International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:9, No:9, 2015

Dynamic Economic Dispatch Using Glowworm Swarm Optimization Technique

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***Abstract*—**This paper gives an intuition regarding glowworm swarm optimization (GSO) technique to solve dynamic economic dispatch (DED) problems of thermal generating units. The objective of the problem is to schedule optimal power generation of dedicated thermal units over a specific time band. In this study, Glowworm swarm optimization technique enables a swarm of agents to split into subgroup, exhibit simultaneous taxis towards each other and rendezvous at multiple optima (not necessarily equal) of a given multimodal function. The feasibility of the GSO method has been tested on ten-unit-test systems where the power balance constraints, operating limits, valve point effects, and ramp rate limits are taken into account. The results obtained by the proposed technique are compared with other heuristic techniques. The results show that GSO technique is capable of producing better results.

***Keywords*—**Dynamic economic dispatch, Glowworm swarm optimization, Luciferin, Valve–point loading effect, Ramp rate limits.

I. INTRODUCTION

DED plays a significant role in power system operation and control. This is considered as dynamic problem owing to dynamic property of power system and the large variation of load demand. This absolute problem is normally solved by splitting the entire dispatch period into a number of small time intervals. The load is assumed to be constant and the system is considered to be in accurate steady state dynamic model which finds the optimum generation schedule for the generating units in real power system framework. The main objective of the dynamic economic dispatch (DED) is to minimizing the generation cost, subject to satisfy the physical and operational constraints. In traditional 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 will observe owing to valve point effect. Mathematically, DED problem with valve point effect can be recognized as a nonlinear, non-convex and large scale optimization problem with various complicated constraints, which finds the optimal result dispatch a new challenge. DED has been recognized as a more accurate problem than the traditional economic dispatch problem. Many traditional optimization techniques have been utilized to solve the DED problems. The standard GSO is an efficient global search technique because of its features of easy implementation, robustness to control parameter and computational efficiency. It is easy to implement in most programming languages and has been proved to be quite effective and reasonably quick when applied to a diverse set of optimization problems. In this paper, the GSO based DED algorithm has presented for the determination of global or near global optimum dispatch solution. mathematical techniques include linear programming [1], decomposition approach (DA) [2], mixed integer quadratic programming (MIQP) [3], Lagrange relaxation (LR) [4], [5] and dynamic programming (DP) [6]. However, most of the traditional techniques cannot lead to optimal solution on the ground of their shortcomings in terms of problem formulation, computation efficiency, and solution accuracy. Wood and Wallenberg suggested dynamic programming, [7] which does not impose any restriction on the nature of cost curves. However, DP suffers from the "curse of the dimensionality" and high computational time is required when the power system is large. More interests have been concentrated on the application of artificial Intelligence [AI] technique for DED problems. Many methods such as genetic algorithm (GA) [8], [9], simulated annealing (SA) [10], evolutionary programming (EP) [11], Combining evolutionary programming (EP) with sequential quadratic programming (SQP) [12]-[14] have been used to solve DED problems because they can give global or near global optimal solution. Particle swarm optimization (PSO) [15]-[17], differential algorithm (DE) [18], [19] and Clonal selection algorithm (CSA) [20] may prove to be very effective in solving non-linear economic dispatch problems without any restriction on the shape of the cost curves. Although these heuristic methods do not always guarantee discovering the global optimal solution in finite time, they often provide fast, reasonable and near global optimal solutions. All of these methods are probabilistic rules to update their candidates' positions in the solution space. Social and cognitive factors are tuned using nonlinear approach for obtaining optimal solution shown in enhanced adaptive particle swarm optimization (EAPSO) [21]. Generally, heuristic methods are implemented for search purpose in order to obtain global or near global optimal solutions. More recently, another heuristic optimization technique, GSO [22] have been developed by K.N. Krishnanand and D. Ghose and the researchers have been directed towards the application of GSO technique to solve the complex optimization problems of power system engineering.

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II. PROBLEM FORMULATION

The main objective of the DED is to determine the outputs of all generating units to minimize the operating cost over a certain period of time under various physical and operational constraints. The formulation of DED problem has expressed as:

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

The fuel cost function with valve point effect of the thermal generating unit is expressed as the sum of a quadratics and sinusoidal-function

$$F_{it}(P_{it})=a_i+b_iP_i+c_iP_i^2+\left|e_i(\sin(f_i(P_{i\min}-P_i))\right| \tag{2}$$

where, F total generating cost (\$), N is number of generating units, T is Numbers of hour in the time horizon, P_{it} is power output of i^{th} unit at t interval, $F_{it}(P_{it})$ is the fuel cost i^{th} unit in terms of its real power output P_{it} at a time t, a_i, b_i, c_i are fuel cost coefficient of i^{th} unit, e_i and f_i are valve point coefficients of i^{th} unit, $P_{i\min}$ is minimum real power output of i^{th} unit. To minimize the aforesaid objective, the following constraints should be satisfied.

A. Real Power Balance

The vital constraint is related to real power balance ensuring that at each time of scheduling, the total thermal power generation is exactly equal to total demand plus total loss.

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

where, P_{Dt} is the total power demand during i^{th} period and P_{Lt} is the total transmission loss during i^{th} dispatch period. In this paper transmission loss is not considered.

B. Real power operating limits

The power generation of each generator should lie between its lower limits and upper limits, so that

$$P_{it\min}\le P_{it}\le P_{it\max}\text{, Where } t = 1, 2\ldots.T \tag{4}$$

$P_{it\min}$ and $P_{it\max}$ are the minimum and maximum power generation of i^{th} unit at t time interval.

C. Generator Unit Ramp Rate Limit

The range of actual operation of online generating unit is restricted by its ramp rate limits. These limits can impact the operation of generating unit. The operational decision at the present hour may affect the operational decision at the later hour due to ramp rate limits.

(a) When generation increases

$$P_{it}-P_{i(t-1)}\le UR_i \tag{5}$$

(b) When generation decreases

$$P_{i(t-1)}-P_{it}\le DR_i \tag{6}$$

where i *=1, 2 …N,* UR_i and DR_i are ramp up and ramp down rate limits of i^{th} generator respectively and these are expressed in MW/h.

III. Overview of GSO

Reference [22] developed a GSO based on the behavior of glowworm (insects). The biological behaviors of the movement of individuals (e.g. ants, honey bee swarm, fish schools) within a group are the main observation in this algorithm. This algorithm consists of agents, which discover the search space and transmit the information regarding fitness with respect to their correct position. The GSO algorithm searches the agents in a group of individuals similar to the other heuristic based optimization methods. All individuals in a swarm approaches to the optimum or quasi-optimum through its randomly chosen direction of luciferin. In GSO algorithm, the search space composed N-dimensional agents called glowworm. Initialize the glowworm randomly in the search space. The position of glowworm i at time t is $X_i(t)=(x_{i1}(t),x_{i2}(t)\cdots x_{iN}(t))$. The GSO algorithm has described by the set of variables such as position vector $X_i(t)$ luciferin level $l_i(t)$ and neighborhood range $r_i(t)$. The number of luciferin level associated with glowworm i at time t. To update the current position of glowworm i, the fitness value of the luciferin is given as:

$$l_i(t)=(1-\rho)l_i(t-1)+\gamma\, J(x_i(t)) \tag{7}$$

where ρ :Luciferin. In decay constant whose value lies between $\rho\in(0,1)$; γ: Luciferin enhancement constant; J: Objective function.

The individual glowworm i encodes the objective function $J(x_i(t)$ at current position $x_i(t)$ into a luciferin values $l_i(t)$ and broadcast the same within its neighborhood. The set of neighborhood $N_i(t)$ is chosen according to higher luciferin value within dynamic search space domain. The chosen numbers of glow in the local decision range is given by

$$N_i(t)=\left\{J:\left\|x_j(t)-x_i(t)\right\|<r_d^i, l_i(t)<l_j(t)\right\} \tag{8}$$

where $N_i(t)<r_d^i$, r_d^i is the local updated decision range. The decision range is bounded by a circular sensor range $r_s(0<r_d^i<r_s)$, $j\in N_i(t)$; $x_j(t)$:Glowworm i^{th} position at t iteration; $l_j(t)$:Glowworm i^{th} luciferin at t iteration.

Each glowworm i selects a neighborhood glowworm j with a probability $P_{ij}(t)$. These movements enable the glowworm into a disjoint subgroup which finds the multiple optimal solutions to the objective function. The selection of the neighborhood glowworm by using probability distribution is given by

$$P_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} (l_k(t) - l_i(t))} \tag{9}$$

The updated luciferin movement is given by

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right) \tag{10}$$

where s is called moving step size.

In the last phase, the fitness of luciferin within a dynamic decision domain is upgraded in order to limit the range of communication and the updated local decision range is given by

$$r_d^i(t+1) = \min\left\{r_s, \max\left\{\begin{matrix}0, r_d^i(t) + \\ \beta(n_i - |N_i(t)|)\end{matrix}\right\}\right\} \tag{11}$$

$r_d^i(t+1)$: is the glowworm $i's$ local decision range at the $(t+1)$ iteration; r_s: The sensor range; n_i: The neighborhood threshold value; β : Constant parameter.

IV. Implementation of GSO to Dynamic ED

This section describes the implementation of GSO algorithm for solving DED problems. This section deals the implementation of the equality and inequality constraints of DED problems when modifying each individual's search space in the GSO algorithm. 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 t interval.

A. Initialization of Glowworm

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 (4). A component of a candidate 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 $(P_{it\min,} P_{it\max})$.

B. Fitness Function Evaluation

The fitness value of individual i is calculated the following (2). The number of population is equal to the number of fitness evaluation.

C. Calculation of Luciferin in Level

Each glowworm carries a luminescent quantity called luciferin. The number of luciferin level associated with each glowworm i at times t. Put the value of objective function $J(x_i(t))$ into the $l_i(t)$ in (7). The number of luciferin level is same as the number of glowworms.

D. Decision of Neighborhood

The better the fitness value, the better the level of luciferin. Each glowworm finds all the glowworms which have the brighter luciferin level within the local dynamic decision range r_d^i. The decision range is bounded by a circular sensor range. The number of brighter glowworm is calculated by following (8).

E. Updated Local Decision Range

At each iteration, the dynamic decision range is upgraded by (11). The suitable value of β is chosen such that how it effects the rate of change over the neighborhood range.

F. Glowworm Velocity Updated

In this section, each glowworm carries their topical information which enables the glowworm to make their division into a number of subgroups. It gives the multiple local optimal solution of the given objective function. In order to select the proper neighbor, a probability distribution is chosen by (9).

G. Position Updated of Glowworms

The position of each glowworm is usually updated by (10). The resultant position of individuals is being violated their operating limits and to keep the position as the individual within the boundary.

V. Simulation Results and Discussion

In this study, proposed GSO algorithm has been applied to DED problems by considering ten unit test systems to investigate the effectiveness and robustness. The results obtained from proposed approach have been compared with previously developed well known techniques; those are reported in the literature. The software has been written in MATLAB-7.5 language and executed on a 2.3-GHz Pentium IV personal computer with 512-MB RAM. For implementing the GSO technique in DED problems, the optimal parameters setting of GSO algorithm have been applied to obtain better optimal solutions. The following parameters are judiciously chosen for obtaining optimal results. The initial value of swarm N_P=150, Initial luciferin value l_0=150, The neighborhood threshold value n_i=6, Constant parameter β =0.05, Luciferin decay constant ρ = 0.3, Luciferin enhancement constant γ=0.7, Moving step size s = 0.038, the maximum number of generations (iterations) of 500 are taken in this simulation study for the test systems only.

Description of the Test Systems

Initially, the proposed GSO technique is applied on a small test system, consisting of ten generating units with a ramp rate limits and valve point effects. The generator cost coefficients, power generation limits and ramp rate limits are taken from [21]. The load profile for a period of 24 hours has come from same reference. In this study, transmission losses are neglected. Table I indicates the generator data of ten units test systems.

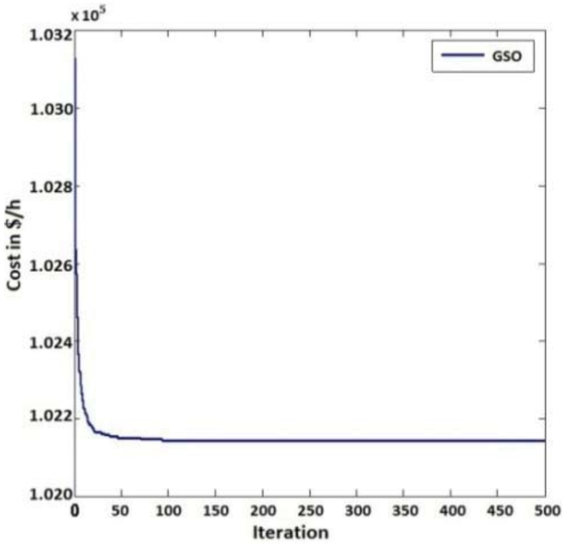

Fig. 1 Convergence behavior of GSO method

The hourly load demand variations are shown in Table II, while the optimal power dispatch results for this case study are shown in Table III. It is seen from Table III that the power output of the generating units in each time interval satisfies the generation limits and the change of power generation from one stage to other stage satisfies the ramp constraints. Hence, GSO has better solution without violating any system operating constraints. The best fuel cost in 30 independent runs for the proposed system is compared with other evolutionary approaches which are reported in [13], [15], [17]-[19] as seen in Table IV. The optimal fuel cost of the given approach in 30 independent runs is found to be **1021210 ($).** It is clearly visible from Table IV that the proposed method yields the best among all the techniques considered. Moreover, it is obtained from Table IV that the CPU time consumption of the given approach is less than the other techniques and it can avoid premature convergence and possess good convergence speed. Fig. 1 shows the convergence behavior of GSO algorithm. From the convergence behavior, it is quite evident that the proposed method has the good convergence characteristics as compared to other approaches. Fig. 2 shows hourly load demand variations while Fig. 3 shows the cost curve of thermal generations by different heuristic methods.

TABLE I
GENERATOR DATA FOR TEN-UNIT TEST SYSTEMS

Unit	a_i $/h	b_i $/MWh	c_i $/MW²h	e_i $/h	f_i rad/MW
1	958.2	21.6	0.00043	450	0.041
2	1313.6	21.05	0.00063	600	0.036
3	604.97	20.81	0.00039	320	0.028
4	471.6	23.9	0.0007	260	0.052
5	480.29	21.62	0.00079	280	0.063
6	601.75	17.87	0.00056	310	0.048
7	502.7	16.51	0.00211	300	0.086
8	639.4	23.23	0.0048	340	0.082
9	455.6	19.58	0.10908	270	0.0980
10	692.4	22.54	0.00951	380	0.094

Unit	$P_{i\max}$ MW	$P_{i\min}$ MW	DR_i MW/h	UR_i MW/h
1	470	150	80	80
2	460	135	80	80
3	340	73	80	80
4	300	60	50	50
5	243	73	50	50
6	160	57	50	50
7	130	20	30	30
8	120	47	30	30
9	80	20	30	30
10	55	55	30	30

TABLE II
LOAD PROFILE DURING 24 HOURS

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

TABLE III
BEST SOLUTION BY PROPOSED METHOD FOR TEN-UNIT SYSTEMS

Hour	Unit1 (MW)	Unit2 (MW)	Unit3 (MW)	Unit4 (MW)	Unit5 (MW)	Unit6 (MW)	Unit7 (MW)	Unit8 (MW)	Unit9 (MW)	Unit10 (MW)
1	150.1	222.63	84.656	122.18	73.968	129.65	130	47.227	20.581	55
2	150	223.38	161.14	76.728	119.12	127.73	129.12	47.15	20.627	55
3	153.44	302.42	185.27	117.93	122.37	122.48	130	48.794	20.303	55
4	224.3	310.04	254.54	120.13	121.89	122.55	130	47.05	20.497	55
5	302.81	305.94	304.21	70.709	121.65	121.94	130	47.002	20.733	55
6	380.37	312.37	315.44	119.3	124.01	124.16	130	47	20.358	55
7	390.13	309.48	327.89	117.94	172.65	131.89	129.55	47	20.462	55
8	456.57	310.53	340	119.4	176.47	119.03	130	48.577	20.424	55
9	454.62	387.28	298.12	119.9	222.33	158.28	129.49	78.577	20.408	55
10	459.46	458.85	314.47	169.41	220.96	159.22	130	84.623	20.021	55
11	456.84	460	314.2	217.87	218.72	158.48	129.36	114.62	20.895	55
12	456.67	459.27	335.09	246.96	240.25	157.3	129.17	118.88	21.41	55
13	457.92	396.28	313.41	239.5	221.18	119.74	129.26	118.06	21.649	55
14	377.92	395.56	318.93	192.48	222.53	123.25	130	88.059	20.275	55
15	381.76	320.05	300.71	178.94	172.53	130.26	128.72	86.808	21.228	55
16	304.22	305.34	276.68	132.59	122.53	122.12	130	85.208	20.309	55
17	302.66	309.4	199.16	85.815	172.05	122.4	128.86	84.161	20.502	55
18	304.23	310.62	258.47	121.62	220.14	124.94	126.61	86.182	20.182	55
19	382.2	388.18	299.93	120.02	173.46	120.18	129.36	86.793	20.875	55
20	456.93	458.86	314.68	170.02	223.16	160	128.47	84.009	20.878	55
21	456.73	395.38	313.08	121.92	222	121.44	129.99	86.58	21.885	55
22	381.71	318.72	259.19	85.532	173.13	121.1	126.28	87.031	20.302	55
23	305.01	243	185.97	63.221	124.56	121.42	129.52	83.952	20.335	55
24	226.82	223.64	182.46	60	76.449	122.07	126.94	88.445	22.176	55

TABLE IV
COMPARISON OF OPTIMAL COST FOR DIFFERENT METHODS

Methods	Minimum Cost ($/h)	Simulation Time (sec)
EP-SQP [13]	1031746	20.51
MDE [18]	1031612	5.30
HDE [19]	1031077	-
DG-PSO [15]	1028835	15.39
IPSO [17]	1023807	---
GSO	1021210	5.28

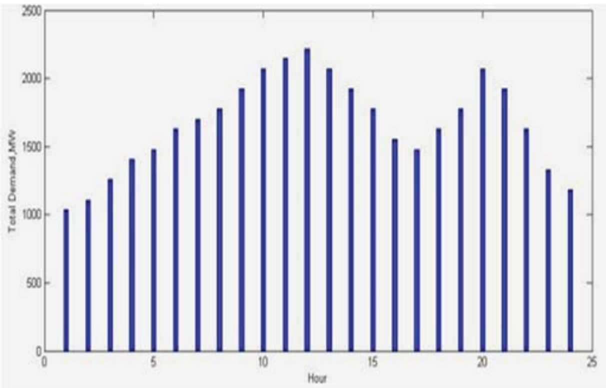

Fig. 2 Hourly load demand profile

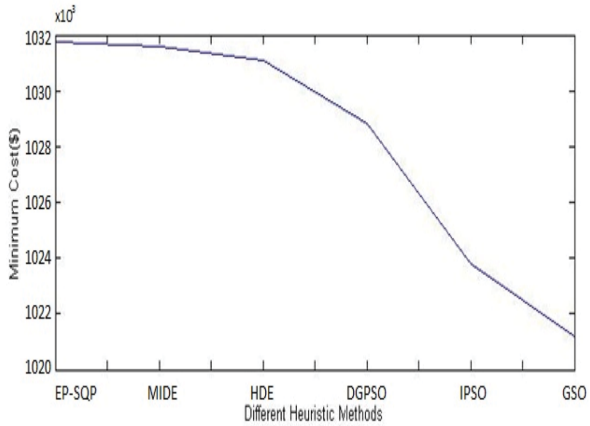

Fig. 3 Fuel costs of power generation by different heuristic methods.

VI. CONCLUSION

This article facilitates a novel GSO method to solve the non-convex DED problem of thermal units with valve point effect for determination of global or near global optimum solution. The feasibility of GSO method has been verified on ten-unit test systems. It is quite apparent from the comparison results that the proposed method imparts better performance with respect to solution quality, simulation time and effort as compared to other well known evolutionary algorithms When more complex fuel cost characteristics are considered, the solution quality and computational efficiency are significantly better than other methods. Because of these important features, GSO method seems to become powerful tool for solving more complicated optimization problems.

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