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Grey wolf optimization applied to economic load dispatch problems

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ABSTRACT

This article presents a new evolutionary optimization approach named grey wolf optimization (GWO), which is based on the behaviour of grey wolves, for the optimal operating strategy of economic load dispatch (ELD). Nonlinear characteristics of generators like ramp rate limits, valve point discontinuities and prohibited operating zones are considered in the problem. GWO method does not require any information about the gradient of the objective function, while searching for an optimum solution. The GWO algorithm concept, appears to be a robust and reliable optimization algorithm is applied to the nonlinear ELD problems. The proposed algorithm is implemented and tested on four test systems having 10, 40, 80 and 140 units. The results confirm the potential and effectiveness of the proposed algorithm compared to various other methods available in the literature. The outcome is very encouraging and proves that the GWO is a very effective optimization technique for solving various ELD problems.

Introduction

Nowadays, the electrical power market becomes highly competitive and more liberal for increasing energy demand. Economic load dispatch (ELD) is one of the useful tools in the modern energy management system of operation and planning. ELD plays a vital role in maintaining the economy of the power system. Reduction of the production cost and growth in the system reliability maximize the energy capability of thermal units through a good load dispatch. The main goal of ELD process is to schedule the power system control variables for sharing the total load to achieve highest economy of operation while satisfying all equality and inequality constraints. To achieve optimal solution of a practical ELD problem, the realistic operation of the ELD problem should consider valve point effects, ramp rate and multiple fuels. Several derivative based approaches such as the classical optimization methods based on Lagrangian relaxation [1], quadratic programming (QP) [2], branch and bound method [3], lambda iteration method (LIM) [4], gradient method [5], linear programming (LP) [6], co-ordination equation [7], dynamic programming (DP) [8] assuming monotonically increasing piecewise linear cost function, have successfully been applied to solve ELD. However, the classical optimization techniques are highly sensitive to staring points and often converge to local optimum or diverge altogether. Solutions of ELD problem applying DP may cause the dimensions extremely large, which requires enormous computational efforts. Due to the presence of nonlinear characteristics such as ramp rate limits, discontinuous prohibited operating zones and non-smooth cost functions of practical ELD problem, these methods are infeasible in practical systems and are unable to locate the global optima solution. To solve non smooth and non convex ELD problem, Yang et al. [9] presented an analytical method named quadratically constrained programming (QCP). Due to a large number of constraints and highly nonlinear characteristics of the ELD problem, the classical calculus based methods cannot perform satisfactorily and are trapped to local optimum. Hence, it becomes essential to overcome these drawbacks and handle such difficulties through developing a robust, improved and reliable technique. In the recent years, complex constrained optimization problems are solved by many artificial intelligent methods such as Hopfield neural network (HNN) [10,11] and adaptive HNN [12]. These techniques have successfully been applied in recent years to solve non-convex, non-smooth and non-differentiable ELD problems. However, due to excessive numerical iterations of these methods, more reliable and fast methods are needed.

With the development of computer technology, the population based modern intelligent heuristic and stochastic optimization methods such as evolutionary programming (EP) [13], hybrid evolutionary programming (HEP) [14], differential evolution (DE) [15], genetic algorithm (GA) [16], adaptive real coded GA (ARCGA) [17],

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Nomenclature

F_t	total fuel cost
Pg_i	power generation of the ith generating unit
$F_i(Pg_i)$	fuel cost function for power generation of the ith unit
n	number of generating units in the thermal power plant
P	population size
I	number of iterations
lb	lower boundary of search area
ub	upper boundary of search area
a_i, b_i, c_i, e_i, f_i	fuel cost coefficients of the ith generating unit
$a_{ik}, b_{ik}, c_{ik}, e_{ik}, f_{ik}$	the Kth type of fuel cost coefficients of the ith generating unit
$Pg_i^{\min}$	minimum amount of power generation of the ith unit
$Pg_i^{\max}$	maximum amount of power generation the ith unit
P_D	the total load demand
B_{ij}, B_{i0}, B_{00}	loss coefficients of the line connected between the ith and the jth bus
P_L	the transmission network losses
URR_i, DRR_i	up rate and down rate limit of the ith generating unit
ni	the number of prohibited zones of the ith generating unit
Pg_{i0}	previous operating zone of the ith generating unit
n_p	population size

hybrid GA (HGA)[18], particle swarm optimization (PSO) [19], anti predatory PSO (APSO) [20], civilized swarm optimization (CSO) [21], modified PSO (MPSO) [22], craziness based PSO (CRPSO) [23], hybrid PSO (HPSO) [24], ant colony optimization (ACO) [25,26], bacteria foraging optimization (BFO) [27], modified BFO (MBFO) [28], artificial bee colony (ABC) [29], seeker optimization algorithm (SOA) [30], chaotic ant swarm optimization (CASO) [31], tabu search (TS) [32], harmony search algorithm (HSA) [33], biogeography based optimization (BBO) [34,35], oppositional BBO (OBBO) [36], and quasi oppositional BBO (QOBBO) [37] algorithms, have been proposed for solving ELD problems. In the year of 2009, the gravitational search algorithm (GSA), a heuristic algorithm based on the Newtonian laws of gravity and motion, was developed by Rashedi et al. [38]. Affijulla et al. solved ELD problems by implementing GSA [39]. Roy et al. implemented GSA [40] to solve unit commitment problem for superior features including stable convergence characteristic and avoids premature convergence. A teaching learning based optimization (TLBO) was introduced to solve combined heat and power dispatch problem [41]. Very recently, quasi oppositional TLBO (QOTLBO) [42] technique which employed opposition based learning for TLBO initialization and generation jumping was proposed by Roy et al. An opposition based harmony search algorithm (OHSA) was introduced by Chatterjee et al. [43], where opposite numbers were utilized to improve the convergence rate of harmony search algorithm (HSA). Krill herd algorithm (KHA), first proposed by Gandomi and Alavi [44], was successfully applied to solve ELD problems [45]. Dutta et al. in their recent endeavour proposed hybrid chemical reaction optimization (HCRO) algorithm to explore the entire search space for solutions [46].

Recently, Barisal and Prusty [47] proposed invasive weed optimization (IWO) to solve ELD problem of large scale power system. Oppositional real coded chemical reaction optimization approach [48] has been extensively used in electrical power systems due to their ability to mould nonlinearity and uncertainty in practical problems. Shanhe et al. [49] in their recent endeavour implemented hybrid PSO/GSA approach to solve non-linearity based ELD problem. A new efficient optimization technique was proposed by Chen et al. [50] to solve wind based ELD problem of a multi-area power system. Bulbul et al. [51] introduced oppositional KHA approach to successfully solve ELD problem of small, medium and large scale power systems.

However, some of these heuristic methods may have poor performance on different set of problems. Some algorithms perform local exploitation at the mature stage of the search and global exploratory search at the early stages of the evolutionary process. Few of the aforementioned methods have excellent global search capabilities but, they have some limitations in their local search ability. Some of the techniques discussed above face premature convergence. To overcome premature convergence and speed up the search process a more powerful method is needed.

In this research work, a newly developed meta heuristic algorithm, named grey wolf optimization (GWO) [52], which does not have any affinity to stick in local optimum points in the complex multimodal optimization problem and which provides a more diverse search of the solution space is proposed to solve complex ELD problems. The GWO is based on behaviour of grey wolf [53]. The better optimum solutions with lower computation burden can be found in GWO compared to the existing stochastic search techniques mentioned above. The GWO is superior to these methods because (i) The GWO has better conveying mechanism and information sharing capability; (ii) it uses random function and considers three candidate solutions for getting better results and converges quickly by making jump from local minima towards global minima.

To justify the effectiveness of the proposed method, the proposed GWO approach is applied to solve different test systems with valve point effects, ramp rate limits, prohibited operating regions, multiple fuels, etc. The performance of the solution results are compared with those of the existing methods available in the literature.

The rest of the paper is organized as follows: ELD problem is formulated in Section 'Problem formulation'. In Section 'Grey wolf optimization algorithm', the original GWO algorithm is briefly described. GWO applied to ELD problem is explained in Section 'Gray wolf optimization applied to ELD'. The system simulation and results are provided in Section 'Case studies and numerical results'. Section 'Conclusion' outlines the, conclusions followed by reference.

Problem formulation

The ELD is one of the important optimization strategies for management of the power system. The following objective and constraints are taken into account in the formulation of ELD problem.

Objective function

The objective of ELD is to minimize the total fuel cost while satisfying all equality and inequality constraints. The various cost functions used in ELD problem are as follows.

Quadratic cost function

The optimization of the ELD problem is formulated mainly in terms of the fuel cost function expressed as the sum of a quadratic function. This function is written as:

$$\sum_{i=1}^{n} F_i(Pg_i) = \sum_{i=1}^{n} \left[a_i(Pg_i)^2 + b_i(Pg_i) + c_i\right] \quad i = 1, 2, \ldots, n \tag{1}$$

Cost function with valve point effect

A rippling effect is produced for the steam admission through the valve in turbine, so it is more practical for considering the valve point effect with the fuel cost function to incorporate flexible operational facilities. The fuel cost in terms of real power output, may be expressed as the sum of a quadratic and a sinusoidal function in the following form:

$$\begin{aligned} F_t &= \sum_{i=1}^{n} F_i(Pg_i) \\ &= \sum_{i=1}^{n} \left[a_i(Pg_i)^2 + b_i(Pg_i) + c_i + e_i \times \left|\sin\left(f_i \times \left(Pg_i^{\min} - Pg_i\right)\right)\right|\right] \end{aligned} \tag{2}$$

Multiple fuel cost functions

Moreover, thermal generating units may supply multiple types of fuel from different fuel sources. Each dispatching unit operates on multiple fuel sources depending upon the load and suitability of power generation. The objective is to find a suitable fuel for each generating unit in order to minimize the total fuel cost while satisfying different constraints including power balance and generation limits. Both multiple fuel options and valve point effects should be considered to obtain a realistic and more accurate ELD solution that is mathematically represented in (3) is given below.

$$F_i(Pg_i) = \begin{cases} a_{i1}(Pg_i)^2 + b_{i1}(Pg_i) + c_{i1} + \left|e_{i1} \times \sin\left(f_{i1} \times \left(Pg_i^{\min} - Pg_i\right)\right)\right| & \text{if } Pg_i^{\min} \leqslant Pg_i \leqslant Pg_{i1} \\ a_{ik}(Pg_i)^2 + b_{i2}(Pg_i) + c_{i2} + |e_{i2} \times \sin(f_{i2} \times (Pg_{i2} - Pg_i))| & \text{if } Pg_{i1} \leqslant Pg_i \leqslant Pg_{i2} \\ a_{ik}(Pg_i)^2 + b_{ik}(Pg_i) + c_{ik} + |e_{ik} \times \sin(f_{ik} \times (Pg_{ik} - Pg_i))| & \text{if } Pg_{ik} \leqslant Pg_i \leqslant Pg_i^{\max} \end{cases} \tag{3}$$

Constraints

Generation capacity constraints

The active power generation of each thermal power unit must be less than or equal to the maximum power permitted and also be greater than or equal to the minimum power permitted on that specified unit and it may mathematically be expressed as:

$$Pg_i^{\min} \leqslant Pg_i \leqslant Pg_i^{\max} \tag{4}$$

Power balance constraints

The total power generation by the thermal units must be equal to the total power demanded by the load and the total transmission loss. Thus, the equality constraint may be mathematically formulated as:

$$\sum_{i=1}^{n} Pg_i = P_D + P_L \tag{5}$$

The transmission loss of the system is calculated using power flow coefficients by the Kron's loss formula or the B coefficient formula:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} Pg_i B_{ij} Pg_j + \sum_{i=1}^{n} B_{i0} Pg_i + B_{00} \tag{6}$$

Prohibited operating zone

The generating units might have prohibited operating zone(s) in the input–output curve of generator due to presence of physical operation such as vibration in its shift bearing, some faults in the generating units or their accessories, like boiler and feed pumps. Each generating unit must avoid operation in those prohibited zones. In practical operation, the feasible operating zone of the ith unit can be expressed as follows:

$$\begin{cases} Pg_i^{\min} \leqslant Pg_i \leqslant Pg_{i,1} \\ Pg_{i,j-1} \leqslant Pg_i \leqslant Pg_{i,j} \quad j = 2, 3, \ldots ni - 1 \\ Pg_{i,ni} \leqslant Pg_i \leqslant Pg_i^{\max} \end{cases} \tag{7}$$

Ramp rate constraints

For successful operation, the operating range of each generating unit is restricted by its ramp rate limits by imposing the units to operate repeatedly between two adjacent specific operation zones. The power output Pg_i, by the ith generator in certain interval may not exceed that of previous interval Pg_{i0} by more than a certain amount URR_i, the up ramp rate limit and neither may it be less than that of the previous interval by more than the amount DRR_i, the down ramp rate limit of the ith generator. This constraint may mathematically be expressed as follows:

$$\max\left(Pg_i^{\min}, Pg_{i0} - DRR_i\right) \leqslant Pg_i \leqslant \min\left(Pg_i^{\max}, Pg_{i0} - URR_i\right) \tag{8}$$

Grey wolf optimization algorithm

Grey wolf optimization (GWO) is a new population based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [52]. The method imitates the hunting behaviour and social hierarchy of grey wolves. The leadership hierarchy in GWO algorithm [52,53] is defined as alpha, beta, delta and omega. The problem is to define the cost efficient level of habitat protection that satisfies a feasibility constraint for a sensitive wildlife population. The viability constraint requires a high probability of attaining a population size target. The alpha, beta, and delta estimate the victim position and update their positions randomly around the victim. The final position would be in a position within a circle which is defined by the positions of alpha, beta, and delta in the search space.

On the basis of behaviour of grey wolves, GWO is implemented where a specific number of grey wolves in a pack moves through a multi dimensional search space to look for prey. In this optimization algorithm, the positions of grey wolves are considered as different position variables and the distances of the prey from the grey wolves determine the fitness value of the objective function. In GWO, the individual grey wolf adjusts its position and moves to the better position. The GWO saves the best solutions obtained through the course of iterations. The goal of this algorithm is to reach to the prey by the shortest possible route. The movement of each individual is influenced by four processes, namely

(i) Searching for prey (exploration)
(ii) Encircling prey
(iii) Hunting
(iv) Attacking prey (exploitation)

These operators are briefly explained and mathematically expressed in the following subsection.

Searching for prey (exploration)

The grey wolves diverge from each other position for searching a victim. Make use of $\vec{AM}$ with random values to compel the search agent to diverge from the victim. The component $\vec{CM}$ provides random weights for searching prey in the search space. Hence exploration through $\vec{AM}$ and $\vec{CM}$ permits this algorithm to globally search the area. $\vec{CM}$ vector also presents the effect of obstacles to impending the prey.

Encircling prey

The alpha, beta and delta estimate the position of the three best wolves and other wolves updates their positions using the positions of these three best wolves. Encircling behaviour can be represented by $\vec{DM}$. The expected boundary is mathematically represented by the following equations:

$$\vec{DM} = \left|\vec{CM} \cdot X\vec{P}(t) - \vec{X}(t)\right| \tag{9}$$

$$\vec{X}(t+1) = X\vec{P}(t) - \vec{AM} \cdot \vec{DM} \tag{10}$$

Here t indicates the current iteration, $\vec{AM}$ and $\vec{CM}$ are coefficient vectors, $X\vec{P}(t)$ is the position vector of prey, $\vec{X}(t)$ represents the position vector of a grey wolf. $r\vec{1}$ and $r\vec{2}$ are random vectors in $[0,1]$. $\vec{a}$ is linearly decreased from 2 to 0.

$$\vec{AM} = 2 \times \vec{a} \times r\vec{1} - \vec{a} \tag{11}$$

$$\vec{CM} = 2 \times r\vec{2} \tag{12}$$

Hunting

Conservation of regional habitat connectivity has the potential to facilitate recovery of the grey wolf. After encircling, alpha wolf guides for hunting. Later, the delta and beta wolves join in hunting. It is tough to predict about the optimum location of prey. The hunting behaviour of grey wolf, based on the position of alpha, beta, gamma (candidate solution) wolf can be represented by

$$\overrightarrow{DM_\alpha} = \left|\vec{CM}_\alpha \cdot X\vec{P}_\alpha(t) + \vec{X}\right| \tag{13}$$

$$\overrightarrow{DM_\beta} = \left|\vec{CM}_\beta \cdot X\vec{P}_\beta(t) + \vec{X}\right| \tag{14}$$

$$\overrightarrow{DM_\partial} = \left|\vec{CM}_\partial \cdot X\vec{P}_\partial(t) + \vec{X}\right| \tag{15}$$

Finally, the position of various category of wolves are modified as follows:

$$\vec{X}_{\alpha 1} = \vec{X}_\alpha - \vec{AM}1 \cdot \overrightarrow{DM_\alpha} \tag{16}$$

$$\vec{X}_{\beta 1} = \vec{X}_\beta - \vec{AM}2 \cdot \overrightarrow{DM_\beta} \tag{17}$$

$$\vec{X}_{\partial 1} = \vec{X}_\partial - \vec{AM}3 \cdot \overrightarrow{DM_\partial} \tag{18}$$

$$\overrightarrow{X(t+1)} = \frac{\vec{X}_{\alpha 1} + \vec{X}_{\beta 1} + \vec{X}_{\delta 1}}{3} \tag{19}$$

Attacking prey (exploitation)

The grey wolves stop the hunting by attacking the prey when it stop moving. It depends on the value of $\vec{a}$. $\vec{AM}$ is a random value in the interval $[-2a, 2a]$. In GWO, search agents update their positions based on the location of alpha, beta, delta wolves mentioned in hunting phase and attack towards the prey.

The GWO algorithm can be summarized as follows:

Step 1: Number of grey wolves or search agents is considered as population size.
Step 2: Initialize the position vectors of search agents for searching and encircling the prey in upper and lower boundary area of grey wolves. Maximum number of iterations is also initialized.
Step 3: Evaluate the fitness values of individual solution. Each fitness value represents the distance of the prey from the individual wolf. Based on the fitness value, three best wolves are identified as α, β and δ categories of wolves. To achieve the prey, the hunting behaviour of various categories of grey wolf are modified using (13)–(15).
Step 4: Update the position of search agents using (16)–(20).
Step 5: Repeat steps 3–4 until they reach to the prey.
Step 6: The termination is done when a specified number of iterations are met.

Grey wolf optimization applied to ELD

The different steps of GWO algorithm for solving ELD problems are described below.

Step 1: Active power generation of all the generating units except the last unit is initialized randomly within their lower and upper real power operating limits, i.e., each component must satisfy generator capacity constraints. The quantity of active power generation of the last unit is evaluated using (5) and tested whether it gratifies the inequality constraint or not. The infeasible solutions are reinitialized. Numerous initial solution sets are generated depending upon the population size. The position of different search agents (grey wolves) are represented through reasonable solution set (control variables). Depending upon the initial search agents (grey wolves) position matrix is created as given below:

$$P = \begin{bmatrix} P_{g_1}^1, & P_{g2}^1 & ,\ldots, & P_{gi}^1 & \ldots, & P_{gn}^1 \\ P_{g_1}^2, & P_{g2}^2 & ,\ldots, & P_{gi}^2 & \ldots, & P_{gn}^2 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ P_{g_1}^i, & P_{g2}^i & ,\ldots, & P_{gi}^i & \ldots, & P_{gn}^i \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ P_{g1}^{n_p}, & P_{g2}^{n_p} & ,\ldots, & P_{gi}^{n_p} & \ldots, & P_{gn}^{n_p} \end{bmatrix} \tag{20}$$

Step 2: Evaluate fitness of each solution of current population using (1)–(3). Each fitness value represents the distance of the individual wolf from the prey.
Step 3: Sort the population from best to worst. The best, second best and third best solutions respectively, represent the positions of α, β and δ categories of wolves.

Table 1
GWO solution of ELD for test system 1 (10 unit with multiple fuels, valve point and without loss).

Generator number	$Pg_i^{\min}$ (MW)	$Pg_i^{\max}$ (MW)	Generation (MW)	Fuel type
1	100	250	213.4586	2
2	50	230	209.7310	1
3	200	500	332.0088	2
4	99	265	238.0269	3
5	190	490	269.1404	1
6	85	265	238.1609	3
7	200	500	280.6101	1
8	99	265	237.8926	3
9	130	440	414.5851	3
10	200	490	266.3856	1
Total fuel cost ($/h)			605.6263	

Step 4: Modify the position of each search agents using the searching prey, encircling prey, hunting and attacking prey concepts. The position of each search agent represents a potential solution comprised of active power generation of ELD problem.
Step 5: Check whether the operating limits of the active power of all generating units except last unit are violated or not. If any power generation is less than the minimum level, it is made equal to minimum value. Similarly, if it is greater than the maximum level, it is assigned its maximum value. Subsequently, last unit of the power generation is evaluated using (5) and whether it satisfies all the inequality constraints or not is checked. The infeasible solutions are exchanged by the best feasible solutions.
Step 6: Go to Step 2 until termination criteria is met. The GWO is stopped executing when the maximum number of iterations (generations) is reached or there is no noteworthy improvement in the solution. In this paper, the ending criterion is the maximum number of iterations for which most of the grey wolves or search agents are idle.

Case studies and numerical results

In this article, to evaluate the effectiveness of the recently developed GWO algorithm, it is implemented to solve various nonlinear, complex ELD problems considering multiple fuels, transmission losses, prohibited operating zones and ramp rate limits. MATLAB 7.1 Software is used to simulate ELD problems and tested on 2 GHz Pentium IV, 1 GB RAM personal computer. The population size and the maximum iteration number are taken as 50 and 100 respectively for the test systems under consideration.

The four sets of experiments are conducted and the simulation results of the proposed method are compared with various existing methods.

Test Case 1: Initially, 10-unit system with multiple fuels and valve point loading effect is considered.
Test Case 2: Secondly, 40-unit system with transmission losses including valve point loading effect is considered.
Test Case 3: Thirdly, 80-unit system with nonlinearities of valve point loading effect and prohibited operating zones is considered.
Test Case 4: Finally, prohibited operating zones and ramp rate limits including valve point loading effect in the 140-unit ELD problem are considered.

Test Case 1

A 10-unit system with multiple fuel is considered as test system 1 but transmission loss is not considered in power balance

Table 2
Statistical comparison on non-smooth 10 unit-generator suit with multiple fuels (P_D = 2700).

Algorithms	Mean cost ($/h)	Best cost ($/h)	Worst cost ($/h)	Standard deviation	Average simulation time (s)
FAPSO [55]	624.2782	624.2189	624.2951	NA	NA
NAPSO [55]	623.6335	623.62170	627.4237	NA	NA
PSO-LRS [17]	625.7887	624.2297	628.3214	NA	88
IGA-MU [17]	627.6087	624.5178	630.8705	NA	7.25
NPSO-LRS [17]	624.9985	624.1273	626.9981	NA	52
NPSO [17]	625.2180	624.1624	623.67543	NA	35
PSO [54]	624.5054	624.3045	625.9252	NA	39
GA [54]	624.7419	624.5050	624.8169	NA	NA
TSA [54]	635.0623	624.3078	624.8285	NA	NA
ARCGA [17]	623.8431	623.8281	623.8550	NA	NA
KHA [45]	605.8043	605.7582	605.9426	NA	NA
GWO	605.6818	605.6263	605.7937	1.02	2.36

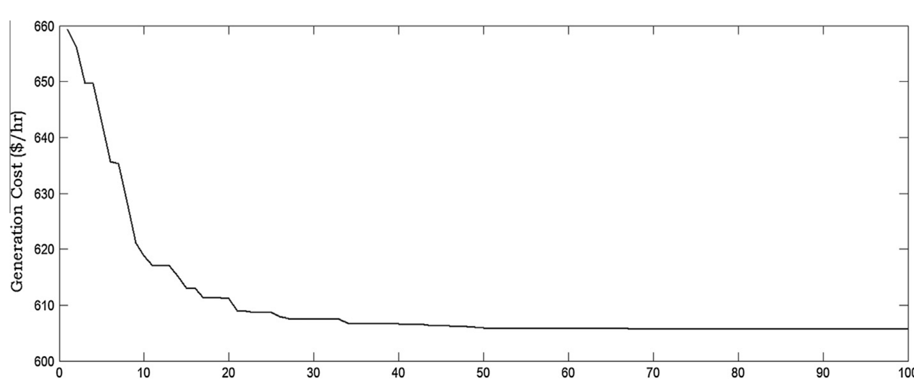

Fig. 1. Convergence characteristic of generation cost using GWO for 10-unit system.

Table 3
Best solution for test system-2 with a demand of 10,500 MW (40-unit with loss and valve point loading effects).

Unit no.	Generation (MW)					
	GA-API [57]	SDE [56]	TLBO [42]	QOTLBO [42]	KHA [45]	GWO
1	114	110.06	114	114.0000	114.0000	114.0000
2	114	112.41	114	114.0000	114.0000	114.0000
3	120	120.00	120	107.8221	120.0000	120.0000
4	190	188.72	182.4448	190.0000	190.0000	181.0490
5	97	85.91	90.6923	88.3702	88.5944	87.8351
6	140	140.00	140	140.0000	105.5166	140.0000
7	300	250.19	300	300.0000	300.0000	300.0000
8	300	290.68	296.0682	300.0000	300.0000	300.0000
9	300	300.00	288.8518	300.0000	300.0000	300.0000
10	205.25	282.01	281.9520	211.2071	280.6777	279.9786
11	226.30	180.82	238.1293	317.2766	243.5399	243.6274
12	204.72	168.74	251.0120	163.7603	168.8017	94.1436
13	346.48	469.96	483.1175	481.5709	484.1198	484.4562
14	434.32	484.17	481.9042	480.5462	484.1662	484.2306
15	431.34	487.73	488.2883	483.7683	485.2375	484.2463
16	440.22	482.30	396.3448	480.2998	485.0698	484.0333
17	500	499.64	494.2577	489.2488	489.4539	489.6295
18	500	411.32	408.3826	489.5524	489.3035	489.3228
19	550	510.47	510.5206	512.5482	510.7127	511.4616
20	550	542.04	521.2217	514.2914	511.3040	511.4932
21	550	544.81	540.5700	527.0877	524.4678	523.4767
22	550	550.00	522.1852	530.1025	535.5799	547.6868
23	550	550.00	526.1804	524.2912	523.3795	523.3738
24	550	528.16	521.1967	524.6512	523.15527	523.1350
25	550	524.16	525.8010	525.0586	524.1916	523.3472
26	550	539.10	526.0022	524.4654	523.5453	523.3578
27	11.44	10.00	13.0804	10.8929	10.1245	10.0678
28	11.56	10.37	11.0397	17.4312	10.1815	10.6337
29	11.42	10.00	12.9373	12.7839	10.0229	10.5181
30	97	96.10	89.7412	88.8119	87.8154	87.8029
31	190	185.85	190.0000	190.0000	190.0000	190.0000
32	190	189.54	190.0000	190.0000	190.0000	190.0000
33	190	189.96	190.0000	190.0000	190.0000	190.0000
34	200	199.90	200.0000	200.0000	200.0000	200.0000
35	200	196.25	200.0000	168.0873	164.9199	200.0000
36	200	185.85	164.7435	165.5072	164.9787	164.8334
37	110	109.72	110.0000	110.0000	110.0000	110.0000
38	110	110.00	110.0000	110.0000	110.0000	110.0000
39	110	95.71	110.0000	110.0000	110.0000	110.0000
40	550	532.47	547.9677	511.5313	512.06775	511.5471
TC ($/h)	139864.96	138157.46	137814.17	137329.86	136670.37	136446.85
TL (MW)	1045.06	974.43	1002.63	1008.96	978.9251	973.2875

Table 4
Comparison of statistical results of various methods for test system-2 (40-unit with loss and valve-point loading effects).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)	Standard deviation	Average simulation time (s)
GA-API [57]	139864.96	NA	NA	NA	NA
SDE [56]	138157.46	NA	NA	NA	NA
TLBO [42]	137814.17	NA	NA	NA	4.83
QOTLBO [42]	137329.86	NA	NA	NA	4.58
KHA [45]	136670.37	136671.24	136671.86	NA	NA
GWO	136446.85	136463.96	136492.07	0.098	4.27

constraint. The coefficients of fuel cost functions we have considered are provided in [24]. In this test system, the load demand is taken as 2700 MW. Table 1 shows the optimal generation scheduling, fuel type and fuel cost achieved by GWO for Test Case 1. The superiority of the proposed method is evident from its ability to satisfy all constraints and produce feasible results.

As GWO technique is stochastic simulation method so randomness in the simulation result is comprehensible. ELD is a real time problem, thus it is desirable that each run of the program should reach close to optimum solution. Fifty independent trials are executed to observe changes in the solutions. Since the GWO always accepts the better results, it is expected that the solution should always improve and this may lead to robust result of this problem. To verify the robustness of the proposed GWO method, the statistical results of the best, mean and worst cost obtained by GWO over the 50 trial runs are compared with the results of PSO [54], GA [54], TSA [54], PSO-LRS [17], IGA-MU [17], NPSO-LRS [17], NPSO [17], ARCGA [17], FAPSO [55], NAPSO [55] and KHA [45]. The comparative statistical results are summarized in Table 2. The statistical results show that the best, worst and mean cost produced by GWO is least compared with other methods emphasizing its better solution quality. Moreover, it is observed from Table 2 that average simulation time of the proposed GWO approach is significantly less than that of other algorithms discussed in this manuscript. Hence,

Table 5
Best solution for test system-3 with a demand of 21,000 MW (80-unit without loss).

Unit no	Generation (MW)	Unit no	Generation (MW)	Unit no	Generation (MW)	Unit no	Generation (MW)
1	110.8188	21	523.2794	41	110.7998	61	523.2794
2	110.7994	22	523.2794	42	110.7998	62	523.2794
3	97.3859	23	523.2794	43	97.3996	63	523.2793
4	179.7327	24	523.2794	44	179.7331	64	523.2793
5	87.7998	25	523.2792	45	87.7999	65	523.2793
6	140.0000	26	523.2797	46	140.0000	66	523.2793
7	259.5978	27	10.0000	47	259.5995	67	10.0000
8	284.6013	28	10.0000	48	284.5992	68	10.0000
9	284.5978	29	10.0000	49	284.6003	69	10.0000
10	130.0000	30	87.8006	50	130.0000	70	87.7998
11	94.0000	31	190.0000	51	94.0000	71	190.0000
12	94.0000	32	190.0000	52	94.0000	72	190.0000
13	214.7612	33	190.0000	53	214.7598	73	190.0000
14	394.2778	34	164.7999	54	394.2790	74	164.7998
15	394.2808	35	194.3976	55	394.2794	75	194.3954
16	394.2775	36	200.0000	56	394.2794	76	200.0000
17	489.2801	37	110.0000	57	489.2795	77	110.0000
18	489.2792	38	110.0000	58	489.2801	78	110.0000
19	511.2794	39	110.0000	59	511.2788	79	110.0000
20	511.2794	40	511.2793	60	511.2798	80	511.2792
TC ($/h)						242825.4799	

Table 6
Comparison of statistical results of various methods for test system-3 (80-unit without loss).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)	Standard deviation	Average simulation time (s)
NPSO [55]	242844.1172	NA	NA	NA	NA
FAPSO [55]	244273.5429	NA	NA	NA	NA
PSO [55]	249248.3751	NA	NA	NA	NA
GWO	242825.4799	242829.8192	242837.1303	0.093	5.27

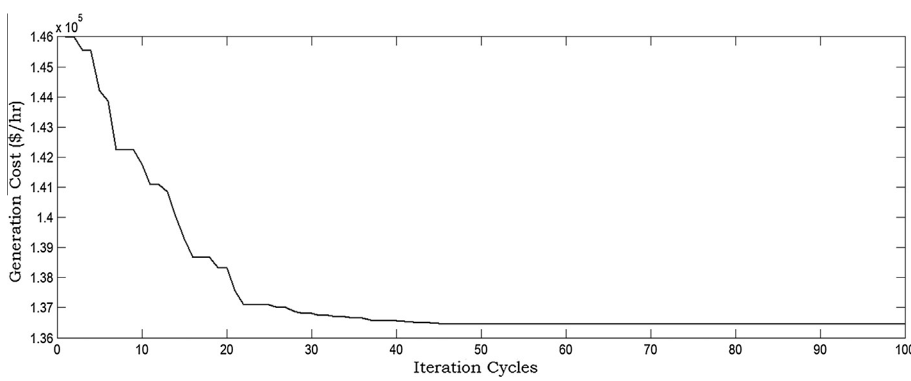

Fig. 2. Convergence characteristic of generation cost using GWO for 40-unit system.

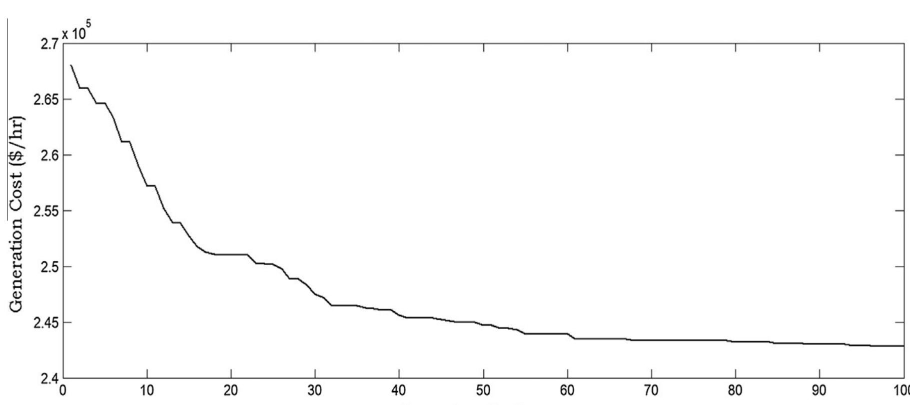

Fig. 3. Convergence characteristic of generation cost using GWO for 80-unit system.

Table 7
Best solution for test system-4 with a demand of 49,342 MW (140-unit without loss).

Unit no	Generation (MW)		Unit no	Generation (MW)		Unit no	Generation (MW)	
	SDE [56]	GWO		SDE [56]	GWO		SDE [56]	GWO
1	116.1654	119.0000	48	250.0000	250.0000	95	978.0000	978.0000
2	189.0000	189.0000	49	250.0000	250.0000	96	682.0000	682.0000
3	190.0000	190.0000	50	250.0000	250.0000	97	720.0000	720.0000
4	190.0000	190.0000	51	165.0000	165.0000	98	718.0000	718.0000
5	168.5398	168.5397	52	165.0000	165.0000	99	720.0000	720.0000
6	190.0000	190.0000	53	165.0000	165.0000	100	964.0000	964.0000
7	490.0000	490.0000	54	165.0000	165.0000	101	958.0000	958.0000
8	490.0000	490.0000	55	180.0000	180.0000	102	1007.0000	1007.0000
9	496.0000	496.0000	56	180.0000	180.0000	103	1006.0000	1006.0000
10	496.0000	496.0000	57	103.0000	103.0000	104	1013.0000	1013.0000
11	496.0000	496.0000	58	198.0000	198.0000	105	1020.0000	1020.0000
12	496.0000	496.0000	59	312.0000	312.0000	106	954.0000	954.0000
13	506.0000	506.0000	60	281.8008	282.8903	107	952.0000	952.0000
14	509.0000	509.0000	61	163.0000	163.0000	108	1006.0000	1006.0000
15	506.0000	506.0000	62	95.0000	95.0000	109	1013.0000	1013.0000
16	505.0000	505.0000	63	160.0001	160.8840	110	1021.0000	1021.0000
17	506.0000	506.0000	64	160.0000	160.0000	111	1015.0000	1015.0000
18	506.0000	506.0000	65	490.0000	490.0000	112	94.0000	94.0000
19	505.0000	505.0000	66	196.0001	196.2621	113	94.0000	94.0000
20	505.0000	505.0000	67	490.0000	490.0000	114	94.0000	94.0000
21	505.0000	505.0000	68	489.9999	489.6013	115	244.0000	244.0000
22	505.0000	505.0000	69	130.0000	130.0000	116	244.0000	244.0000
23	505.0000	505.0000	70	234.7198	234.7006	117	244.0000	244.0000
24	505.0000	505.0000	71	137.0000	137.0000	118	95.0000	95.0000
25	537.0000	537.0000	72	325.4956	325.8216	119	95.0000	95.0000
26	537.0000	537.0000	73	195.0000	195.0000	120	116.0000	116.0000
27	549.0000	549.0000	74	175.0000	175.3892	121	175.0000	175.0000
28	549.0000	549.0000	75	175.0000	175.0000	122	2.0000	2.0000
29	501.0000	501.0000	76	175.0001	175.9936	123	4.0000	4.0000
30	501.0000	501.0000	77	175.0000	175.4087	124	15.0000	15.0000
31	506.0000	506.0000	78	330.0000	330.0000	125	9.0000	9.0000
32	506.0000	506.0000	79	531.0000	531.0000	126	12.0000	12.0000
33	506.0000	506.0000	80	531.0000	531.0000	127	10.0000	10.0000
34	506.0000	506.0000	81	368.6177	366.4013	128	112.0000	112.0000
35	500.0000	500.0000	82	56.0000	56.0000	129	4.0000	4.0000
36	500.0000	500.0000	83	115.0000	115.0000	130	5.0000	5.0000
37	241.0000	241.0000	84	115.0000	115.0000	131	5.0000	5.0000
38	241.0000	241.0000	85	115.0000	115.0000	132	50.0000	50.0000
39	774.0000	774.0000	86	207.0000	207.0000	133	5.5666	5.0000
40	769.0000	769.0000	87	207.0000	207.0000	134	43.3363	42.0000
41	3.0000	3.0000	88	175.0000	175.0000	135	43.1223	42.0000
42	3.0000	3.0000	89	175.0000	175.0000	136	41.0000	41.0000
43	249.9989	250.0000	90	175.0000	175.0000	137	17.0000	17.0000
44	247.1855	249.9988	91	175.0000	175.0000	138	12.7652	17.0000
45	250	250.0000	92	580.0000	580.0000	139	8.1120	7.0000
46	250	250.0000	93	645.0000	645.0000	140	27.1470	26.1302
47	242.2959	249.9785	94	984.0000	984.0000	TC($/h)	1560146.95	1559953.18

Table 8
Comparison of statistical results of various methods for test system-4 (140-unit without loss).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)	Standard deviation	Average simulation time (s)
SDE [56]	1560236.85	NA	NA	NA	NA
GWO	1559953.18	1560132.93	1560228.40	1.024	8.93

it may be concluded that the GWO method is computationally more efficient than the other methods. Convergence characteristic of the GWO for this test system is presented in Fig. 1.

Test Case 2

To verify the validity of the method for medium size ELD problem, a slightly complicated power system with forty thermal power units is considered. The transmission loss is taken into consideration for this test system. The total load demand is considered as 10,500 MW. To validate the proposed GWO based approach, its simulation results for this test system is compared with the results of SDE [56], GA-API [57], TLBO [42], QOTLBO [42] and KHA [45]. The best solutions, optimal generation scheduling and comparison with other optimization methods in the literature are summarized in Table 3. It can be observed from Table 3 that the proposed technique provides significantly better results in comparison with the previously developed techniques. Hence, it may be concluded that the GWO optimization is computationally more well organized than the other methods in terms of quality of solution.

Moreover, the results of the proposed GWO method are compared in terms of minimum cost, mean cost and maximum cost over 50 runs with the results of GA-API [57], SDE [56], TLBO [42], QOTLBO [42] and KHA [45]. The statistical results of the aforementioned methods, presented in Table 4, are directly quoted from their respective references. It can be observed that the solution

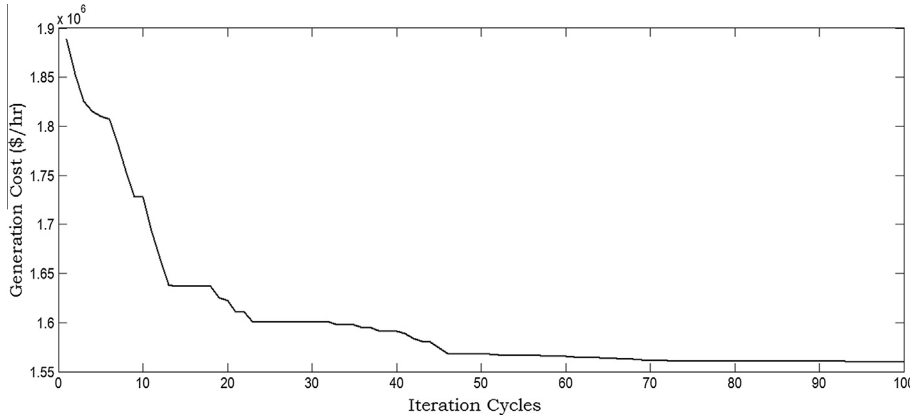

Fig. 4. Convergence characteristic of generation cost using GWO for 140-unit system.

obtained from the proposed method is better than other techniques reported in the literature. Convergence characteristic of the GWO approach for 40-generator test case is depicted in Fig. 2.

Test Case 3

In order to validate the feasibility of the proposed GWO method for the EED problems, it is employed on a relatively large system consisting of 80 generating units. The load demand used in the simulations is 21,000 MW. In order to judge the efficacy of the proposed in nonlinear environment, the valve-point effect and prohibited operating zones are considered. However, to keep the test system intact, the transmission loss is not taken into consideration in this case. The full system data are taken from [55]. Table 5 illustrates the optimal generation schedule of 80 generating units and fuel cost obtained using the proposed GWO method. The simulation results clearly suggest that GWO produces feasible solutions. To judge the superiority and robustness, the statistical results obtained by the proposed GWO algorithm are compared with those obtained by PSO [55], NPSO [55] and FAPSO [55]. The statistical results of the aforesaid methods are illustrated in Table 6. The comparative results show that the proposed GWO method outperforms the other techniques. The convergence characteristic of fuel cost obtained by the proposed GWO technique is shown in Fig. 3. The graph shows that the proposed method smoothly converges to the optimal solution.

Test Case 4

To explore the opportunity of the GWO to the large scale power system, experiments are conducted on the Korean power system [56]. This system is a large and complicated system having 140 generating units each having valve point loading effects, ramp rate limits and some units having prohibited operating zones. The total load demand is set to 49,342 MW. The transmission loss of this test system is neglected. The system data including fuel cost coefficients are adopted from [56,58]. The optimal economic dispatch scheme achieved by the proposed GWO algorithm along with SDE [56] is shown in Table 7. It is clear that for this large and complex system, GWO efficiently converges in the vicinity of the optimal solution with full constraint satisfaction. It is also clear that the algorithm proposed by this paper can lower the fuel cost effectively as compared to SDE.

The statistical results of the proposed GWO approach are compiled in Table 8. The statistical results signify the robustness and superiority of the GWO algorithm compared to existing SDE approach. The nature of convergence characteristic of the proposed GWO for this test system is shown in Fig. 4. This figure shows that the GWO takes few iterations to reach near the optimal solution and there is almost no deviation after 45 iterations in fuel cost. It shows that the proposed GWO method can quickly reach to the optimal solution. Results obtained by the proposed method are encouraging and suitable for the practical systems.

Conclusion

In this work, an efficient and comparatively new algorithm named GWO is proposed to solve the ELD problem taking the valve point loading effects, multiple fuel, prohibited operating zone, ramp rate limits into consideration. Four case studies are employed to demonstrate the applicability of the GWO method. The benefit of the proposed GWO is that it does not impose any convexity limitations on the generating unit characteristics. Numerical results show that the GWO method has superior features, advantages over other algorithms in terms of robustness, less computational efforts, avoids premature convergence, simple applicability and stable convergence characteristic. Although, the proposed algorithm is applied to solve ELD problems in the current study, it seems from its unique feature that GWO has the potential to solve many other optimization problems in the field of power system planning and operation.

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