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An Analysis of Dynamic Economic Dispatch Using Search Space Reduction Based Gravitational Search Algorithm

K. C. Meher, R. K. Swain, C. K. Chanda

***Abstract*—**This paper presents the performance analysis of dynamic search space reduction (DSR) based gravitational search algorithm (GSA) to solve dynamic economic dispatch of thermal generating units with valve point effects. Dynamic economic dispatch basically dictates the best setting of generator units with anticipated load demand over a definite period of time. In this paper, the presented technique is considered that deals an inequality constraints treatment mechanism known as DSR strategy to accelerate the optimization process. The presented method is demonstrated through five-unit test systems to verify its effectiveness and robustness. The simulation results are compared with other existing evolutionary methods reported in the literature. It is intuited from the comparison that the fuel cost and other performances of the presented approach yield fruitful results with marginal value of simulation time.

***Keywords*—**Dynamic economic dispatch, dynamic search space reduction strategy, gravitational search algorithm, ramp rate limits, valve-point effects.

NOMENCLATURE

$\alpha_i, \beta_i, \lambda_i$	fuel cost coefficient of *i*-th generating unit
η_i, τ_i	valve point coefficient of *i*-th generating unit
P_{it}	real power output of *i*-th generator at time t
F_{it}	fuel cost function of *i*-th unit at time t
F	total fuel cost
T	total number of hours in the schedule horizon
P_{Dt}	total load demand at time t
P_{Lt}	total transmission losses at time t
N	number of committed online generators
B_{ij}, B_{0i}, B_{00}	B-matrix coefficients for transmission loss
$P_{i\min}$	real power output of *i*-th generator
$P_{i\max}$	maximum real power output of *i*-th generator
UR_i	up ramp limits of *i*-th generator
DR_i	down ramp limits of *i*-th generator

I. INTRODUCTION

MOST of power system optimization problems including dynamic economic dispatch (DED) have complex and non-linear characteristics with heavy equality and inequality constraints. DED is a decisive task in power system operation and control. The sole objective is to determine the best generation outputs of available units to fulfill the forecasted load demand in most economical manner, while preserving the various physical and operational constraints.

In conventional economic dispatch, the cost function is quadratic in nature. In practice, a generating unit cannot exhibit a convex fuel cost function, so a non-convex characteristic is observed owing to valve point effect. Mathematically, DED can be recognized as anon linear, non-convex and large scale optimization problem with various complicated constraints which finds the optimal result dispatch a new challenge. The DED has been recognized as a more precise modeling than the conventional economic dispatch problem. During the last few decades, most of the conventional optimization techniques have been implemented to solve DED problems. The various techniques include Lagrange relaxation (LR) [1], [2], linear programming (LP) [3], mixed integer quadratic programming (MIQP) [4], decomposition approach (DA) [5] and dynamic programming (DP) [6]. However, many of these techniques can not provide best solutions owing to their drawbacks in terms of problem computational efficiency. formulation, and solution accuracy. To make these methods more convenient and simpler toward solving of DED problem, computational algorithms have been applied. In this respect, most of the modern heuristic techniques such as genetic algorithm (GA) [7], [8], simulated annealing (SA) [9], [10], evolutionary programming (EP) [11], particle swarm optimization (PSO) [12]–[14], artificial bee colony [15], differential evolution (DE) [16], [17] have been used effectively in solving non-linear economic dispatch problems for obtaining the global best or sub optimal solution. Although these methods always do not give guarantee global best solution in finite time, but often they achieve near global best solutions. These methods follow probabilistic rules to update their positions in complex solution space. EP with SQP technique [18]–[20] has been used to solve DED problems. Initially, the stochastic methods have been employed for finding the optimal solution in the complex search space, but owing to proper setting of tuned parameters, these approaches give better global optimal solutions within a reasonable time. It is very difficult to set the tuned parameters for optimization technique and exploring new ideas for solving the DED problem. It is also seen that SQP guides SOA [21] to obtain optimal or near optimal solution in the complicated search

K. C. Meher is with the Orissa Engineering College, Bhubaneswar, India (phone: +919861146617, e-mail: kc_meher@yahoo.co.in)
R. K. Swain is with the Silicon Institute of Technology, Bhubaneswar, India (e-mail: r_kswain@yahoo.co.in).
C. K. Chanda is with the Indian Institute of Engineering Science and Technology, Kolkata, India (e-mail: ckc_math@yahoo.com).

space with minimal simulation time. Introduction of wind power with quantum GA has been facilitated to dynamic dispatch problem [22] for better solution. Dynamic power dispatch based on real-time application [23], and the utility of renewable energy for improving the micro grid reliability have been presented [24] for obtaining optimal or near optimal solutions in complex search space. A novel optimization algorithm based on the law of gravity, GSA, is proposed by Rashedi et al. in 2009 [25]. Adaptive PSO approach for dynamic economic load has been discussed [26] for obtaining global optimal solution

GSA [27] follows the principle of gravity: "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them [28]. In the proposed algorithm, agents are considered as objects and their performance is measured by their masses. The agents attract each other by gravitational force and this force causes a global movement of all agents towards the agents with heavier masses. Hence, the masses are directly cooperating through gravitational force. The heavier the masses, the agents move slowly than lighter one, this statement is considered as exploitation step of the algorithm. In GSA, each mass has four specifications: Position, initial mass, active gravitational mass, and passive gravitational mass. In this paper, DSR strategy has been implemented for solving the DED problems. Due to DSR, the convergence speed to the solution can be accelerated faster and constraints of DED problem can be dynamically adjusted. The proposed method has been devised based on the distance between the best position of group and the inequality boundaries. The DSR based GSA approach is examined on five unit test systems by considering transmission losses and the results are compared with most of the recently published DED problems in the literature.

The remainder of this paper is organized as follows: Section II deals with the mathematical formulation of DED problem. The GSA algorithm for the DED problem is described in Section III. The proposed method, DSR-GSA is summarized in Section IV. The result analysis of the test systems is discussed in Section V to show the effectiveness of the proposed algorithm. Finally, some relevant conclusions are drawn in Section VI.

II. Problem Formulation

The prime objective of DED problem with valve point effect is to minimize the total fuel cost by determining the optimal combination of all outputs of all generators over the whole dispatch period subject to satisfy various physical and operational constraints.

The formulation of DED problem has been expressed as:

$$Min\ F = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(P_{it}) \tag{1}$$

Traditionally, the relation between the consumed fuel and generated power of the thermal power plants are approximated using a simple smooth quadratic function. This approximation is widely used in literature for modeling the cost function of thermal units.

In reality, modern thermal power plants equipped with multivalve turbines to produce requested incremental power by valve opening process. The multiple steam admission valves make the objective function discontinuous, non convex and with multiple minima. This process is called valve point loading (VPL) and it occurs as each steam admission valve in a turbine starts to open. The sequential valve opening process for multivalve steam turbines produces ripple, shown in Fig. 1 like effect in the heat rate curve in generator. This effect is included in ELS by superimposing the basic quadratic fuel cost characteristics with a rectified sinusoidal component. Hence, the fuel cost function of the thermal generating unit is modified as:

$$F_{it}(P_{it}) = \alpha_i + \beta_i P_i + \lambda_i P_i^2 + \left|\eta_i (\sin(\varepsilon_i (P_{i\min} - P_i))\right| \tag{2}$$

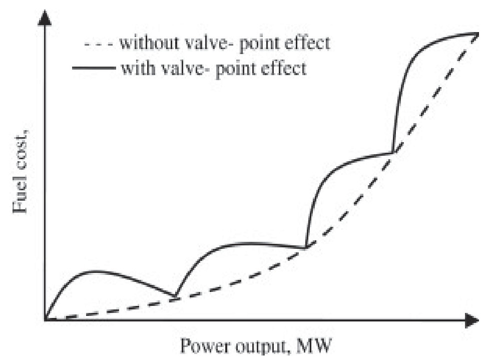

Fig. 1 The valve-point effect

A. Real Power Balance Constraint

On account of the principle of energy equilibrium law, the total real power generation from thermal units is exactly equal to the total predicted power demand plus total losses, at each time interval over the scheduling horizon.

$$\sum_{i=1}^{N} P_{it} - P_{Dt} - P_{Lt} = 0 \tag{3}$$

Due to geographical distribution of power stations, transmission losses are taken into account to get realistic solution. The total transmission loss can be calculated using Krons loss formula, known as B-matrix coefficient. The total transmission loss is a function of the unit power outputs that can be represented using B -loss coefficient as:

$$P_{Lt} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{4}$$

The B-loss coefficients represent the transmission line loss and the corona loss.

B. Real Power Operating Limits

The generation output of each generator should be between its minimum and maximum limits for ensuring the stable operation. The following inequality constraint for each unit should be satisfied.

$$P_{i\min} \le P_{it} \le P_{i\max} \text{ where } i = 1, 2....N, t = 1, 2.....T \quad (5)$$

C. Generator Unit Ramp Rate Limit

The range of actual operation of online generating unit is restricted by its ramp rate limits for adjusting the generation operation between two operating periods. Ramp rates are the maximum rates specified for each unit at which the power output of a unit can be increased (up ramp rate) or decreased (down ramp rate) in a time interval. These limits can impact the operation of generating unit. Violation of ramp rate limits also decrease the life span of rotor.

If generation increases

$$P_{it} - P_{i(t-1)} \le UR_i \quad (6)$$

If generation decreases

$$P_{i(t-1)} - P_{it} \le DR_i \quad (7)$$

where, $i = 1, 2....N$, $t = 1, 2.....T$

III. Overview of Standard GSA

A novel heuristic search algorithm, called gravitational search algorithm GSA has been proposed by Rashedi et al. in 2009 [25]. GSA follows the gravitational laws of motion. The gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the square of the distance between them. In the proposed algorithm, a set of agent called as objects. All these objects attract each other by their gravitational force, and this force causes a global movement of all objects towards the objects with their heavier masses. In the initialization process, a set of individuals created at random. Therefore, individual of i^{th} position of mass can be represented as the vector of p_i as:

$$P_i = (p_i, ...p_i^d, ...p_i^n), \text{ where } i = 1,2......m \quad (8)$$

where, p_i^d is the position of i^{th} mass in d^{th} dimension and n is the dimension of the search space. At specific time t, a gravitational force forms mass j act on mass i and is defined as

$$F_{ij}^d(t) = g(t)\frac{M_{pi}(t) \times M_{qj}(t)}{R_{ij}(t) + \varepsilon}(k_j^d(t) - k_i^d(t)) \quad (9)$$

where; M_i :mass of the of the object i, M_j : mass of the object j, $g(t)$: gravitational constant at time t, $R_{ij}(t)$: Euclidian distance between the two objects i and j, ε: small constant value.

$$R_{ij}(t) = \left\| k_i(t), k_j(t) \right\|_2 \quad (10)$$

The total force acting on the agent i in the dimension d is calculated as:

$$F_i^d(t) = \sum_{j=1\, j=i}^{N} rand_j F_{ij}^d(t) \quad (11)$$

where, $rand_j$ is a random number in the interval [0, 1]. The acceleration $a_i^d(t)$ of the agent i at time t, in the d^{th} dimension, is given as,

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (12)$$

Next step is to find out the velocity generation. To find the update velocity as well as position of a particle could be calculated as

$$u_i^d(t+1) = rand_i \times u_i^d(t) + a_i^d(t) \quad (13)$$

$$k_i^d(t+1) = k_i^d(t) + u_i^d(t+1) \quad (14)$$

where, $rand_i$ is a uniform random variable in the interval [0,1]. The gravitational constant g is initialized at the starting time and this value will be decreased with increase in time. In other words, g is related the starting value (g_0) and time (t).

$$g(t) = g(g_0, t) \quad (15)$$

$$g(t) = g_0 e^{\frac{-z}{T}} \quad (16)$$

where, z is taken as small value and T is the total time.

The fitness evaluation addresses the mass of an agent. The heavier mass gives a more efficient agent. In other words better agents have higher attractions and moves more gradually. The gravitational and inertial masses are updating by

$$m_i(t) = \frac{Fit_i(t) - Worst(t)}{Best(t) - Worst(t)} \quad (17)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (18)$$

where, $Fit_i(t)$ is fitness value of the agent i at time t, $Best(t)$ is Strongest agent i at time t, $Worst(t)$ is weakness agent i at time t.

For a minimization problem, the following equations have been developed:

$$Best\ (t) = \min_{j \in [1,2,\ldots\ldots N]} Fit_j(t), \tag{19}$$

$$Worst\ (t) = \max_{j \in [1,2\ldots\ldots N]} Fit_j(t) \tag{20}$$

IV. DSR Based GSA for DED

In order to accelerate the convergence speed to solution, the GSA has utilized search space reduction strategy known as DSR based GSA. The dynamic space reduction strategy has been applied to the existing algorithm for improving the better solution in the search space. The proposed strategy has been applied, when the performance is not activated during a specified period of time. For this condition, the search space is dynamically reduced based on distance between the Best(t) and the maximum as well as minimum value of generator output. To find the adjusted maximum and minimum output of generator at iteration *k*, the distance is multiplied by small step size. Therefore, maximum and minimum values of generator output have been modified according to the newly developed search space equations which are given below:

$$P_{it\max}^{k+1} = p_{it\max}^{k} - (P_{it\max}^{k} - Best(t)) \times s \tag{21}$$

$$P_{it\min}^{k+1} = p_{it\min}^{k} + (P_{it\min}^{k} - Best\ (t)) \times s \tag{22}$$

where, s is small step size, whose value lies between 0 and 1.

V. Implementation of Proposed Method

In order to handle the constraints conveniently, the structure of solutions for DED problem has solved by the proposed method and is composed of a set of real power output decision variables for each unit in all over the scheduling periods. The section provides the solution methodology to the above-mentioned dynamic problems throughGSA.

A. Search Space Identification

For T intervals in the generation scheduling periods, there are T dispatched for the *N* generating units. An array of decision variable vectors can be expressed as:

$$P_{it} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & & \vdots \\ p_{T1} & p_{T2} & & p_{TN} \end{bmatrix}$$

where, P_{it} is the real power output of *i-th* generator at time *t* interval.

B. Initialization

In the initialization procedure, the candidate solution of each individual (generating unit's power output) is randomly initialized within the feasible range in such a way that it should satisfy the constraint given by (5). A component of acandidate is initialized as $P_{it} \sim U\ (P_{it\min,} P_{it\max})$,where U is the uniform distribution of the variables ranging in the interval of $(P_{it\min,} P_{it\max})$.

C. Fitness Evaluation (Objective Function)

The fitness evaluation in each agent in the population set is evaluated using (2). Iteration count from this step, t=1.

D. Update the Parameters

Update gravitational constant G (t), pbest (t) and worst (t) and calculate the acceleration and velocity of an agent for $i = 1\ 2\ 3 \ldots\ldots\ldots\ldots m$.

E. Agent Force Calculation

The total force acting on the agent *i* in the dimension *d* is calculated in (9).

F. Evaluation of Acceleration of an Agent

The acceleration of an agent in d^{th} dimension over T dispatch period has evaluated using (12).

G. Update the Agents' Position

The next velocity of an agent is calculated by adding the acceleration of an agent to the current velocity and also position of an agent will updated.

H. Stopping Criterion

Repeat the step from *C* to *G* until the stopping criteria is reached. There are various criteria available to stop a stochastic optimization algorithm. In this paper, to compare with the previous results, maximum number of iterations is chosen as the stopping criterion. If the stopping criterion is not satisfied, the above procedure is repeated from fitness evaluation with incremented iteration.

The computational procedures of proposed method are as:

1) Search space identification
2) Generate initial population between minimum and maximum values.
3) Fitness evaluation of agents.
4) Update gravitational constant G (t), pbest (t) and worst (t) Calculation of acceleration and velocity of an agent.
5) Force calculation in different direction.
6) Calculation of acceleration and velocity of an agent.
7) Updating the position of an agent.
8) Repeat step 3 to step7 until the stop criteria is not satisfied
9) Stop

VI. Results and Discussions

This research work has been implemented in Matlab-7.10.0.499 (R2010a) environment on a 3.06 GHz, Pentium – IV; with 1GB RAM PC for the solution of DED problem by considering five unit test systems. The systems under study have been considered and the programs have been written (in.mfile) to calculate the solution of DED problems and its results are compared with previously developed techniques such as SA, artificial bee colony [ABC], Enhanced adaptive PSO [EA-PSO], GA, PSO, adaptive PSO [APSO] and proposed DSR-GSA technique have been successfully applied to DED problems by considering all equality and inequality constraints.

TABLE I
LOAD DEMAND PROFILE FOR FIVE UNIT SYSTEMS

Hour	Load(MW)	Hour	Load(MW)
1	410	13	704
2	435	14	690
3	475	15	654
4	530	16	580
5	558	17	558
6	608	18	608
7	626	19	654
8	654	20	704
9	690	21	680
10	704	22	605
11	720	23	527
12	740	24	463

Implementation of proposed DSR-GSA technique requires the determination of some fundamental factors like: initialization, termination and fitness value, step size, mass of an agent, gravitational constant, number of iterations, acceleration of agent, and velocity of agent. The proposed algorithm is heavily dependent on setting of control parameters. While applying this technique, its control parameters should be properly regulated for successful implementation of the algorithm. To select the control parameters of the proposed DSR-GSA technique, a number of experiments have been conducted. In order to quantify the results, 30 independent runs are executed for each parameter variation. The best setting of control parameter is the mass of an agent M=100, gravitational constant g = 50 and total number of iteration T=500. The tuned value of S is taken as 0.25. The results obtained from proposed approach have been compared with previously developed well known techniques; which are reported in the literature. The DSR-GSA method has been implemented to obtain the global or near global optimal solutions by accelerating the optimization process without changing the inherent characteristics of GSA.

Case Study: Five Unit Test Systems

In this study, a five-unit test system with non-smooth fuel cost function is employed to show the performance of proposed method. In this paper, transmission losses, VPL and ramp rate limits are taken into account. The dynamic scheduling problem takes 24 intervals of a day. The system data such as cost coefficient, ramp rate limits, power generation limits and load demands are taken from [13]. The best fuel cost obtained in 30 independent runs by the proposed method is **43349.32 $/h**. Table I shows the load demand profile for 24 intervals of a day. Similarly, Tables II and III depict the corresponding dispatch of generators using proposed DSR-GSA and GSA methods, where the power output of each generator satisfies the generation limits constraints and change in generating output from one interval to next complies with ramp rate limits. It is clearly seen from comparison Table IV, that the proposed algorithm gives better results than other evolutionary methods. Hence, it is cleared that the proposed algorithm is efficient and can give a cheaper generation cost than other methods. Moreover, the CPU time is taken as performance measure to compare the computation efficiency between different methods, though those compared algorithms are coded by different programming languages and run on different CPU conditions. It is cleared from comparison results that the proposed algorithm takes less computation time to produce the best solutions.

Control parameters have significant effects on the proposed DSR-GSA method. To escape local minima, a suitable value of S has been taken for obtaining better global optimal solutions. The best fuel cost in 30 independent runs for the proposed system is compared with the other results reported in [10], [13], [15], [26] and are shown in Table IV. Fig. 2 shows the convergence characteristics of proposed algorithm. From the convergence behavior, it is quite evident that the proposed method has good convergence characteristics as compared to other approaches and Fig. 3 indicates hourly power generations of five-unit systems while Fig. 4 shows the fuel cost of different methods. As noticed from Fig. 4 that the minimum cost of our proposed algorithm is well below the minimum cost of other algorithms. Similarly, Fig. 5 indicates hourly power loss variation of GSA technique and DSR-GSA approach. Fig. 6 indicates the total fuel cost distribution obtained by proposed algorithm.

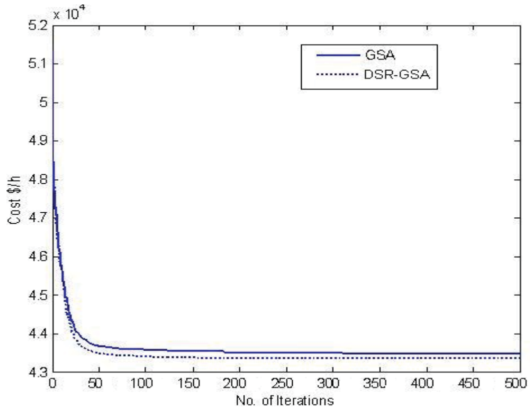

Fig. 2 Convergence characteristics of proposed method

TABLE II
GENERATION SCHEDULE USING DSR-GSA METHOD

Hour	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Total Load (MW)	Total Loss (MW)	Total Cost ($/h)
1	16.733	99.470	113.77	41.140	139.76	410	0.873	1256.09
2	10.835	99.682	113.16	70.718	141.58	435	0.975	1450.08
3	10.841	97.303	110.64	118.02	139.44	475	1.244	1418.73
4	40.089	103.58	115.55	129.73	142.54	530	1.489	1670.86
5	38.541	98.506	112.98	169.77	140.05	558	1.847	1819.36
6	39.852	107.07	112.91	209.54	142.07	608	2.447	1818.00
7	16.827	98.439	112.76	209.90	190.41	626	2.336	1926.08
8	10.227	98.026	111.85	209.41	226.80	654	2.313	1800.07
9	39.231	98.491	112.79	209.37	231.50	690	1.382	1969.06
10	56.120	98.344	112.80	209.76	229.40	704	2.424	1992.43
11	73.452	97.945	112.44	209.60	229.07	720	2.507	2000.82
12	74.258	98.797	112.88	225.24	231.59	740	2.765	2152.86
13	55.731	98.735	112.83	209.64	229.49	704	2.426	1993.17
14	41.512	98.566	112.85	209.85	229.61	690	2.388	1955.79
15	16.727	97.307	112.39	200.84	228.93	654	2.194	1867.44
16	10.332	97.356	93.224	151.22	229.31	580	1.442	1859.43
17	10.541	93.613	101.60	124.31	229.15	558	1.214	1644.42
18	39.536	100.12	113.30	126.16	230.29	608	1.406	1783.48
19	46.308	99,115	115.45	165.15	229.82	654	1.843	2073.03
20	56.418	98.647	112.66	209.59	229.12	704	2.435	1994.03
21	36.812	98.354	112.36	205.92	228.87	680	2.316	1955.03
22	10.300	98.614	112.38	156.51	228.84	605	1.644	1826.16
23	10.625	98.056	112.68	125.38	182.60	527	1.341	1674.57
24	10.325	91.876	98.799	124.36	138.82	463	1.180	1448.33
Total Cost: 43349.32 (($/h)								

TABLE III
GENERATION SCHEDULE USING GSA METHOD

Hour	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	Total Load (MW)	Total Loss (MW)	Total Cost ($/h)
1	16.381	99.545	30.142	125.00	139.86	410	0.928	1234.21
2	41.659	98.468	30.984	125.09	139.78	435	0.981	1366.33
3	57.785	98.517	54.131	125.51	140.16	475	1.063	1584.03
4	74.162	98.389	93.603	125.21	140.03	530	1.394	1652.13
5	74.249	99.388	112.66	133.38	139.93	558	1.607	1668.15
6	74.402	99.991	112.64	182.68	140.44	608	2.153	1888.18
7	68.410	97.957	112.85	209.64	139.63	626	2.487	1790.39
8	73.915	102.73	117.21	209.85	152.88	654	2.585	1973.53
9	74.085	98.122	112.28	209.69	198.33	690	2.507	2099.39
10	56.449	98.540	112.12	209.40	229.92	704	2.429	1998.03
11	72.843	98.421	112.58	209.49	229.18	720	2.514	1999.07
12	74.089	98.874	113.98	225.78	230.05	740	2.773	2152.61
13	56.600	98.225	112.62	209.70	229.29	704	2.435	1993.35
14	34.842	99.828	118.00	209.98	229.77	690	2.420	1983.95
15	10.613	96.337	112.18	208.26	228.90	654	2.290	1802.15
16	10.634	97.998	83.351	159.80	229.70	580	1.583	1917.07
17	10.265	98.241	98.051	124.16	228.50	558	1.217	1642.26
18	10.648	97.724	112.70	159.27	229.33	608	1.672	1840.03
19	10.173	96.106	112.13	208.39	229.48	654	2.279	1797.10
20	21.698	105.26	140.30	209.76	229.62	704	2.638	2113.25
21	20.799	105.17	114.07	211.30	231.09	680	2.429	1940.89
22	10.234	97.941	96.096	173.91	228.55	605	1.731	1932.19
23	10.377	98.073	113.10	125.12	181.67	527	1.340	1674.39
24	10.985	97.989	91.497	124.28	139.42	463	1.181	1448.51
Total Cost: 43491.18($/h)								

TABLE IV
COMPARISON OF OPTIMAL COST FOR DIFFERENT METHODS

Methods	Minimum Cost ($/h)	Simulation Time (sec)
SA [10]	47356.00	351.98
ABC [15]	44045.83	
APSO [26]	44678.00	--
GA [15]	44862.42	--
PSO [15]	44253.24	
EAPSO [13]	43784.00	20
GSA	43491.18	30
DSRGSA	43349.32	29.76

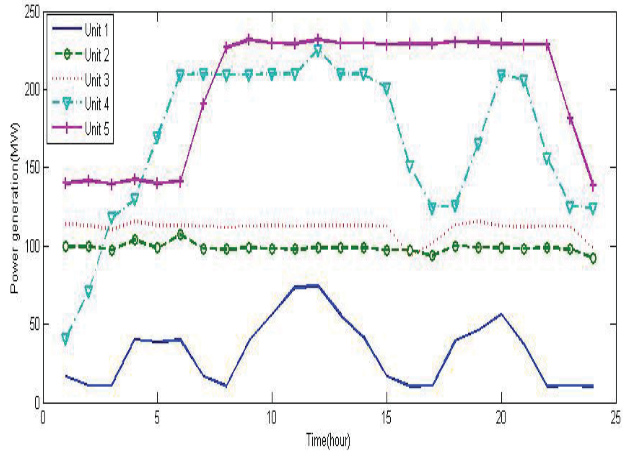

Fig. 3 Hourly power generations of units by DSR-GSA method

VII. CONCLUSION

This article facilitates a DSR based GSA approach to DED problem while retaining the intrinsic properties of GSA. The presented approach is implemented to handle the constraints more effectively, prevent premature convergence and obtaining the optimal solution in complex search space. The proposed method has imparted best solution within a reasonable simulation time with respect to the cited methods.

The DED problems can also be extended by inclusion of more inequality constraints such as wind farm, photovoltaic units and spinning reserves, etc. to obtain more realistic features for practical power system framework.

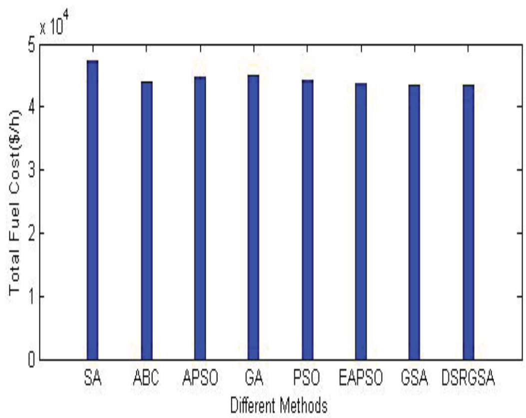

Fig. 4 Fuel cost bar chart of different methods

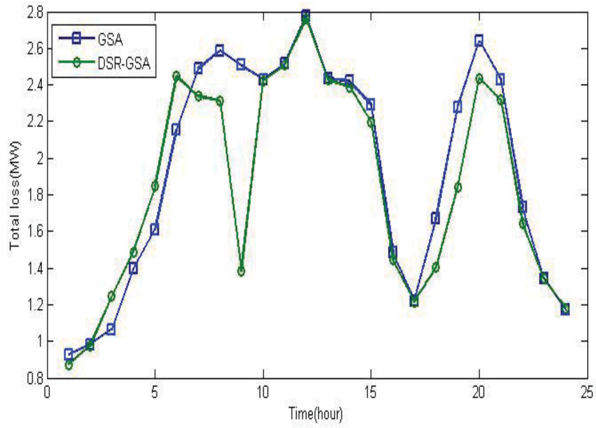

Fig. 5 Hourly power loss profile by proposed method

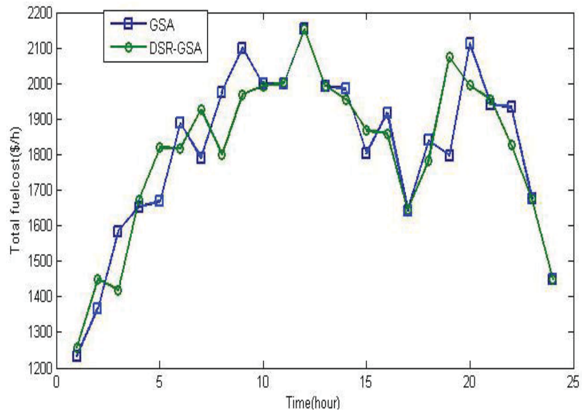

Fig. 6 Cost distribution obtained by proposed algorithm

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K. C. Meher has received Bachelor of Engineering in Electrical, from IE (India) in 1995 and M. Tech degree in Electrical Engineering with specialization in Power Electronics & Drives from KIIT University, Bhubaneswar in 2006. He was working as Lecturer in Electrical Engineering Department, KIIT (KP) Bhubaneswar, Odisha, from 2001 to 2008. Since 2008, he is working as an Assistant Professor in Electrical Engineering Department at Orissa Engineering College, Bhubaneswar, India. Now he is pursuing his PhD at Indian Institute of Engineering Science and Technology (IIEST), Kolkata. His research interests include economic load dispatch, hydrothermal scheduling and soft computing applications to different power system problems.

R. K. Swain is an Associate Professor at Silicon Institute of Technology, Bhubaneswar, India. He has received his Ph.D degree from Jadavpur University, Kolkata, India in 2010 and M.E degree in Electrical Engineering with specialization in Power System from VSSUT, Burla, India in 2001.He obtained, Bachelor of Engineering in Electrical from IE (India) in 1998. His research interests include economic load dispatch, hydrothermal scheduling and soft computing applications to different power system problems. He has published more than 15 national and international journals.

C. K. Chanda has received his B.E with honors from NIT, Durgapur, India in1983.He received M.Tech from the department of electrical engineering, IIT Kharagpur, India in 1989 and PhD degree from Bengal Engineering &Science University (Presently IIEST), Kolkata, India in 2003.Now he is working as Professor at IIEST, Kolkata, India. He has published more than 100 national and international journals. His research interests include soft computing applications to different power system problems.