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Novel Optimal Dispatch Method to Hybrid Power System Suitable for Competitive Power Market

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ABSTRACT

Integration of renewable energy sources with conventional power production is the scenario today in the power industry. Clustered gravitational search algorithm (CGSA) for the optimal dispatch of hybrid system such as wind thermal power system (WTPS) has been presented. The stochastic behavior of wind speed and wind power is represented by Weibull probability density function. The objective is to minimization of total cost which includes the cost of energy provided by thermal generating units, wind turbine generators (WTG), and the cost of reserves provided by conventional thermal generators. In Gravitational search algorithm (GSA), the searcher agents are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion. This paper proposes a novel CGSA that equipped with a new workforce such as leader, the follower and the freelancer to improve the convergence and solution quality of GSA. The proposed algorithm is tested on standard 6 unit and 40 unit system. The results obtained confirm the potential and success rate of the proposed algorithm compared to other algorithms available in the existing literature. This technique can be readily implemented in the energy control centers of the deregulated power market.

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INTRODUCTION

Power system of this modern age is witnessing more optimistic changes both in the control and production areas. Higher penetration of renewable into the grid has become common due to the exploration of the methods by countries around the globe for price reduction and for addressing global warming. The integration of wind power plant and thermal power plant has sharply increased in the last decade. Though there are many positive signs, it poses greater challenges to the system operators in maintaining reliability and stability. Scheduling of hybrid systems such as wind and thermal power system for economical reasons has become vital due to the more stringent regulations prevailing in the power system arena today.

Different techniques have been developed and reported in the literatures pertaining to the scheduling problem. Dynamic programming (Synder, David Powell, & Rayburn John,1987), Lagrangian relaxation (LR) (Vo Ngoc Dieu & Weerakorn Ongsakul, 2011), and mixed integer programming (MIP) (Chen & Wang, 1993 ; Juan Alvarez Lopez, Ceciliano-Meza Jose, Isaias Guillen Moya, & Rolando Nieva Gomez, 2012) are the most commonly used conventional techniques. The main disadvantage of dynamic programming method is that the computational time increases rapidly with the system size which is termed as curse of dimensionality. Though LR method provides a fast solution, it may encounter feasibility problem due to the dual nature of the method. MIP guarantees convergence to the optimal solution in a finite number of steps while providing flexible and accurate framework. The major drawback of using MIP formulation is that the execution time needed to find a good solution. So, artificial intelligence techniques like, genetic algorithm (GA) (Kaveh Abookazemi, Hussein

Ahmad, Alireza Tavakolpour, & Hassan Mohd, 2011), simulated annealing (SA) [Christober Asir Rajan & Mohan, 2007), evolutionary programming (EP) (Juste, Kita, Tanaka, & Hasegawa, 1999) tabu search (Mantaway, Abdel-Magid, & Selim, 1998) particle swarm optimization (PSO) (Ting, Rao, & Loo, 2006) and ant colony optimization(Simon, Padhy, & Anand , 2006) are most commonly used.

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From the literatures cited above it is inferred that, still there is ample scope for research in this area. In this paper, a new conceptual model is proposed to improve the convergence and solution quality of GSA. The proposed CGSA is equipped with a new workforce such as leader, the follower and the freelancer. The organization of the paper is as follows: Problem formulation is explained in section II and section III describes the wind speed and power probability density function, Gravitational search algorithm and clustered Gravitational search algorithm are explained in sections IV and V. Discussion on results is presented in section VI and conclusion is outlined in section VII.

Problem Formulation of EDP:

In a competitive electricity market, the suppliers can suggest both energy and spinning reserve (SR) through bids. In the proposed method, system operator handles the wind power uncertainties through costs for reserve requirement and excess power available.

Objective Function:

The economic dispatch (ED) problem with conventional thermal generators and wind generators is formulated as follows.
Minimize Total Cost (TC):

$$\sum_{i=1}^{Ng}[F_i(P_{Gi})+F_{SRi}(P_{SRi})]+\sum_{j=1}^{N_W}[(F_{wj}(P_{wi})+F_{r.wj}(P_{wj}-P_{wj.av})+F_{p.wj}(P_{wj.av}-P_{wj})] \quad (1)$$

where N_g is the number of generating units and N_w is the number of wind generators/farms . P_{Gi} is the power generated by the unit i, P_{Wj} is the scheduled wind power, and $P_{Wj\cdot av}$ is the available wind power from the j^{th} wind power generator. $P_{Wj\cdot av}$ is a random variable, with a range of $0 \le P_{wj.av} \le P_{rj}$, and P_{rj} is the rated wind power. $F_i(P_{Gi})$ is the fuel cost of generator i, $F_{SRi}(P_{SRi})$ is the cost of the spinning reserve supplied by the thermal generator i, $F_{p.wj}$ is the penalty cost function for not using all available power from j^{th} wind power generator, and $F_{r.Wj}$ is the reserve cost function relating to uncertainty of wind power. This is effectively a penalty associated with over-estimation of the available wind power. The mathematical expression for five terms in equation (1) is given in Appendix.

System Constraints:

Power balance constraints:

For Study 1 the power balance condition is expressed as

$$\sum_{i=1}^{N_G}P_{Gi}=P_D+P_{loss} \quad (2)$$

For Study 2 the power balance condition is expressed as

$$\sum_{i=1}^{N_G}P_{Gi}+\sum_{j=1}^{N_w}P_{wj}=P_D+P_{ioss} \quad (3)$$

where P_D is the total system demand. The transmission line losses (P_{loss}) can be represented as a function of the real power output of the thermal units.

Total spinning reserve requirement constraints:

In the proposed energy and spinning reserve (SR) scheduling problem, the required amount of spinning reserve (SR) depends on protecting the system against outage of largest online generator ($P_{G.largest}$) and the reserve required due to wind power forecast uncertainty. The total amount of SR required (TSR_{req}) is given by

$$TSR_{req}=P_{G,l\arg est}+\sum_{j=1}^{N_w}(P_{wj}-P_{wj.av}) \quad (4)$$

This TSR_{req} will be provided by the online conventional thermal generators, and it is expressed as

$$\sum_{i=1}^{N_g}P_{SRi}=TSR_{req} \quad (5)$$

Unit Constraints:

Generation of real power constraints:

Each generator output power is restricted by their minimum, maximum limits and generation rate constraints (GRC).

$$\max[P_{Gi}^{\min},P_{Gi}^0-R_{Gi}^{down}]\le P_{Gi}\le\min[P_{Gi}^{\max},P_{Gi}^0-R_{Gi}^{up} \quad (6)$$

$$P_{wj}^{\min}\le P_{wj}\le P_{wj,f} \quad (7)$$

where P_{Gi}^0 is the output power from i^{th} conveintional thermal generator in previous hour, $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ are the minimum and maximum generation limits of thermal generators. R_{Gi}^{up} and R_{Gi}^{down} are the ramp up and ramp down limits of conventional thermal generators (MW/ h). $P_{wj.f}$ is the forecasted wind power from j^{th} wind generator, which is obtained from the forecasted wind speed.

Generator spinning reserve (SR) constraints:

The operating status of generating unit determines the spinning reserve(SR) capacity. The SR limit is expressed as,

$$0\le P_{SRi}\le\min(R_{Gi}^{up},P_{SRi}^{\max}) \quad (8)$$

where $P_{SRi}^{\max}$ is maximum reserve capacity, and it is defined as,

$$P_{SRi}^{\max}=P_{Gi}^{\max}-P_{Gi} \quad (9)$$

Wind Speed and Power PDF:

A major difficulty to the integration of the wind power generation into the power grid is its variability and uncertainty. Wind power forecast plays an important role in the system integration of the large scale wind power. As a result of wind uncertainty SR requirement also varies. In most part of the world a method of estimating wind profile is by means of

Wei-bull probability density function (PDF).When compared to other methods, this probability distribution method has certain degree of accuracy in wind speed forecasting.

In order to obtain a value for the reserve and penalty costs, it is necessary to assume the PDF for the wind power output and load forecasts. Rayleigh distribution and Weibull distribution are the most commonly used distributions for the wind speed variations. At a given location, the wind speed profile most closely follows a Weibull distribution over time. In this paper, the Weibull PDF for the wind speed is assumed and then, transformed to the corresponding wind power distribution for use in the ED model, because of its simplicity.

Gravitational Search Algorithm:

The algorithm was proposed by Rashedi et.al (Rashedi, Nezamabadi, & Saryazdi ,2009) that uses the Newton's Gravitational Principle to search the optimum solution. In this algorithm, the coordinates or the agents in the search space are considered as masses. All these masses attract each other according to laws of Gravity and form a direct means of communication through it. The agents or particles in the algorithm follow the following two principles:

1. Law of Gravity (Halliday, Resnick, & Walker,1993): Each particle attracts the other particle with a force which is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. In GSA we take the force to be inversely proportional to the distance between them as this has been found to give better results.
2. Law of Motion: Current velocity of any particle is equal to the sum of the fraction of its previous velocity and variation in velocity.

Consider a system with N agents and the position of the i_{th} agent being defined by the coordinates:

$X_i = (x_i^1, x_i^2, \ldots, x_i^d, \ldots, x_i^n)$ for i=1,2,…,N

Where x_i^d is the position of the i^{th} agent in the d^{th} dimension.

At any time instant the gravitational force acting on the i^{th} particle due to the effect of j^{th} particle is given by:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij} + \varepsilon}(x_j^d(t) - x_i^d(t) \qquad (10)$$

Where *G(t)* is gravitational constant at time t, $M_{aj}(t)$ and $M_{pi}(t)$ is the active and passive gravitational masses related to the particle j and i, ε is a small constant, *Rij(t)* is the Euclidian distance between the particles (or agents) i and j:

$$R_{ij}(t) = \|Xi(t), Xj(t)\|_2 \qquad (11)$$

To give a random nature to the search we consider that the total force acting on the system is given by the weighted sum of the forces acting on the particle in the d^{th} dimension due to all the other particles:

$$F_i^d(t) = \sum\nolimits_{j=1, j\neq i}^{N} rand_j F_{ij}^d(t) \qquad (12)$$

Where randj is a random number in the interval [1,0].

Now the acceleration of this agent in the d^{th} dimension can be known by the equation:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \qquad (13)$$

Where M_{ii} is the inertial mass of the ith particle or agent. The velocity and position of the agents can be determined by the following equations:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(T) \qquad (14)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (15)$$

Where $rand_i$ is a random number in range [0,1] to give a random characteristic to the search. Gravitational Constant will reduce with time to control the speed and accuracy of the search, while its initial value shall be given earlier.

$$G(t)=G(G_0,t) \qquad (16)$$

Where G_0 is the initial value of Gravitational Constant at the first cosmic time interval. Fitness evaluation gives the value to the gravitational and inertial masses, a higher fitness shows more efficient agent, resulting in more attraction and slow movement. We calculate the masses using the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \qquad (17)$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \qquad (18)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \qquad (19)$$

Where $fit_i(t)$ is the fitness value and determined by the function being optimized. And *worst(t)* and *best(t)* are given by the following equations:

$$best(t) = \begin{cases} \min_{j\in\{1,2....N\}} fit_j(t), for\ minimization \\ \max_{j\in\{1,2....N\}} fit(t), for\ maximization \end{cases} \qquad (20)$$

$$worst(t) = \begin{cases} \max_{j\in\{1,2....N\}} fit_j(t), for\ minimization \\ \min_{j\in\{1,2....N\}} fit(t), for\ maximization \end{cases} \qquad (21)$$

Initially all the agents apply force, this is the time exploration is going on. For better results in the final part of the search the exploration fails and exploitation starts where only few more efficient agents continue to apply force. In order to avoid into local minima we go for exploration initially and gradually shift to exploitation where only *Kbest* agents apply force. This *Kbest* set is decreased gradually to make the change.

$$F_i^d(t) = \sum\nolimits_{j\in kbest, j\neq i} rand_j F_{ij}^d(t) \qquad (22)$$

Where *Kbest* is the set of more efficient agents with more masses.

This means near the end of the iteration nearly 2% of the initial particles shall only apply force. Recently, in many article GSA is successfully implemented for solving discrete and continuous optimization problem. In the proposed work new methodology is implemented to improve the convergence and solution quality of GSA which is discussed in next section.

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Clustered Gravitational Search Algorithm:

To keep the exploration in GSA alive without killing the exploitation, in this paper, a group method is proposed. Here, the whole population is divided into three basic groups: namely the Leader, the follower and the freelancer. The Leaders are the best particles obtained at the end of the first iteration. Each leader particle shall lead a group of optimizers. The Leader and the optimizer group together shall work like a simple GSA population thereafter. In this way there would be some independent GSA populations led by their leader that will search for the optimum solution. The last group, the freelancers shall be randomly initiated every iteration and in this way they shall keep the search alive. Each group those led by a leader and the freelancers shall have a best particle. The best out of these bests shall be the final best particle of the iteration.

Depending on the requirements of the function, the ratio of the population of Leader, follower and the freelancer can be adjusted. The pseudo-codes are given below:

Step 1. Initialize the random population of agents.
Step 2. Evaluate the population on the given function.
Step 3. Sort the population on the fitness values.
Step 4. The first 10% of the population (size can vary according to function) is called the Leader.
Step 5. The next 80% of the population (size can vary according to function) is called the follower.
Step 6. The last 10 % of the population (size can vary according to the function) is called the freelancer.
Step 7. To each of the agent in the leader group a set of agents from follower group is allotted and they together make a single sub-population.
for i=1 to max no of iterations.
{
for j=1 to max no of sub-population
{
Run GSA for each of the sub group.
}
Evaluate each particle in the freelancer group.
Find the minimum (according to the requirements of the problem) of the best fitness values obtained among all the sub groups and the freelancer group.
Again randomly initialize the entire freelancer population. (But see to it that the best particle is from the freelancer group, then that is not deleted in the next iteration.)
}
Step 8. *The best population is thus the minimum of all the best fitness values at the end of the iterations.*

Now there is no form of communication between the subpopulations so they would always be searching independently (and exploring), rather than exploiting at the same place. The problem of exploitation is solved by the subgroups themselves. They exploit their local search spaces to get a minimum out of that region while since they do not communicate the exploration happens. The flowchart for the implementation of CGSA in the ED problem for wind thermal power system is shown in Fig. 1.

RESULTS AND DISCUSSION

The matlab coding is developed for ED problem using CGSA in Pentium – IV 3.20 GHz, 2 GB RAM processor. To validate the proposed algorithm, two different test systems such as 6 unit, and 40 unit systems and four different test cases are considered to confirm the efficiency of the CGSA in solving the ED problem for wind thermal power system.

Case 1	Solving economic dispatch (ED) for thermal power system with spinning reserve (SR) requirement is equal to 10% of total demand. (without considering wind power)
Case 2	Solving ED for conventional power system with SR requirement is equal to the largest on-line thermal generator. (without considering wind power)
Case 3	Solving ED for wind-thermal power system with SR requirement is equal to 10% of total demand plus SR required due to wind power forecast uncertainty.
Case 4	Solving ED for wind-thermal power system with SR requirement is equal to the largest on-line thermal generator plus SR required due to wind power forecast uncertainty.

Six Unit System:

The wind and thermal generator unit data is adapted from ref. (Surender Reddy, Panigrahi, Rupam Kundu, Rohan Mukherjee, & Shantanab Debchoudhury, 2013). Here, the second generator is considered as the largest generator, even though the capacity of first generator is highest. This is because, if the first generator is out, than the total demand cannot be met by other generators.

Good converge performance can be obtained if the control parameters of CGSA size can be optimally tuned. Setting of these parameters optimally would also yield better solution and lesser computational time. By default setting of parameters taken initially, varying one of the parameter and the other parameters are kept constant. It has been tested for each parameter under different values within a boundary limit. In order to achieve some statistical information about the average evolution more than 10 simulations for each setting are performed. Based on the above guidelines, numerical analysis is carried out to get the best selection of parameter values.

Population size: 100 No. of iterations: 2000
G0=100 Alfa=21
No of clusters: 8 No of leaders: 10
No of followers: 80 No of free lancers: 10

Out of 10 trials, the best solution (generation dispatch and total cost) using the CGSA for all the four cases is given in Table 1. Table 2 gives the comparison of proposed methodology with the existing method available in the literature. The proposed approach provides slightly better results than methods reported in the literature for ED problem. It is noted that a cost saving obtained is small amount per hour using proposed algorithm. However, a significant amount of saving will be reflected per day and for per annum using proposed algorithm. The convergence graph of CGSA for all the cases is shown in Fig. 2.

Forty unit system:

To validate the proposed method with largest system, ED problem is solved for 40 unit system. The energy and spinning reserve scheduling is also performed on 40 unit system. The energy and spinning reserve cost coefficient, generation limits and ramp rate limits are adapted from Ref.(Surender Reddy, Panigrahi, Rupam Kundu, Rohan Mukherjee, & Shantanab Debchoudhury, 2013). Out of 10 trails, the best solution using proposed algorithm for all the case is given in Table 3.

Conclusion:

In this paper, novel method of solving economic dispatch problem for hybrid power system which is suitable for competitive power market is presented. Clustered based gravitational search algorithm is tested and validated for solving wind thermal power system. This algorithm maintains the correct balance between the exploration and exploitation. The stochastic behavior of wind power effect is considered and ED problem is solved and the results are presented. Finally, proposed algorithm results are compared with that of those surfaced in the recent literature. The comparison validates the effectiveness and the superiority of the proposed clustered approach. The encouraging results obtained confirm the suitability of this method for today's power industry and it can provide ideal solution for system operators.

Table 1: ED solution for wind thermal power system.

	Unit No.	P_G (MW)	$C(P_G)$ $	P_{SR} (MW)	$C(P_{SR})$ $
Case 1	Pg1	151.51	921.85	13.34	30.4002
	Pg2	50.00	190	15.00	35.2850
	Pg5	31.27	154.89	0	25
	Pg8	23.00	56.16	0	30
	Pg11	18.00	44.1	0	25
	Pg13	25.00	90.62	0	30
	TC	1633.31 $			
Case 2	Pg1	151.67	922.3953	14.95	30.3774
	Pg2	50.00	189.9978	14.99	35.2748
	Pg5	31.09	154.8015	10.83	25.4550
	Pg8	23.00	56.1606	4.63	30.0565
	Pg11	18.00	44.0820	0.51	25.0811
	Pg13	25.00	90.3447	4.09	30.1357
	TC	1633.16 $			
Case 3	Pg1	161.88	983.11	15.00	30.450
	Pg2	43.220	189.99	14.48	35.275
	Pg5	33.411	130.56	16.50	25.528
	Pg8	22.648	56.158	7.963	30.246
	Pg11	17.060	42.622	0	0
	Pg13	19.077	61.531	0	0
	TC	1586.38 $			
Case 4	Pg1	161.88	1004.94	15.00	30.45
	Pg2	43.22	166.72	14.48	35.27
	Pg5	33.41	170.00	16.50	25.52
	Pg8	22.64	55.23	7.96	30.24
	Pg11	17.06	42.65	0	0
	Pg13	19.07	57.23	0	0
	TC	1618.84 $			

Table 2: Comparison of results

Algorithm	Total cost ($)			
	Case 1	Case 2	Case 3	Case 4
PSO	1642.73	1645.89	1646.42	1662.44
DE	1641.86	1643.38	1645.55	1660.21
CMA-ES	1637.97	1637.99	1641.97	1657.25
CMA-ES with MLT	1633.45	1633.97	1636.57	1651.81
CGSA(proposed)	1633.31	1633.13	1586.38	1618.84

Table 3: Comparison of results.

Algorithm	Total cost ($)			
	Case 1	Case 2	Case 3	Case 4
CMA-ES with MLT	172256.74	165262.63	174197.78	161713.34
CGSA	169515.1	148189.2	165246.8	158096.6

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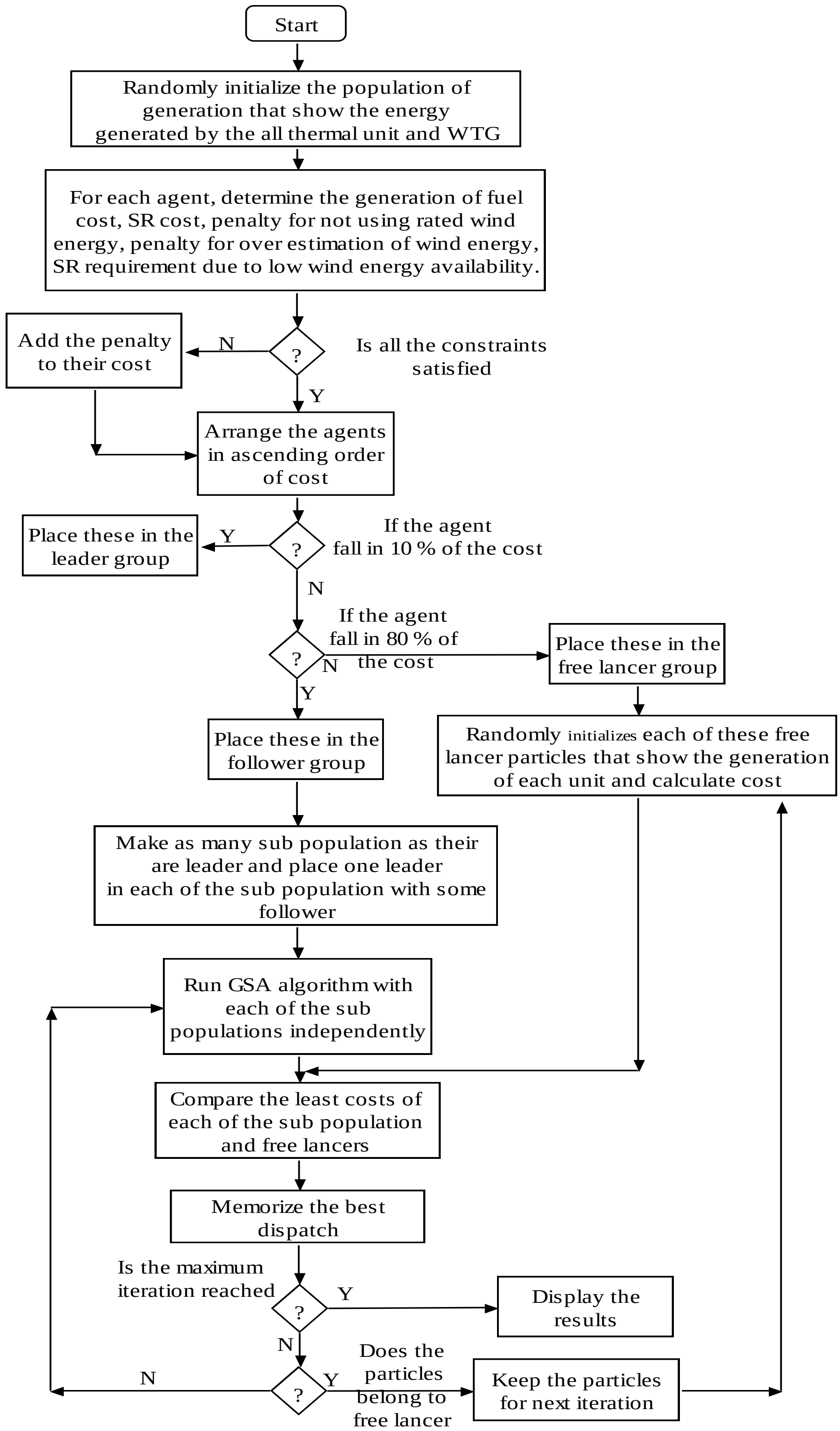

Fig. 1: Flowchart for ED using CGSA.

Appendix A:

In the above objective function (Eq. (1)) the first term is the fuel cost of conventional thermal generators considering valve-point effect, and is given by

$$Fi(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + |e_i \times \sin(f_i(P_{Gi}^{\min} - P_{Gi}))| \quad (A.1)$$

where a_i, b_i, and c_i are the cost coefficients of i^{th} thermal generator and e_i ,f_i are the coefficient of generators i reflecting valve-point effect. The second term is the SR cost of conventional thermal generators, and is given by

$F_{SRi}(P_{SRi}) = x_i + y_i P_{SRi}$ (A.2)

The third term is the direct cost paid to the wind farm owner for a scheduled wind power. A linear cost function is used for the scheduled wind power, and is given by

$F_{wj}(P_{wj}) = d_j P_{wj}$ (A.3)

The fourth term in the above objective function (Eq. (1)) is the reserve requirement cost, which represents the cost due to the available wind power being less than the scheduled wind power generation. This cost function helps to determine the deficit power it might produce, from the distribution function . This reserve cost function is given by

$F_{r.wj}(P_{wj} - P_{wj.av}) = K_{r.j}(P_{wj} - P_{wj.av}) = K_{r.j}\int_0^{P_{wj}} (P_{wj} - p) f_p(p)dp$ (A.4)

where $k_{r.j}$ is the reserve cost coefficient for the j^{th} wind generator, p is the Wind Energy Generator (WEG) power output, and $f_p(p)$ is the WEG/wind power probability density function (PDF).The fifth term is the penalty cost. This is obtained from the concept of under-estimation of wind power. This cost function helps to determine the excess power it might produce, from the scheduled value (Synder, David Powell, & Rayburn John,1987).

$F_{p.wj}(P_{wj.av} - P_{wj}) = K_{p.j}(P_{wj.av} - P_{wj}) = K_{p.j}\int_0^{P_{rj}} (p - P_{wj}) f_p(p)dp$ (A.5)

where $k_{p.j}$ is the penalty cost coefficient for the *jth* wind generator. The above problem is solved by considering the equality and inequality constraints.

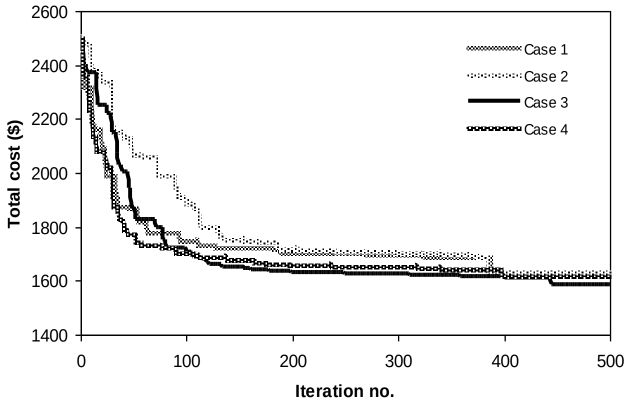

Fig. 2: Convergence graph.

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