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Economic Load Dispatch Using Glowworm Swarm Optimization

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Abstract: Economic load dispatch (ELD) is an important issue in the energy scheme that is tried by allocating the generation through a set of units to minimize fuel costs and is subject to equality and inequality limitations linked to power balance and power production, respectively. ELD is formulated as a non-convex, nonlinear, constrained problem of optimization that can not be easily solved using conventional techniques. This paper introduces a fresh stochastic optimization strategy to fix ELD problems using Glowworm Swarm Optimization (GSO). GSO is a recently established derivative-free, meta-heuristic optimization algorithm that inspires as its agents the swarm of glowworms. The agents are considered the prospective solutions to an issue. It is memoryless and does not involve the understanding of any worldwide data. The solution methodology is easy to solve ELD issues with distinct limitations, such as power balance, generator ramp rate restrictions, and forbidden working areas. Simulations are carried out on two test schemes with distinct generating unit numbers. In addition, a comparative research is conducted with approaches to GA and PSO. The results support the robustness and skill of the suggested GSO-based ELD methodology over the other current methods.

Keywords: Economic load dispatch, Glowworm Swarm Optimization, Particle Swarm Optimization, Smooth cost function.

1. NOMENCLATURE

F_i	total fuel cost of the generators
a_i, b_i, c_i	cost coefficients of generator i.
P_D	power demand
P_L	transmission losses
B_{ij}	line loss coefficients
$P_{i,min}, P_{i,max}$	minimum and maximum generation of unit i.
P_i, P_i^0	current and previous power output of i^{th} unit respectively
UR_i, DR_i	up and down ramp limits of i^{th} unit respectively
k	index of prohibited zone
nz	number of prohibited zones of unit i
$P_{i,k}^L, P_{i,k}^U$	lower and upper limits of kth prohibited zone of generator i
ρ	luciferin decay constant
γ	luciferin enhancement constant
di,j (t)	Euclidian distance between glowworms i and j at time t
s	moving step size
$r_d^i(t)$	variable local decision range associated with the glowworm i at time t
$l_j(t)$	luciferin level associated with the glowworm j at time t
rs	radial range of luciferin sensor
β	constant parameter

2. INTRODUCTION

ELD is one of the most important issues to solve for a power system to operate smoothly and economically. It is a process of sharing the total load on a power system between different generating plants in order to achieve the greatest operating economy. Conventional techniques such as linear programming algorithms[1], quadratic programming algorithms[2], non-linear programming algorithms[3], dynamic programming algorithms[4,5], Lagrangian relaxation algorithms[6,7] etc. have been implemented to ELD issues. The classical calculus-based methods can not perform satisfactorily to solve ELD problems due to highly non-linear features of the problem and a large number of constraints. For instance, recent meta-heuristic algorithms, particle swarm optimization (PSO)[8-12], Adaptive PSO[13], chaotic PSO[14], differential evolution (DE)[15], evolutionary programming (EP)[16], genetic algorithm (GA)[17,18], real coded GA[19], bacterial foraging optimization (BFO)[20], biogeography-based optimization (BBO) [21], gravity search algorithm (GSA)[22], pattern search technique (PSM)[23], Clonal search algorithm [24] and artificial bee colony (ABC) [25, 26] are promising alternatives to solving complicated ELD issues. An opposition-based learning idea is implemented to enhance GSA's performance [27]. Liao provided GA algorithm based on nicheimmune isolation to solve dynamic ELD (DELD) problem [28]. Modified chaotic DE (MCDE) is suggested to solve the DELD issue of a large-scale integrated power system [29]. Chaotic map update mechanism and metropolis rule are used in the MCDE to improve normal DE features. Modified shuffled frog jumping algorithm is implemented to solve the ELD problem [30]. Iteration-based PSO alogorithm is introduced to solve the ELD issue. [31]. Modified PSO that combines the merits of PSO and BF is provided to solve the restricted dynamic ELD problem [32]. In the BF-PSO-DE algorithm, BFO, PSO and DE algorithms are hybridized to solve static and dynamic ELD issues of multiple test systems [33].

Glowworm swarm optimization (GSO) suggested by Krishnanand and Ghose is a fresh algorithm for optimizing multimodal functions[34]. It is mimicked from the conduct that glowworms exchange data with their colleagues to search for food. GSO algorithm displays superior function to achieve the ideal solution for multimodal tasks.

Therefore, this paper introduces the GSO algorithm to fix the ELD issues with different limitations and test schemes. In addition, to compare the efficiency of the GSO strategy, GA and PSO methods are compared.

3. PROBLEM DESCRIPTION OF ELD

The goal of the ELD problem is to find an optimal power generation schedule while minimizing fuel costs and also satisfying the operating constraints of different power systems.

3.1 Objective Function

The problem with ELD is formulated as follows:

$$Minimize\ F = \sum_{i=1}^{ng} F_i(P_i) \qquad (1)$$

The generator's total fuel cost is defined by:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i$$

3.2 System Constraints

3.2.1 Power balance constraints

The generators' complete power output must be equal to the sum of power requirements and complete transmission losses and is provided by:

$$\sum_{i=1}^{ng} P_i = P_D + P_L$$

The transmission losses are expressed as

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i} P_i + B_{00}$$

3.2.2 Generator capacity constraints

Each unit's output power needs to be restricted by limiting inequality between its limits. This constraint is represented by

$$P_{i,min} \le P_i \le P_{i,max}$$

3.2.3 Ramp rate constraints

The actual working range of all generating units is restricted by the ramp rate constraint and is provided as follows:

$$P_i - P_i^0 \le UR_i$$

$$P_i^0 - P_i \le DR_i$$

3.2.4 Prohibited operating zone

Prohibited operating zones constraint is defined by

$$P_{i,min} \le P_i \le P_1$$

$$P_{i,k-1}^U \le P_i \le P_{i,k}^L \qquad k = 2, \ldots nz$$

$$P_{i,nz}^U \le P_i \le P_{i,max}$$

4. GLOWWORM SWARM OPTIMIZATION

GSO algorithm, a fresh algorithm for swarm optimization is launched by K.N. Krishnanad and D. Ghose [34]. It mimics the motions of natural glowworms at night. The Glowworms practice in nature in a cluster, interacting and inter-attracting with each other by luciferin. If the glowworm releases lighter luciferin, more glowworms can be magnetized to move towards it. By simulating this natural phenomenon, combined with the features of natural glowworm populations, each glowworm moves to the strongest glowworm in its own field of perspective in search of the glowworm, which releases the strongest luciferin.

The GSO algorithm begins by randomly placing the glowworms in the search space so that they are well dispersed. Initially, all glowworms contain an equal amount of luciferin. Each generation consists of a luciferin-update phase, followed by a transition-based movement phase

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4.1 Luciferin update phase

The luciferin update stage relies on the function value at the glowworm position and so, although all glowworms begin with the same luciferin value during the original generation, these values shift at their present roles according to the function values. During this phase, each glowworm adds a luciferin quantity proportional to the measured value of the sensed profile (fitness) at that point to its previous luciferin level. This would be the objective function value at that stage in the event of a function optimization problem. A part of the luciferin value is also subtracted to simulate the decline in luciferin over time. The luciferin update rule is defined as,

$$l_j(t+1) = \max\left[0, (1-\rho)l_j(t) + \gamma F_j(t+1)\right] \quad (2)$$

4.2 Movement phase

During this stage, each glowworm chooses to move towards a neighbor with a luciferin value more than its own using a probabilistic mechanism. This implies they are drawn to neighbors that are growing brighter. For each glowworm i the probability of shifting towards a neighbor j is represented by,

$$P_j(t) = \frac{l_j(t)}{\sum_{k \in N_i(t)} l_k(t)} \quad (3)$$

Where , $k \in N_i(t)$

$$Ni(t) = \left(j : di, j(t) \le r_d^i(t); l_i(t) \le l_j(t)\right)$$

Let, the glowworm i select a glowworm $j \in N_i(t)$ with $p_j(t)$ is expressed in the above Eq. Then, the discrete-time model of glowworm movements can be described as

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\left\| x_j(t) - x_i(t) \right\|}\right) \quad (4)$$

Where, S = δ if $d_{ij}(t) \ge \delta$
$d_{ij}(t)$ otherwise

4.3 Local-decision range update rule

When the glowworms rely on only local data to determine their motions, the number of peaks recorded is anticipated to be a powerful function of the radial sensor range. For example, if each agent's sensor ranges cover the entire workspace, all agents move to the optimum global point, and the local optima is ignored. Since we regarded that prior data about the objective function is not accessible, in order to detect different peaks, a varying parameter must be made of the sensor range. To this end, we combine each agent i with a local decision domain whose radial range r_d^i is is dynamic in nature $0 \le r_d^i \le r_s^i$. The appropriate function is chosen to adapt the local-decision domain variety of each glowworm and is expressed by,

$$r_d^i(t+1) = \min\left[rs, \max\left[0, r_d^i(t) + \beta(n_t - |N_i(t)|\right]\right] \quad (5)$$

5. SOLUTION METHODOLOGY

To demonstrate the adequacy of the GSO, it is applied to solve the ELD problem as one of the most important and complex problems in the operation and utilization of the power system. The issue solving algorithm based on the suggested technique is as follows:

Step 1: Read the input data including the generator real powers, generator fuel cost coefficients, ramp rate limits and prohibited zone values.

Step 2: Read GSO algorithm parameters.

Step 3: Initialize initial luciferin value l_o and local decision range r_o.

Step 4: Initialize the glowworm within the limits of each variable.

Step 5: Find the fuel cost values using Eq. (1) and the luciferrin value of all glowworms using Eq. (2).

Step 6: Find the neighborhood glowworms having brighter glow and are in the local decision range.

Step 7: Find the probability of glowworm moving towards a neighbor using Eq. (3).

Step 8: Update the glowworm movement using Eq. (4) and check the limits.

Step 9: Update the local decision range of all glowworms using Eq. (5).

Step 10: Repeat the above steps 5 to 9, until maximum iterations are attained.

Step 11: Display the optimal scheduled generation values and their corresponding fuel cost values.

6. PERFORMANCE EVALUATION

To explore the efficiency of GSO-based ELD issues, numerical simulations are performed on 6 1nd 15-unit schemes and the outcomes acquired are compared with those of GA and PSO methods. The numerical assessments are conducted by EMA approach based on Matlab simulation.

The parameters used in GSO parameters are as follows:

- Luciferin decay constant = 0.97,
- Luciferin enhancement constant = 0.97,

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- Constant parameter = 0.0005;
- Neighborhood threshold (nt) = 4;
- Radial range of Luciferin sensor (rs) = 0.005; and
- Local decision domain range (rd) = 0.0005.

Table 1. System data for 6-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	P^{UR}	P^{DR}	Pi^{prev}	POZs
1	100	500	240	7.0	0.0070	80	120	440	[210,240],[350,380]
2	50	200	200	10.0	0.0095	50	90	170	[90,110],[140,160]
3	80	300	220	8.5	0.0090	65	100	200	[150,170],[210,240]
4	50	150	200	11.0	0.0090	50	90	150	[80,90],[110,120]
5	50	200	220	10.5	0.0080	50	90	190	[90,110],[140,150]
6	50	120	190	12.0	0.0075	50	90	110	[75,85],[100,105]

Table 2. Comprision of best solution for 6-unit system

Unit (MW)	GA	PSO	GSO
P_1	474.8066	447.4970	446.892
P_2	178.6363	173.3221	175.4966
P_3	262.2089	263.4745	262.4621
P_4	134.2826	139.0594	137.0965
P_5	151.9039	165.4761	164.5297
P_6	74.1812	87.1280	89.3483
P_L	13.0217	12.9584	12.5273
Minimum cost ($/hr)	15,459	15,450	15,448

Table 3. Results obtained by various methods for 6-unit system

Compared items	GA	PSO	GSO
Max. cost	15524	15492	15486
Min. cost	15,459	15,450	15,448
Mean cost	15469	15454	15450
CPU time (sec)	41.89	14.89	9.45

Table 4. System data for 15-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	P^{UR}	P^{DR}	Pi^{prev}	POZs
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185,225],[305,335],[420,450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.4	0.000205	80	120	90	[180,200],[305,335],[390,420]
6	135	460	630	10.1	0.000301	80	120	400	[230,255],[365,395],[430,455]
7	135	465	548	9.80	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	

12	20	80	230	9.90	0.005513	80	80	40	[30,40],[55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 5. Comparision of best solution for 15-unit system

Unit (MW)	GA	PSO	GSO
P_1	415.31	439.12	455
P_2	359.72	407.97	380
P_3	104.42	119.63	130
P_4	74.98	129.99	130
P_5	380.28	151.07	170
P_6	426.79	459.99	460
P_7	341.32	425.56	430
P_8	124.79	98.56	72.0672
P_9	133.14	113.49	60
P_{10}	89.26	101.11	158.487
P_{11}	60.06	33.91	80
P_{12}	50.0	79.96	80
P_{13}	38.77	25.0	25
P_{14}	41.94	41.41	15.274
P_{15}	22.64	35.61	15.0592
P_L	38.2782	32.4306	30.927
Minimum cost ($/hr)	33113	32858	32706.9

Table 6. Results obtained by various methods for 15-unit system

Compared items	GA	PSO	GSO
Max. cost	33337	33331	33217
Min. cost	33113	32858	32708
Mean cost	33228	33039	32953
CPU time (sec)	49.31	26.59	14

6.1. 6-unit system

The suggested GSO method is applied to a tiny test scheme composed of 6 generating units with a load demand of 1263 MW. For this test scheme, transmission loss, ramp rate restrictions and forbidden working areas are regarded. The system information for this test case is provided in Table 1. Table 2 shows the optimum schedule of generation and the total cost of generation obtained by approaches to GA, PSO and GSO. It is found from the Table that the proposed GSO approach provides lesser fuel cost than the other approaches. In addition, the statistical results of the minimum, maximum and mean fuel price and the calculation time acquired by different methods are contrasted. It is obvious from Table 3 that the suggested GSO approach outperforms the other approaches.

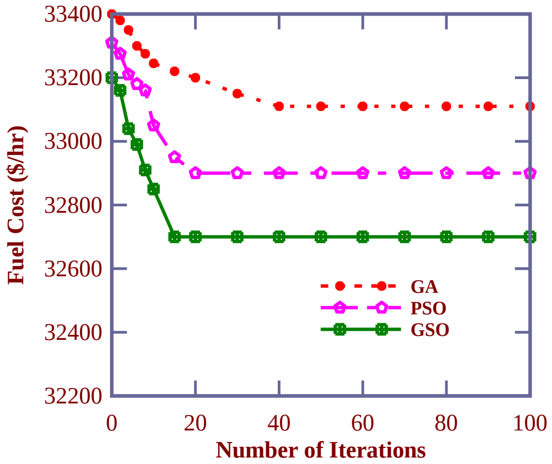

Figure 1. Convergence Characteristic of GSO for 15-unit system

6.2. 15-Unit System

The GSO is introduced on a bigger test scheme that consists of the 15 generating units. Transmission losses and forbidden area of operation are included. The system's complete load demand is regarded to be 2630 MW. Table 4 presents the generator coefficients, capacity limits, ramp rate limits and forbidden areas. In Table 5, the ideal generation plan, cost and power loss acquired by the suggested GSO method is contrasted with GA and PSO methods.

In addition, the statistical results of 50 independent trials for the 15-unit system are presented in Table 6. The comparative results clearly show that the GSO technique is proficient of offering better solution quality than the other heuristic algorithms.

The convergence behaviour of GSO is depicted in Figure 1. It is seen from Fig. that GSO converges more quickly. It is observed from Tables 3and 6 that the cost obtained from GSO is the lowest among the GA and PSO approaches.

7. CONCLUSION

This paper provided the GSO algorithm for solving the restricted ELD issue. Since GSO is a memory-free strategy and does not involve worldwide data, it is simpler to enforce for the highly restricted ELD issue. The limitations include several nonlinear features, such as ramp-rate boundaries and forbidden operating regions. Two sample schemes are used to explore the effectiveness of the GSO algorithm and the numerical outcomes acquired are contrasted with GA and PSO approaches. The suggested strategy has produced better outcomes for those generated by solutions to GA and PSO. The solutions obtained by the GSO algorithm have superior quality of solution and good characteristics of convergence. From this comparative research, it can be concluded that the GSO method can be used effectively to solve the restricted ELD issues.

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