)	(8.2025)	(9.8261)	(7.9309)	(5.9029)	(5.7266)
0.3	4248.6550	4244.8860	4249.7958	4246.1348	4235.5954	4235.7111
	(11.9355)	(10.0549)	(11.0522)	(9.7759)	(1.5268)	(2.9054)
0.5	4255.9395	4290.0304	4252.0294	4263.1457	4235.6405	4235.5686
	(11.5898)	(13.1865)	(13.3577)	(15.7834)	(0.3725)	(0.0001)
0.7	4247.7355	4246.4361	4264.0642	4268.9442	4237.7463	4235.5686
	(15.3737)	(13.1480)	(12.7686)	(16.9026)	(18.4848)	(3.638)
0.9	4248.2908	4264.9099	4256.1083	4252.0886	4238.7265	4235.5697
	(14.9995)	(13.7498)	(17.3706)	(17.3034)	(28.2241)	(28.9507)

TABLE IV. EFFECT OF MUTATION FACTOR AND CROSS OVER RATE ON MEAN AND S.D.IN DE (10-UNIT SYSTEM; 50 TRIALS) MS V

TABLE V.	EFFECT OF WIND GENERATION AND RAMP LIMITS ON COST							
Case 1		Case 2	Case 3					
81280 358	7	63752 1045	71700 3775					



Figure 1. Effect of mutation & crossover rates on convergence (MS II)



Figure 2. Effect of mutation & crossover rates on convergence (MS III)







Figure 4. Convergence characteristics for differet wind powers The stable convergence behavior of the proposed method is shown in Fig. 4 for different wind power values.

Now Table 6 and Table 7 Show the Results of Dynamic Wind-Thermal Dispatch Without and With Ramp rate limits respectively.

TABLE VI. RESULTS OF DYNAMIC WIND-THERMAL DISPATCH WITHOUT RAMP-RATE LIMITS (CASE2)

										/
Hours	P1	P2	P3	P4	P5	P6	P 7	P8	P9	P10
1	10.1241	32.2304	41.3279	60.6746	87.9600	122.8163	156.0564	321.3068	383.3139	384.1891
2	10.2259	30.5843	38.6318	59.8634	85.7910	119.0273	156.0679	317.9959	381.7270	380.0855
3	10.0616	29.3797	36.5640	57.4834	81.5896	116.4904	151.4629	311.3940	373.7024	371.8720
4	10.0374	25.1429	34.9088	55.3644	75.1075	114.1009	146.3256	304.1235	366.5463	368.8720
5	10.2625	23.4146	32.7697	49.7228	69.9999	107.2960	142.0494	296.6334	355.9466	351.9052
6	10.1088	23.9920	31.1159	54.0503	74.4789	110.8419	146.0381	298.9805	359.1044	361.2892
7	10.0874	20.9905	31.3249	49.5938	67.9151	104.9691	143.4529	293.2094	343.2853	355.1717
8	11.0097	20.3938	30.7079	43.0457	50.2686	93.5034	133.7501	269.2190	320.9524	327.1495
9	10.3535	21.7885	30.1843	27.9831	51.0365	79.2274	121.7503	223.2066	265.3608	279.1092
10	10.2975	20.0921	31.8955	26.1353	50.4659	76.0604	120.7615	170.7271	250.0032	253.5616
11	10.0000	20.0000	30.0000	25.0000	50.0000	75.0000	120.0000	125.0000	250.0000	250.0000
12	10.1887	20.0005	30.0946	25.1656	50.0006	75.3430	120.3825	138.0891	250.5574	250.1781
13	10.1363	20.8266	30.4593	25.4508	50.0000	75.5239	120.0000	155.5460	252.0574	250.0000
14	10.5055	20.3754	30.5707	26.7557	50.3095	75.3405	120.5217	163.1997	251.7731	250.6480
15	11.3232	21.0645	30.4750	26.1829	50.2465	76.7985	120.0000	196.8776	256.9495	250.0824
16	10.2490	20.0139	30.2717	25.9472	50.8486	75.2593	120.2287	178.7047	250.2606	256.2165
17	10.1581	20.0061	30.0018	25.0000	50.4529	75.1375	120.3175	143.6895	250.0000	250.2365
18	10.0296	20.3159	30.7416	25.7181	51.0144	75.7101	120.4836	153.2583	250.3258	252.4026
19	11.0756	20.9214	31.3611	35.1528	51.3796	75.5911	123.0253	242.1978	285.0025	284.2926
20	10.1623	20.5473	30.5745	43.9331	57.9229	97.4479	130.9950	265.5514	321.7890	321.0766
21	10.0995	20.8042	30.4232	50.5478	64.0962	104.9610	144.7019	290.4163	345.6265	358.0766
22	10.0463	27.8279	34.2389	55.7261	74.4423	113.3448	149.1164	303.9575	361.5272	369.3235
23	10.0984	30.2833	35.8721	58.5202	80.7029	114.9145	153.6597	312.1325	375.1063	378.7099
24	10.2043	32.5758	40.8187	62.9482	84.7210	118.9810	157.3232	320.1809	379.5930	382.6538
Total Co	ost(S)	63752.1	045							

TABLE VII. RESULTS OF DYNAMIC WIND-THERMAL DISPATCH WITH RAMP-RATE LIMITS (CASE3)

Hours	P1	P2	P3	P4	P 5	P6	P7	P8	P9	P10	P _{WIND}
1	10.5866	48.8894	58.1659	78.8240	117.7763	146.6953	180.7396	367.5720	435.5530	435.4822	119.7
2	10.0403	34.0971	44.5404	66.1763	93.0612	126.1242	160.7994	331.4178	394.9659	395.8997	322.9
3	10.0117	28.3564	37.2568	58.6674	82.3718	116.1523	150.8686	313.0228	373.6134	375.4572	394.2215
4	10.0110	30.7525	39.7065	59.7584	85.7983	119.7272	155.4829	317.8397	381.7342	381.6482	317.5410
5	10.0050	33.4306	40.3906	62.1227	87.4834	122.3147	156.9870	322.8948	384.5318	385.8994	233.9400
6	10.0758	43.9530	52.7707	75.1804	109.1207	140.0127	173.1564	355.8250	420.1329	420.3804	69.3920
7	10.0078	29.1910	34.0579	52.9432	69.8801	108.2080	143.7561	298.1851	354.6420	350.0603	369.0685
8	10.0730	20.1408	30.3580	46.1157	60.0198	97.9512	137.4032	281.3803	336.3414	344.6957	335.5208
9	10.3407	20.7061	30.1473	27.2027	51.0011	76.3543	120.3207	233.3522	270.9073	279.4313	390.2363
10	10.0476	20.2933	30.4798	31.1506	50.9081	79.5077	124.8444	240.6764	298.1009	300.6240	223.3670
11	10.3483	20.1578	30.5843	25.2811	52.2240	76.4021	123.2361	184.0931	250.0070	251.1882	331.4782
12	10.0798	20.3545	30.0251	42.9932	51.7814	88.7082	130.8282	267.9821	322.2525	321.5037	83.4914
13	10.1196	20.0930	30.1340	40.6613	53.2116	91.1157	129.2644	267.0326	319.5225	319.0459	109.7994
14	10.0636	21.0380	30.3509	37.1227	51.0270	87.1163	129.4386	263.5969	316.4582	322.3871	131.4007
15	10.3134	21.8411	30.2545	27.4569	50.6198	78.6289	121.7429	230.7271	284.4342	291.1099	292.8712
16	10.0333	20.7222	30.3358	44.7157	56.2659	98.7586	136.6555	278.3158	330.9107	342.8309	68.4556
17	10.0625	20.1359	30.0784	25.3594	50.0000	75.6729	120.2245	164.0185	250.0000	250.0000	379.4479
18	10.1254	21.4366	31.7584	26.7904	50.8122	77.6576	121.5151	209.0503	260.9480	267.5155	302.3905
19	10.0708	20.8885	30.1060	38.1765	50.3470	88.1248	127.2781	262.5320	317.4512	322.2192	292.8058
20	10.1135	20.6515	30.6684	47.2868	57.5848	99.1706	135.4947	282.8630	336.9967	343.8143	335.3558
21	10.0218	34.5734	42.1728	64.1358	92.0183	125.5016	159.8571	329.2988	392.0251	392.9079	177.4874
22	10.0165	38.4531	46.9190	68.4853	98.0814	130.0206	165.3935	338.0079	403.4625	403.9285	197.2317
23	10.0277	48.3209	57.3500	78.6037	117.5754	146.9741	178.8337	366.3960	435.2884	434.4735	76.1566
24	10.0882	46.5777	55.0064	77.3670	114.4870	144.4415	177.5976	361.0266	429.4758	428.9710	144.9613
Total Co	ost(\$)	71700.377	75								

V. CONCLUSION

The effect of wind power generation in reducing the operating cost of power grid having conventional thermal power plants has been presented. Differential evolution based optimization model has been built to solve the complex constrained optimization problem. The results show the efficiency of the proposed method in producing optimal schedules with satisfaction of equality and inequality constraints. The paper also explores the dependence of the DE algorithm on the five DE mutation strategies and mutation & crossover rates in achieving global convergence. The results are very encouraging and consistent.

Acknowledgements

The authors sincerely acknowledge the financial support provided by UGC under major research project entitled Power System Optimization and Security Assessment Using Soft Computing Techniques, vide F No.34-399/2008 (SR) dated, 24th December 2008. The second author acknowledges UGC, New Delhi financial support for PD work sanctioned vide (F-30-120(SC)/2009 (SA-II)). The authors also thank the Director, M.I.T.S. Gwalior for providing facilities for this work.

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