Power System Dispatch with Integrated Wind Power Plants

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Abstract-* As the integration of wind power generation increases in power system, its coordination with other conventional sources of generation possesses both technical and economic challenges to the reliable operation of power system. Therefore, development of improved and faster economic dispatch is imperative to effectively integrate wind power reliably into power system. In this paper, Differential Evolution (DE) is utilized to coordinate the wind –thermal generation dispatch and to minimize the total production cost in the economic dispatch considering generator ramp-rate and valve point effect of thermal unit. Ten thermal units system incorporating one wind power plant was utilized for numerical simulation. Different simulation scenarios with and without wind power production were simulated and the results shows the effect of wind power generation in reducing total production cost.

***Indexed Terms-* Differential Evolution, Economic Load Dispatch and Quadratic Cost Function.**

I. INTRODUCTION

The trend of large scale integration and utilization of renewable energy has gained more and more attention in recent years due to dwindling of traditional fossil fuels reserves and environmental concern.

The penetration of renewable generation has changed the existing electricity market structures and policies, unit commitment and economic dispatch methods, bidding strategies and forecasting methodology. But, with the increase penetration of renewable energy into the transmission network comes many challenges to service provider because of the “nature” of the renewable source i.e. its variability and uncertainty [1] Economic load dispatch (ELD) is an important task in the electricity market operation, ELD aim to allocate power generation to match load demand at minimal possible cost while satisfying all the power units and system constraints [2].

For the purpose of economic dispatch studies, online generators are represented by functions that relate their production costs to their power outputs. Quadratic cost functions are used to model generator in order to simplify the mathematical formulation of the problem and to allow many of the conventional optimization techniques to be used. The ELD problem is traditionally solved using conventional mathematical techniques such as lambda iteration and gradient schemes. These approaches require that fuel cost curves should increase monotonically to obtain the global optimal solution. The input-output of units are inherently non-linear with valve point loading or ramp rate limits and having multiple local minimum points in the cost function.

Techniques such as dynamic programming might not be efficient since they require too many computational resources in order to provide accurate results for large scale systems. But, with the advent of evolutionary algorithm which are stochastic based optimization techniques that searches for the solution of problems using simplified model of the evolutionary process found in nature, this type of constrained optimization problem can easily be solved providing better and faster results. The success of evolutionary algorithm is partly due to their inherent capability of processing a population of potential solutions simultaneously, which allows them to perform an extensive exploration of the search space [2].

Evolutionary algorithm includes Genetic Algorithm (GA), Simulated Annealing (SA), Hybrid Particle Swarm Optimization (PSO) with Sequential Quadratic Programming approach (PSO-SQP), Evolutionary Programming (EP) and Artificial Bee Colony (ABC)

[4]-[7], etc. GA methods have been employed successfully to solve complex optimization problems, though recent research has identified deficiencies in its performance which is apparent in applications when optimized parameters are highly correlated thereby, hampering crossover and mutation operations and compromising the improved fitness of offspring because population chromosomes contains similar structures [4].

SA is designed to solve the high non-linear ELD problem without restriction on the shape of the fuel cost function. EP also takes a long computation time to obtain solutions. PSO converges more quickly than EP, but has a slow fine tuning ability of the solution [5].

Differential Evolution (DE) is a recently developed heuristic evolutionary method for solving constrained optimization problems. DE is a powerful algorithm that improves the population of individuals over several generations through the operators of mutation, crossover and selection. Differential Evolution offers great convergence characteristics and requires few control parameters which remains fixed throughout the solution process and requires minimal tuning.

II. WIND POWER PLANT MODELLING

The modelling of the wind power plant is based upon a conversion of wind speed to real power. Wind speed variability is modelled statistically by using the Weibull two parameter distribution functions [9]. The wind speed variation is described by its shape and scale parameters.

The Weibull probability density function of a two parameter continuous distribution is defined as the derivative of the cumulative distribution function (cdf) as expressed by

$$f_w(\mathrm{K, C}) = \frac{K}{C}\left(\frac{K}{C}\right)^{K-1}\exp\left[-\left(\frac{V}{C}\right)^{K}\right] \qquad (1)$$

Where f_w= Weibull density function, K= Shape Parameter
C= Scale Parameter

The Cumulative distribution F (V) defined in equation (2) is the integral of the probability density function, and it is expressed as

$$\mathrm{F\ (V)} = 1- e^{-\left(\frac{v}{c}\right)^{K}} \qquad (2)$$

Wind speed changes with height and most wind speeds are observed at height less than the hub height. It is therefore necessary to re-define the wind speed from the observed height to the hub height using the expression

$$\frac{V}{V_o} = \left(\frac{h}{h_o}\right)^{\alpha} \qquad (3)$$

v= Wind speed at hub height h, v_o= Wind speed at the original h_o, α = surface roughness coefficient

The electrical power of the wind energy conversion system is based on known turbine power curve is estimated as

$$P_e\ (V) = c_{p*}0.5\eta\ p\ (h)\ a \int_0^{\infty} v^3 f\ (v)\ dv \qquad (4)$$

$P_e\ (V)$ = Electrical output power, c_p= rotor efficiency η =efficiency, v= wind speed. $f\ (v)$ = Weibull wind distribution, $p\ (h)$ = time varying air density and a = rotor swept areas.

The actual output (P_w) of wind generator *can* be obtained from the wind speed by applying equation (4). The total actual wind power generation can be easily calculated using the equation:

$$P_{wt} = \sum_{w=1}^{w} P_w$$

Where *nw* is the number of connected wind generator

III. PROBLEM FORMULATION

The Economic dispatch in a power system with integrated wind power plant involves the allocation of generation among wind generator and thermal plants so as to minimize the total production cost while satisfying various constraints.

The ELD problem is formulated as follows:

$$Minimize\ \ F_T = \sum_{i=1}^{n} C_i\,(P_i) \qquad (6)$$

F_T is the total generation cost.

$$C_i\,(P_i) = \alpha_i + \beta_i P + \gamma_i P^2 \qquad (7)$$

is a quadratic cost function of the unit i^{th}, α_i, β_i, and γ_i are cost coefficient of the i^{th} generator, which are found from the input-output curves of the generators and are dependent on the particular type of fuel used. P_i: The power output of i^{th} unit of thermal plants.

It is assumed that the marginal cost of the wind power plant is zero.

But, when the generation unit changes its output, there is a nonlinear cost variation due to valve point effect. Typically, the valve point results as each seam begins to open, the ripple like in Fig. 1 [5}. The fuel cost of a thermal generation unit considering nonlinear effect of valve will be a nonlinear function as

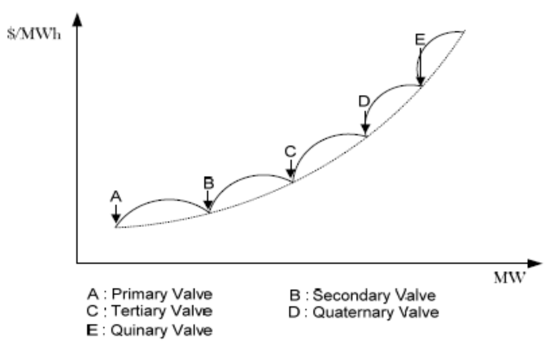

Fig. 1.Valve Point Effect

$$C_i\,(P_i) = \alpha_i + \beta_i P + \gamma_i P^2 + |\, e_1 * \sin(f_1 * (P_i^{min} - P_i))| \qquad (8)$$

Where e_i and f_i are cost coefficients of the i^{th} generator.

The minimization is subject to the following constraints:

- *Power balance*

$$\sum_{i=1}^{N} P_i + \sum_{w=1}^{W} P_w = P_D \qquad (9)$$

Where P_D is the power demand
The transmission losses is neglected

- Maximum and minimum power limits

The power generated by each generator has some limits and can be expressed as:

$$P_i^{min} \le P_i \le P_i^{max} \qquad (10)$$

Where:
P_i^{min}: The minimum power output
P_I^{max}: The maximum power output

- Ramp –rate constraints

The operating range of all online units is restricted by their corresponding ramp-rate limits. The inequality constraints due to ramp-rate can be written as:

$$P_I\,(t) - P_i\,(t-1) \le UR_i \qquad (11)$$

$$P_i\,(t-1) - P_i\,(t) \le DR_i \qquad (12)$$

Where P_i (t) is the present output power and P_i (t-1) is the previous power output, UR_i is the up-ramp limit of the i^{th} generator; DR_i is the down – ramp limit of the i^{th} generator.

IV. SOLUTION OF THE PROBLEM USING DE

Differential Evolution (DE) is an evolutionary algorithm proposed by Storn and Price (1995) [16]. The algorithm is simple, yet powerful, for solving complex optimization problems. Practical optimization problems are often characterized by several non-linearities and competing objectives.

In a DE algorithm, candidate solutions are randomly generated and evolved to individual solution by a simple technique combining simple arithmetic operators with the classical operators of mutation, crossover and selection.

The generalized steps of the DE algorithm as presented in detail and are pertinent in its application to the economic load dispatch problem under consideration. As a first step in DE, we randomly generate an initial population comprising feasible power generated at all the on-line thermal units within the multi-dimensional search space. We define the initial power generated population matrix $[P^O]$ dimensioned $\mathcal{R}^{\mathcal{M}X\mathbb{N}_P}$ thus:

$$[P^O] = \begin{bmatrix} P_{11}^0 & \cdots & P_{1\mathbb{N}_P}^0 \\ \vdots & P_{ij}^0 & \vdots \\ P_{\mathcal{M}1}^0 & \cdots & P_{\mathcal{M}\mathbb{N}_P}^0 \end{bmatrix}$$

$$P_{ij}^0 = P_i^{min} + rand * \left(P_i^{max} - P_i^{min}\right)$$

$$i = 1,2,3 \ldots .\mathcal{M};\ j = 1,2,3 \ldots \ldots N_p \qquad (13)$$

Where, P_{ij}^0 : is the initialized i^{th} candidate power generated of j^{th} column of population matrix;
$'rand'$: is function that generates random values uniformly in the interval [0, 1];
N_p : is the population size;
$\mathcal{M}$: is the number of online generating units;
P_i^{min} and P_i^{max} : are the lower and upper bound on the i^{th} generating unit, respectively.
In each generation, N_p competitions are held to determine the composition of the next generation via mutation, crossover and selection processes which are basically similar to those of genetic algorithm (GA).

Mutation operations are applied in DE during offspring generation and of necessity play pivotal role in the reproduction cycle. The mutation operation creates mutant population vector $\bar{P}_i'^{(k)}$ by perturbing a randomly selected vector or best current population vector (based on minimum objective function value returned) $\bar{P}_{l_1}^{(k)}$ with the difference of two other randomly selected vectors $\bar{P}_{l_2}^{(k)}$ and $\bar{P}_{l_3}^{(k)}$ at k^{th} iteration according to eqn. (14).

$$\bar{P}_i'^{(k)} = \bar{P}_{l_1}^{(k)} + F * \left(\bar{P}_{l_2}^{(k)} - \bar{P}_{l_3}^{(k)}\right) \qquad i = 1,2,3 \ldots N_p$$
(14)

Where,
$\bar{P}_i'^{(k)}$: is generated i^{th} column population vector after performing mutation operation at k^{th} iteration;
$\bar{P}_{l_1}^{(k)}$, $\bar{P}_{l_2}^{(k)}$ and $\bar{P}_{l_3}^{(k)}$: are randomly chosen vectors at k^{th}
iteration; $l_1,\ l_2$ & $l_3 \in \{1, N_p\}$: are randomly chosen integers, mutually different and also chosen to be different from the running index i (i.e. $l_1 \neq\ l_2 \neq l_3 \neq i$).

F : is scaling factor for mutation and its value is typically (0 ≤ F ≤ 1.2) to control amplification of the differential perturbation in the mutation process so as to secure good convergence characteristics.

The next task after mutation operation is crossover process so introduced to diversify the perturbed population matrix for the online thermal units. Fundamentally, crossover operation represents a typical case of 'genes' exchange. Here, the j^{th} column target power output vector $\bar{P}_j^{(k)} = [P_{1j}^{(k)}, P_{2j}^{(k)} \ldots P_{ij}^{(k)} \ldots P_{\mathcal{M}j}^{(k)}]^T$ is mixed with the j^{th} column mutated power output vector $\bar{P}_j'^{(k)} = [P_{1j}'^{(k)}, P_{2j}'^{(k)} \ldots P_{ij}'^{(k)} \ldots P_{\mathcal{M}j}'^{(k)}]^T$ to create a j^{th} column trial power output vector $\bar{P}_j''^{(k)} = [P_{1j}''^{(k)}, P_{2j}''^{(k)} \ldots P_{ij}''^{(k)} \ldots P_{\mathcal{M}j}''^{(k)}]^T$. Thus, the procedure to building trial power output vector is anchored on eqn. (15):

$$P_{ij}''^{(k)} = \begin{cases} P_{ij}'^{(k)} \ if \ (randb(i) \leq CR \ or \ i = rnbr(j) \\ P_{ij}^{(k)} \ if \ (randb(i) > CR \ or \ i \neq rnbr(j) \end{cases}$$
(15)

Where: $j = 1,2,3 \ldots N_p;\ i = 1,2,3 \ldots .\mathcal{M}$.
$P_{ij}^{(k)}$, $P_{ij}'^{(k)}$ and $P_{ij}''^{(k)}$: are i^{th} individual of the j^{th} target power output vector, mutant power output vector and trial power output vector at k^{th} iteration, respectively; $randb(i)$: is i^{th} randomly generated value in the interval [0, 1];

CR : is crossover constant ϵ [0,1] that regulates the diversity of the population and aids the algorithm escape from local optima;
$rnbr(j)$:is randomly chosen index $\in (i = 1,2,3 \ldots, \mathcal{M})$ to insure that the trial vector, $\bar{P}_j''^{(k)}$ gets at least one value from the mutated vector, $\bar{P}_j'^{(k)}$.

The selection procedure is the final step of any classical DE algorithm. More specifically, selection procedure is used among the set of trial vector and the target vector to choose the better vector. Each solution in the population has equal chance of being selected as parents. Selection process is realized by comparing the objective function values of target vector and trial vector. For a minimization problem for example, if the trial vector has lower value of the objective function, then it replaces the target vector in the next generation otherwise the current target vector is retained. This is cast mathematically, using objective function evaluation criterion $F(.)$, as follows:

$$\bar{P}_j^{(k+1)} = \begin{cases} \bar{P}_j^{\prime\prime(k)} \ \ if\ F(\bar{P}_j^{\prime\prime(k)}) \leq \ F(\bar{P}_j^{(k)}) \\ \bar{P}_j^{(k)} \ if\ F(\bar{P}_j^{\prime\prime(k)}) > \ F(\bar{P}_j^{(k)}) \end{cases} \quad (16)$$

We have also incorporated the application of elitist strategy of GA to keep track of the fittest vector and the specification of algorithmic convergence criterion. If the convergence criterion is met, the power output values contained in the fittest vector are returned as the desired optimal values. With the desired optimal values of power output specified at the respective thermal generating units, fuel cost and generating units loading profile.

V. SIMULATION RESULTS

To examine the effectiveness of the proposed method, a ten thermal unit and one wind generator test system is considered [6]. The system unit data is given in Table 1, the load demand of the system is divided into 24hours as shown in Table 2.

TABLE 1
DATA FOR THE TEN UNIT SYSTEM

	Unit 1	Unit 2	Unit3	Unit4	Unit 5
Pmax(MW)	470	460	340	300	243
Pmin(MW)	150	135	73	60	73
α($/MWh)	0.00043	0.00063	0.00039	0.0007	0.00079
β($/MWh)	21.6	21.05	20.81	23.9	21.62
γ($/h)	958.2	1313.6	604.97	471.6	480.29
e ($/h)	450	600	320	260	280
f($/h)	0.041	0.036	0.028	0.052	0.063
UR	80	80	80	50	50
DR	80	80	80	50	50

	Unit 6	Unit 7	Unit8	Unit 9	Unit 10
Pmax(MW)	160	130	120	80	55
Pmin(MW)	57	20	47	20	55
α($/MWh)	0.00056	0.00211	0.0048	0.10908	0.00951
β($/MWh)	17.87	16.51	23.23	19.58	22.54
γ($/h)	601.75	502.7	639.4	455.6	692.40
e ($/h)	310	300	340	270	380
f($/h)	0.048	0.086	0.082	0.098	0.094
UR	50	30	30	30	30
DR	50	30	30	30	30

TABLE 2
LOAD DEMAND FOR 24 HOURS

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	1036	9	1924	17	1480
2	1110	10	2072	18	1628
3	1258	11	2146	19	1776
4	1406	12	2220	20	2072
5	1480	13	2072	21	1924
6	1628	14	1924	22	1628
7	1702	15	1776	23	1332
8	1776	16	1554	24	1184

TABLE 3
PARAMETER SETTING FOR DE

Control Parameters	DE Setting
Maximum Generation,	200
Population size, NP	30
Scaling factor for Mutation, F	0.8
Crossover constant, CR	0.5

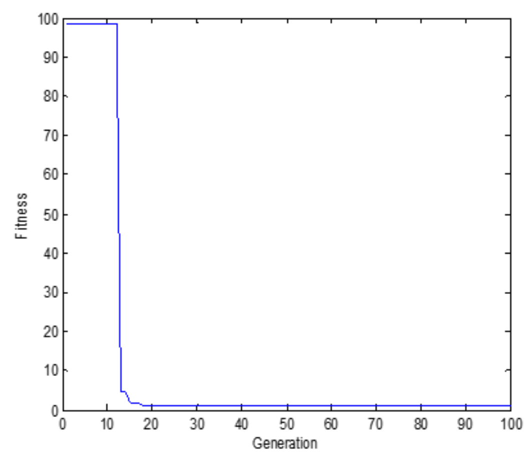

Fig 2. Convergence characteristics of DE without Wind Power

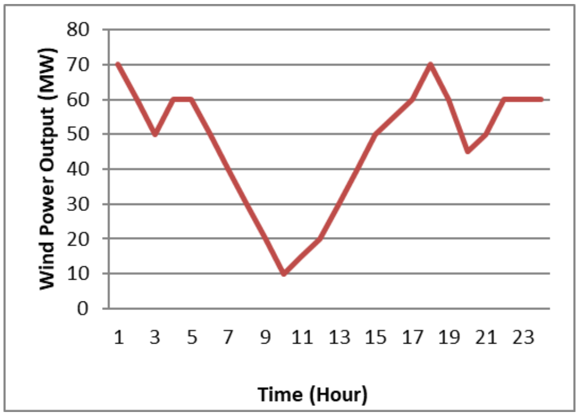

Fig.3. Average wind energy output at different intervals

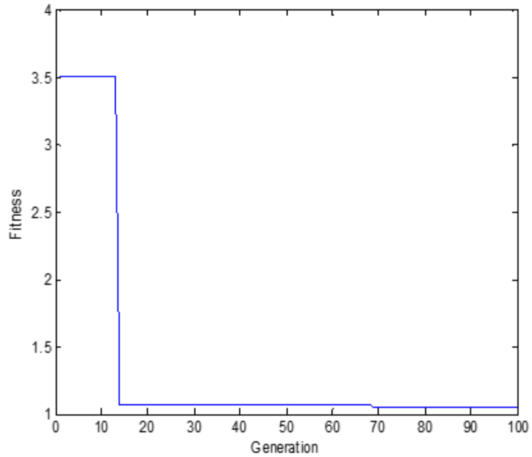

Fig. 4. Convergence characteristic of DE with wind Power

Table 4
ECONOMIC DISPATCH SHEDULE WITHOUT WIND POWER GENERATION

Time/Unit	1	2	3	4	5	6	7	8	9	10
1	175.38	171.77	98.22	102.39	144	74.18	101.01	87.41	26.65	55
2	159.19	137.06	90	150.98	173.36	135.77	95.15	70.6	45.78	55
3	203.88	153.97	120.12	118.78	212.95	102.15	94.55	70.04	76.58	55
4	201.89	166.46	246.26	120.26	227.89	142.84	80.97	100.25	64.21	55
5	212.14	177.66	224.11	139.5	236.64	152.06	87.06	116.52	79.37	55
6	235.97	189.22	266.83	271.84	211.02	149.38	126.88	50.4	71.48	55
7	327.78	155.65	324.31	277.63	206.31	148.13	33.63	99.03	74.55	55
8	362.48	260.87	287.88	229.4	195.07	129.57	127.53	72.33	55.87	55
9	309.75	355.09	280.9	287.14	215.64	137.49	115.51	110.8	56.66	55
10	399.12	368.28	296.1	294.76	237.53	145.33	118.56	94.38	62.71	55
11	433.32	373.17	335.84	276.5	242.26	152.75	115.41	101.07	60.72	55
12	448.52	415.73	304.45	291.09	231.52	156.99	127.89	109.05	79.63	55
13	391.77	375.7	318.42	284.25	231.55	140.43	117.01	86.82	71.02	55
14	299.07	365.09	269.03	288.19	216.21	139.02	117.87	115.19	59.33	55
15	281.62	306.79	290.35	278.8	209.74	147	106.52	69.17	31	55
16	216.53	233.63	245.64	282.12	123.37	155.94	104.92	70.42	66.36	55
17	236.38	146.64	197.88	179	217.7	153.87	110.71	103.55	79.31	55
18	153.47	278.05	248.26	284	177	145.97	97.83	108.88	79.56	55
19	368.92	225.66	334.3	190.22	189.61	145.03	129.84	71.93	65.23	55
20	384.22	388.91	336.04	266.43	222.43	120.32	113.21	115.18	70.26	55
21	328.5	318.56	335.67	269.39	218.65	150.5	94.51	105.08	48.15	55
22	271.39	224.11	285.58	152.38	217.48	159.49	88.19	101.07	73.32	55
23	175.57	176.66	174.76	144.74	181.34	144.97	87.16	113.38	78.51	55
24	164.14	137.46	141.03	245.81	95.35	121.06	80.15	91.01	53	55

TABLE 5
ECONOMIC DISPATCH SCHEME WITH WIND POWER GENERATION

Time/Unit	1	2	3	4	5	6	7	8	9	10
1	162.61	151.28	102.52	89.86	113.6	110.26	64.76	61.04	54.98	55
2	156.42	161.86	92	130.45	194.03	88.64	56.75	83.38	29.16	55
3	181.12	142.65	242.28	136.59	89.98	116.6	126.17	90.14	27.51	55
4	222.34	166.6	195.36	230.95	158.35	131.25	54.25	75.24	56.17	55
5	176.87	145.93	259.29	258.84	213.75	155.89	32.52	76.86	45.14	55
6	154.37	248.65	303.64	267.71	203.26	104.43	59.61	111.51	70.05	55
7	226.44	223.97	219.52	286.21	240.33	155.06	114.44	84.84	56.17	55
8	279.19	247.64	310.81	234.16	194.67	142.63	104.44	117.55	56	55
9	364.66	304.72	322.01	257.43	199.68	150.05	108.9	78.2	63.32	55
10	418	368.84	322.31	279.36	229.54	132.17	126.83	67.33	62.71	55
11	344.46	448.03	330.61	287.61	222.98	158.36	109.3	114.42	60.26	55
12	431.84	423.3	300.73	295.18	242.43	151.83	117.79	108.24	73.52	55
13	406.44	388.21	304.98	299.11	240.72	122.44	88.75	112.87	78.34	55
14	461.25	160	294	266.88	232.23	133.25	107.66	97.48	75.54	55
15	340.67	266.78	285.63	259.51	195.72	117.32	76.12	88.46	40.67	55
16	193.96	216.61	312.07	235.53	218.77	143.24	41.63	48.15	33.48	55
17	158.93	155	238.4	270.57	189.61	69.07	94.56	114.98	73.88	55
18	289.13	173.25	166.64	216.38	235.77	156.51	84.12	110.36	70.6	55
19	286.48	261.05	291.39	199.1	231.41	156.09	97.12	93.02	45.33	55
20	354.31	397.22	335.01	291.21	232.54	95.2	92.07	84.91	79.5	55
21	424.37	162.9	323.65	296.71	235.6	95.65	117.2	104.39	58.33	55
22	207.3	201.72	278.47	245.82	226.77	97.72	73.91	118.18	67.17	55
23	173.54	143.71	220.68	198.14	126.54	129.22	98.94	69.21	57	55
24	155.45	178.12	94.75	147.9	90.36	153.27	108.68	91.99	48.52	55

Economic dispatch was carried out using DE. The economic dispatch was carried out with and without wind generation. The minimum production cost was recorded for 60 trials. The minimum production cost without wind generation is $10082 while the minimum production cost with wind generation inclusive is $87057. The integration of wind generation reduces the production cost. An increase in the contribution of wind power causes the reduction in fossil fuel consumption and environmental degradation by thermal plants.

CONCLUSION

This paper shows a new approach for the independent system operator to solving the economic load dispatch optimization problem, of a power system with integrated wind generation using differential evolution approach. The comparative simulations with and without wind generator illustrate that the wind power contribution minimizes the total production cost. The results shows that total production cost and consumption of fossil fuel can be minimized notably by utilizing wind power generation.

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