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Solution for Different Convex and Non-Convex Economic Dispatch Problems for Large Scale System by Stochastic Search Algorithm

K. Sarker[1], B. Roy[2], J. Sarker[3], D. Santra[4]
[1, 3]Assistant Professor, [2]Student, [4]Associate Professor
[1, 2, 3, 4]Department of Electrical Engineering,
[1, 2]Saroj Mohan Institute of Technology, Hooghly, West Bengal, India
[3]Techno India, Salt Lake, Kolkata, India
[4]RCC Institute of Information Technology, Kolkata, India
Email: *krishna80sarker@gmail.com*
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Abstract

The main objective of the Economic Load Dispatch (ELD) is to determine the power by all committed generating units so that generating cost is minimized, while satisfying the load demand and inequality constraints. This paper represents an algorithm motivated by the 'law of gravity' and interaction among the masses to solve ELD problems, called 'Gravitational Search Algorithm'. This proposed algorithm has been tested on some standard power systems including 40-unit, 110-unit, 140-unit, 160-unit, 320-unit systems using different non-linear effect like valve point loading, multi fuel option etc. This result obtained by using proposed method compared with other methods shown less computational time over other existing algorithm.

Keywords: *Economic Load Dispatch, Gravitational Search Algorithm, Multi fuels, Valve point loading effect*

INTRODUCTION

Engineers are very much concerned about the cost of products and services. In power system, minimization of production cost in any thermal unit is important. Economic load dispatch is an important and one of the fundamental optimization techniques in power system operation. The aim of ELD problem is to reduce transmission loss, minimize generating cost of thermal units and optimize the power generation at particular load demand and subjected to satisfying equality and inequality constraints [1, 2]. A lot of examinations have been done on ELD problems till date [3]. The cost function of ELD problem is expressed as particular quadratic function and the problem is resolved by numerous derivative based techniques as Lagrangian multiplier method, lambda iteration method, gradient method, Newton's method, etc., [4]. In reality, characteristics are complex and non-linear because of valve point loading effect [5, 6], ramp rate limit [7], prohibited operating zones [8, 9] etc.

Due to the restriction of the traditional techniques for non-convex characteristics in solving ELD problems, there are huge optimization techniques which have been effectively used to solving this problems like Biogeography Based Optimization (BBO) [2, 7], Bat Algorithm (BA) [9], Improved Genetic Algorithm (IGA) [10], Pattern Search(PS) [11], Improved Particle Swarm Optimization (PSO) [12], Neural Network (NN) [13], Firefly algorithm (FA) [14], Cuckoo Search Algorithm (CSA) [15], Real-Coded Genetic Algorithm(RCGA) [16], Imperialist Competitive Algorithm (ICA) [17] Flower Pollination Algorithm (FPA) [18], Grew Wolf Optimiser (GWO) [19], Shuffled

Frog Leaping Algorithm (SFLA) [20], Genetic Algorithm(GA) [21] etc.

This paper is organised as following: Related work is discussed in section III. In section IV the basic ELD problem formulation is discussed along with various linear and non-linear constraints. Section V briefly stresses on the basic features of Gravitational Search Algorithm (GSA) and optimization strategy of proposed GSA algorithm. In section VI, the discussion of simulation outcomes for five different test cases followed by comparison and analysis is presented. Finally, the study is concluded with achievement and limitation of the present study in Section VII.

Motivation

The economic load dispatch (ELD) optimization problem is one of the essential issues in power systems towards acquiring optimal profits with the reliability, stability and security [43]. Basically, the ELD problem is a constrained optimization problem in power generation systems that have the aim of separating the total power demand among different on-line generators which are usually sharing the generation load while fulfilling equality and inequality constraints having complex and nonlinear characteristics. Consequently, good solutions of the ELD problem would result in immense economical benefits for the power generation industry as well as the end users.

Over the years, many attempts have been made to solve this problem with a variety of constraints and/or multiple objectives, through various mathematical programming and optimization techniques [44]. In the conventional methods, for example the lambda-iteration method, the gradient methods etc., have necessary assumption that the fuel cost curves of the units are monotonically increasing piece-wise linear functions, but practically the cost curves are nonlinear in nature [43]. Hence, global optimization techniques, such as the genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), firefly algorithm (FA) and gravitational search algorithm (GSA) have been studied in the last three decades and have been successfully used to solve the ELD, though each method has its own limitations and solution inaccuracies. However, GSA being quite effective (with certain limitation) for ELD, till date no experimentation has been done with GSA for the large scale power system optimization problems. Rather different hybrid algorithms involving GSA has been experimented with ELD.

The aim of this work is to apply the GSA in its pure form to the large scale ELD problem and compare its effectiveness and feasibility with other heuristic methods like the Biogeography-Based Optimization (BBO) [2], oppositional invasive weed optimization OIWO [23], cuckoo search algorithm CSA [25], Oppositional based grey wolf optimization algorithm OGWO [28], Oppositional real coded chemical reaction optimization ORCCRO [31], Shuffled differential evolution (SDE) [33], Hybrid differential evolution with biogeography-based optimization DE/BBO [35], hybrid hierarchical evolution (HHE) [38] hybrid differential evolution and harmony search (DE-HS) [39] etc. that have been applied to large scale ELD problem.

Related Work

In the past decades, a global optimization technique GA is extensively used in optimization problems. But it suffers from some disadvantages like using of complex operator for selection, taking long computational time etc. Glover [45] introduces TS algorithm which is a meta-heuristic local search algorithm and it is used to find improved solution from current solution. Due to the local and random interaction between particles in swarm-based algorithm, PSO is widely used in ELD problem. But it suffers from slow convergence and it gets trapped while solving complex optimization problems. Bhattacharya et al., proposed biogeography-based optimization (BBO) [2] to solve both convex and non-convex ELD problems with considering different constraints of thermal power plants. Biogeography related with the geographical distribution of biological species are geographical distributed. Mathematically biogeography illustrates how a species starts, migrates from one to another environment and gets exhausted. This algorithm explore for the global optimum primarily through two steps: migration and mutation. The effectiveness of the proposed algorithm has been verified on 6, 10, 20 and 40-unit test systems. The proposed technique has been established to perform better in a number of cases.

Ghasemi [6] proposed multi objective interactive honey bee mating optimization (IHBMO) in 2013 for large scale nonlinear EELD with Valve Point Effect, that is non-convex problem. In this technique, Pareto dominance idea is used to produce and sort the dominated and non-dominated solutions. Furthermore, fuzzy set theory is engaged to extract the best compromise solution. The propose method has been individually examined and applied to the 6, 14 and 40 unit test systems.

In 2005, Chiang [10] presented an improved genetic algorithm with multiplier updating (IGA_MU) to solve non-convex ED problems. The IGA arranged with an improved evolutionary direction operator and a migration operation can competently search and actively explore solutions, and the MU is in use to handle the equality and inequality constraints of the PED problem. The advantages of the method, which was applied to 10, 13, 20, 40, 80, and 160-units test system, was compared with previous methods and the conventional genetic algorithm (CGA) with the MU (CGA_MU), revealing that the proposed IGA_MU is more effective than previous approaches, and applies the realistic ED problem more efficiently than does the CGA_MU. Specially, the proposed method is extremely capable for the large-scale system of the real ED process.

In 2015, Barisal et al., [23] introduced Oppositional Invasive Weed Optimization (OIWO) by hybridizing IWO, characterized by the colonizing behaviour of weed plants, and OBL empowered by quasi opposite numbers. IWO is anovel population based stochastic, derivative-free optimization algorithm developed by Mehrabian and Lucas [46]. The algorithm exploits some of the interesting characteristics of weed plants namely fast reproduction, distribution and self adaptation to the changes in climatic conditions. OBL assists to reach global optima of IWO which in turn reaches encouraging results of ELD problem.

Sahoo et al., [25] in 2015 Cuckoo Search algorithm (CSA) was applied to non-convex economic load dispatch problems. To verify the robustness of the proposed Cuckoo Search based algorithm, multiple constraints are also incorporated in the system. In this algorithm, the levy flights and the behavior of alien egg discovery is used to search the optimal solution. In comparison with the solution, quality and execution time obtained for 6, 15, 40,140, 320-unit test system, the algorithm seems to be a promising method to solve realistic dispatch problems.

Mandal et al., in 2014 represented a novel and efficient krill herd algorithm (KHA) [27] to solve both convex and non-convex multi-constraint ELD problems. To improve the overall effectiveness and performance of the proposed algorithm, the crossover and mutation operation of differential evolution (DE) are incorporated with the proposed method. The different versions of KHA are successfully applied to different scale like 6, 15, 40, 80-unit power systems for solving different ELD problems.

Pradhan et al., presented [28] oppositional based grey wolf optimization (OGWO) algorithm in 2017 for ELD problem. The proposed algorithm merges two basic ideas. Initially, the hunting behaviour and social hierarchy of grey wolves are used to search optimal solutions and then, oppositional concept is integrated with the grey wolf optimization (GWO) algorithm to accelerate the convergence speed of the conventional GWO algorithm. The performance of the algorithm has been measured on being applied on small, medium and large scale test systems for solving of 13, 40 and 160-unit ELD problems.

In 2013, Roy et al., presented [29] teaching learning based optimization (TLBO) for non-convex ELD problem considering VPL effect. TLBO is based on two concepts of education that is teaching phase and learning phase. In the beginning, learners get knowledge during the teaching methodology of teacher and lastly learners enhance their knowledge by communications among themselves. TLBO technique is a promising method for solving ELD.

In 2014, Bhattacharjee et al., [31] have represented the oppositional real coded chemical reaction optimization (ORCCRO) by fitting in the concept of quasi-opposition based learning (QOBL) in RCCRO inspired by the computational efficiency of QOBL. Effectively, the convergence speed of RCCRO gets accelerated by comparing the fitness of a solution approximate to its opposite and retaining the fitter one in the arbitrarily chosen population set. ORCCRO has been successfully tested on non-convex large scale ELD problems.

In 2013, Reddy et al., proposed a hybrid shuffled differential evolution (SDE) [32] algorithm which combined the benefits of shuffled frog leaping algorithm (SFLA) and DE to solve non-convex ELD problem with transmission loss. SDE, characterized by a fresh mutation operator, mixes the exploration and exploitation mutation capabilities of DE and therefore helps conquer the inherent limitation of DE and SFLA in solving large scale non-convex ELD.

In 2010, Bhattacharya et al., suggested combination of differential evolution (DE) and with biogeography-based optimization (BBO) [34] used to solve non-convex ELD. This hybrid technique improves the searching capability of DE employing BBO algorithm successfully and can produce the promising candidate solutions. In this paper, the migration operator of BBO together with mutation, crossover and selection operators of DE have been combined together to effectively develop the decency of both DE and BBO to improve the convergence speed and to improve quality of solution. This technique has been applied on customary 40-unit test case system with valve point effect, i.e., non convex solution.

Vishwakarma et al., in 2012 presented a simulated annealing (SA) approach [35] for solving ELD problems. Global optimization approach is motivated by annealing process of thermodynamics. The proposed technique works very fast, this feature of algorithm is striking when applied for a large ELD system. Simulation has been presented over two different cases as 38, 110-units, both cases having convex fuel cost characteristics. The results produced by the method have been compared with other approaches and finally SA proves glowing feasibility, robustness and fast convergence for optimization of ELD problems.

In 2013, Kim et al.[36] implemented Mean-Variance Optimization (MVO) algorithm with Kuhn Tucker condition and swap process to improve a global minimum searching capability for solving economic dispatch (ED) problems with non-convex cost functions. Kuhn-Tucker condition is a mathematical judgment for heuristic method, i.e., an experience-based technique for solving the problem. Swap process is a technique that changes the generator outputs in the direction of reducing total generation cost for searching local minimum. These two methods are applied to MVO algorithm so that optimal solution can be obtained.

Khoa et al., presented swarm based mean-variance mapping optimization (MVMO) [37] in 2015 for solving ED problem. The proposed technique is the extension of the original single particle mean-variance mapping optimization (MVMO). The original feature is the special mapping function applied for the mutation based on the mean and variance of n-best population. The MVMOS do better than the classical MVMO in global search ability due to the development of the mapping. The proposed MVMOS is study on 3, 13, 20-units and large-scale 140 units system and the achieved results are compared with many other known methods given in the paper. Test results prove that the proposed technique can competently apply for solving ED problem.

In 2008, Kuo proposed [41] a new approach and coding scheme for solving ELD problem through simulated annealing like particle swarm optimization (SA-PSO). This novel coding scheme could effectively prevent obtaining feasible solutions through the application of stochastic search methods, thereby dramatically improving search efficiency and solution quality. The effectiveness and feasibility of the proposed method were verified by applying it to 6, 13, 15, 40-units and compared with similar works reported in recent literature in terms of solution quality and computational efficiency which showed encouraging results, suggesting that the proposed approach was capable of efficiently determining higher quality solutions of ED problems.

Wang et al., proposed [42] estimation of distribution and differential evolution cooperation (ED-DE) in 2010, which is a consecutive hybrid of two efficient evolutionary computation (EC) techniques: estimation of distribution and differential evolution. The advantages of ED-DE over the previous ELD optimization algorithms are experimentally confirmed on non-convex ELD problems of 10, 20, 40, 80 and 160-unit ELD problems. To further evaluate the efficiency and effectiveness of ED-DE, this algorithm is compared with other recent published evolutionary algorithms on typical function optimization tasks showing better result than others.

GSA [9] is a meta-heuristic algorithm based on Newton’s law related to gravity and motion. According to Newton, every object in the universe attracts each other by the gravitational force. The magnitude of the force is directly proportional to the product of masses and inversely proportional to the square of the distance between them. The direction of movement of the particle occurs towards the particle of higher masses. In GSA every object in the universe is treated as an agent. The heavier masses move more slowly than the lighter one. This ensures the exploitation steps of this algorithm.

This paper presents a heuristic approach based on GSA for the solution of economic power dispatch with non-linear constraints. GSA is applied to standard test system of 40-unit, 110-unit, 140-unit, 160-unit, and 320-unit. For more realistic solution, loss co-efficient and different non-linear factors like valve point loading effects and with multi-fuel source are considered. This MATLAB simulation result has been compared by many well-known heuristic search algorithms, among which the result of our proposed technique is better.

ECONOMIC LOAD DISPATCH PROBLEM

The ELD problem is a nonlinear programming optimization technique [3]. The main objective of ELD is to minimize the fuel cost by generating real power output for a specific period of operation while satisfying several equality and inequality constraints. Two models of ELD are considered, viz. convex ELD problem which assumes the quadratic cost function along with the system load demand and non-convex ELD problem which contains generator nonlinearities such as valve point loading effects, ramp rate limits, prohibited zones and multi-fuel options. Both convex and non-convex ELD problems are discussed in this paper. Generally, ELD mathematical model can be mathematically described as follows.

IELD with Quadratic Cost Function

The total cost of ELD problem may be written as:

$$F_{Total} = min\left(\sum_{i=1}^{n} F_i\left(P_{Gi}\right)\right) = min\left(\sum_{i=1}^{n} a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \quad (1)$$

Where $F_i(P_{Gi})$ is the i^{th} generator cost function and generally expressed as quadratic equation, a_i, b_i and c_i are the cost coefficient of i^{th} generator, n is the generator connected to the system, P_{Gi} is the power output of the i^{th} generator.

Generator Capacity Constraints

The power generated by each generator must be in between the maximum and minimum value as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \quad i \in \{1, 2, 3, ..., n\} \quad (2)$$

P_{Gi}^{min} is the minimum value below which it becomes uneconomical and P_{Gi}^{max} is the maximum value power of the i^{th} transmission line.

Real Power Balance Constraint

In this world, power generated P_{Gi} by the generators must be equal to the sum of power demand P_D by the consumers and total power loss P_L in the transmission line. That is expressed by the following equation:

$$\sum_{i=1}^{n} P_{Gi} - P_D - P_L = 0 \quad (3)$$

As the total power loss function of power generation, so it can be calculated by solving the power equation as follows:

$$P_L = \sum_{i=1}^{m}\sum_{j=1}^{m} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{m} B_{0i} P_{Gi} + B_{00} \quad (4)$$

Where, B_{ij} is the ij^{th} element of loss co-efficient square matrix, B_{0i} is mathematical model can be mathematically described as follows.

ELD with valve point loadings

The total cost F_{Total} of power generation in any thermal unit is expressed by equation (1). As ELD problem with valve point loading introduces ripple in the heat-rate curve, so it becomes complex. The model of valve point loading has been discussed by introducing a sinusoidal function with the quadratic equation [21, 22]. The variation of fuel cost $F_i\,(P_{Gi})$ due to effect of valve point loading with the change of generated output power P_{Gi} is shown in Fig. 2.The actual cost function with valve point is given by equation (5).

$$F_T = min\left(\sum_{i=1}^{n} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left|e_i \times \sin\left\{f_i \times \left(P_{Gi}^{\min} - P_{Gi}\right)\right\}\right|\right) \quad (5)$$

ELD with VPL effects and multi-fuel options

For m number of generator and N_F fuel option for each generator the cost function with valve point and multi-fuel options is expressed by equations (6) and (7), where $\boldsymbol{P}_{Gik}^{\min}$ and $\boldsymbol{P}_{Gik}^{\max}$ are the minimum and maximum power generation limit of the i^{th} generator with fuel option k respectively.

$$\text{if } P_{Gik}^{\min} \le P_{Gi} \le P_{Gik}^{\max} \text{ for fuel option k; k=1,2,...}N_F \quad (6)$$

$$F_T = a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 + \left| e_{ik} \times \sin\left\{ f_{ik} \times \left(P_{Gik}^{\min} - P_{Gik} \right) \right\} \right| \quad (7)$$

For more realistic representation of generating unit, each unit is supplied from different fuel sources. The main aim is to get accurate and practical economic dispatch solution by combining sinusoidal and quadratic function. The generator with multi-fuel source becomes more appropriate when cost function with piecewise quadratic function is represented by (8) below.

$$F_i\left(P_{Gi}\right) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 + \left| e_{i1} \times \sin\left\{ f_{i1}\left(P_{Gi1}^{\min} - P_{Gi1} \right) \right\} \right| \\ \text{if } P_{Gi1}^{\min} \le P_{Gi} \le P_{Gi1}, \text{ fuel-1} \\ a_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 + \left| e_{i2} \times \sin\left\{ f_{i2}\left(P_{Gi2}^{\min} - P_{Gi2} \right) \right\} \right| \\ \text{if } P_{Gi1} \le P_{Gi} \le P_{Gi2}, \text{ fuel-2} \\ \vdots \\ a_{in} + b_{in}P_{Gi} + c_{in}P_{Gi}^2 + \left| e_{in} \times \sin\left\{ f_{in}\left(P_{Gin}^{\min} - P_{Gin} \right) \right\} \right| \\ \text{if } P_{Gin-1} \le P_{Gi} \le P_{Gi}^{\max}, \text{ fuel-n} \end{cases} \quad (8)$$

METHODOLOGY

Gravitational Search Algorithm

Till date a number of evolutionary algorithms have been studied in power system to obtain the optimal solution. Among them, GSA is a newer technique, having capability to handle the multi-dimensional problem. GSA has been implemented up till now on limited number of power system problems, such as for post-outage bus voltage magnitude calculations, combined economic and emission dispatch problems of power systems, optimal power flow and parameters identification of hydraulic turbine governing system, multi–objective economic emission load dispatch, and solution of unit commitment problem.

GSA is based on Newtonian law of gravity. In this algorithm, the solutions are analyzed in terms of masses of respective agents. Each mass has their own position, inertial mass, active gravitational mass and passive gravitational mass. The solution of the problem is represented by the position of the respective mass. Good solution and worst solution are represented by heavier and lighter mass respectively. Two well-known equations used in GSA are:

$$F = G\frac{M_1 M_2}{R^2} \quad (9)$$

And equation of acceleration of a particle when a force applied to it, written as:

$$a = \frac{F}{M} \quad (10)$$

Gravitational constant value $G(t)$ is represented as

$$G(t) = G(t_0) \times \left(\frac{t_0}{t} \right)^{\beta} \quad (11)$$

In the above equations, M_1 and M_2 are two different masses, F represents force, a is acceleration, R represents the distance between two masses, t is the actual time and $G(t_0)$ is the value of the gravitational constant at the initial time, t_0 respectively. $\beta < 0$.

Active gravitational mass (M_a), passive gravitational mass (M_p) and inertial mass (M_i) are defined in physics.

The equation representing the decrease in gravitational constant can be represented as

$$G(t) = G_0 e^{-\frac{\alpha t}{T}} \quad (12)$$

Where, α is a user specified constant, T is the total number of iteration, and t is the current iteration. If i^{th} active and passive gravitational masses are equal, then $M_{a_i} = M_{p_i} = M_{i_i} = M_i$ and for $i = 1, 2, \cdots, N$ number of masses, these gravitational masses can be represented in terms of their respective fitness values and the equations can be represented as:

$$m_i(t) = \frac{fitness_i(t) - worst(t)}{best(t) - worst(t)},$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (13)$$

The total force acting on mass i in d dimensions may be represented as,

$F_i^d(t) = \sum_{j\varepsilon Kbest, j\neq 1}^{N} rand_j F_{ij}^d(t)$ (14)

Where, r and j is the random number between 0 and 1, *Kbest* is the set of first K objects with the best fitness value and biggest mass, F_{ij}^d is the force on mass i from mass j in d dimensions.

The acceleration in d^{th} dimension, velocity (v) and position (x) at time (t+1) of object i may be expressed as:

$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d, x_i^d(t+1) = x_i^d + v_i^d(t+1)$ (15)

Where, r *and* $_1$ is the random number between 0 and 1.

The procedural steps of ELD problem solution with GSA is shown in Fig. 1.

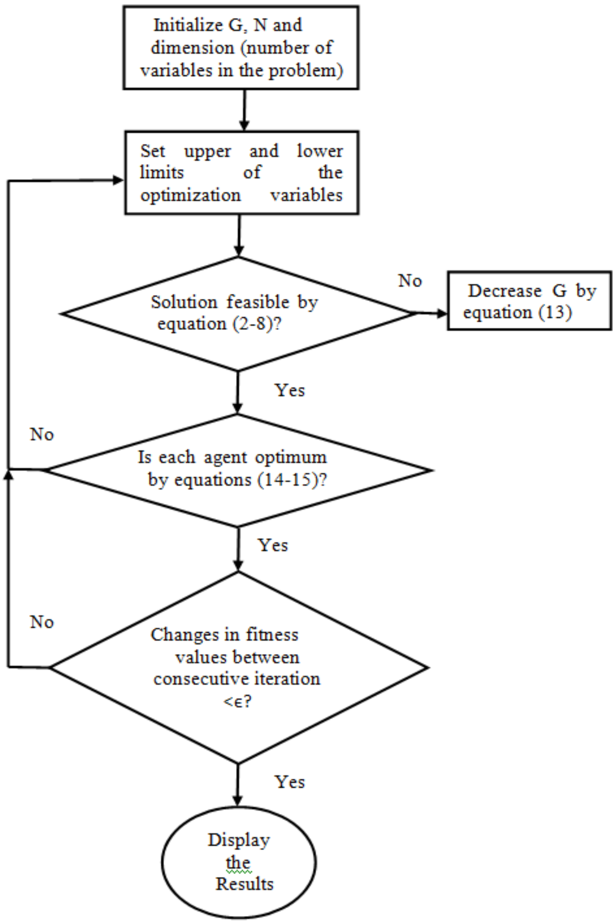

Figure 1: *Flow chart of GSA algorithm.*

Results and Discussion

The proposed GSA has been applied to solve ELD problems of different test systems to demonstrate its performance in comparison to several established optimization techniques reported in literature. The GSA has been implemented using Matlab-8.1 environment on a core i5/4GB/500 GB/Win 8.1 personal computers. Details simulation results could not be presented due to page limitation.

Case Study 1: 40 generator test system with non-convex constraints

For 40-unit test, system transmission loss with VPL has been considered. The system load demand is 10500 MW. The input data and B- loss coefficients are taken from [6, 11, 23]. We have calculated cost and loss for different operating conditions. The best power output for 40 generator system considering transmission loss with VPL compare with other recently published methods shown in Table 1.

Table 1: *Comparison between different methods taken after 50 trials (40-generators system) Load Demand-10,500 MW.*

Methods	Power (MW)	Ploss (MW)	Cost ($/h)
Proposed GSA	**11425.5429**	**925.5429**	**136445.452**
OIWO [27]	11457.2965	957.2965	136452.68
KHA[27]	11478.9251	978.9251	136670.370
OGWO[28]	11474.43	974.43	136440.62
TLBO [29]	11502.63	1002.63	137814.17
QOTLBO[29]	11508.96	1008.96	137329.86
GAAPI[30]	11545.06	1045.06	139864.96
ORCCRO[31]	11458.75	958.75	136855.19
SDE[32]	11474.43	974.43	138157.46
OCRO[33]	11468.9607	968.9607	136563.48
DE/BB0[34]	11457.83	957	136950.77

From this Table 1, it can be seen that proposed method in terms of total cost and loss are calculated for 40 generating units compared with different algorithms as shown is better. The convergence characteristics loss withVPL and is depicted in Fig. 2, which is only 7 nos. iterations have been made.

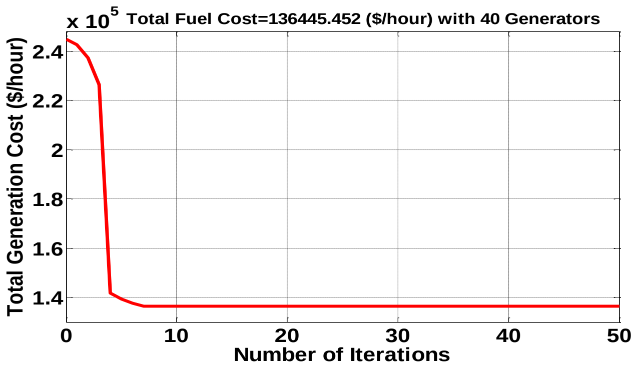

Figure 2: *Convergence characteristics of 40 generatorssystem with transmission loss VPL.*

Case Study 2: 110 generator test system
The input system data of 110 generating units for the load demand of 15000 MW is taken from [23].The power output with quadratic cost function minimum fuel cost is 197983.453 $/h obtained by GSA algorithm and compared to other method for ELD gives better result is shown in Table 2.

Table 2: *Comparison between different methods taken after 50 trials (110-generators system) Load Demand-15,000 MW.*

Methods	Best costs($/hr)	Time(s)	No. of hits
IHBMO [6]	197,989.1358	-	-
OIWO[23]	197,989.1358	31	-
ORCCRO [31]	198,016.29	0.15	48
DE/BBO [34]	198,231.06	0.46	43
SA [35]	198,352.6413	-	-
Proposed **GSA**	**197983.4538**	**0.33**	**20**

Case Study 3: 140 generator test system
The input data are taken from [24].The proposed algorithm provides total cost of 1557461.7934 $/hr for load demand of 49342 MW. In terms of results, GSA algorithm gives better result than the result obtained by other methods. This system consisted of 140 thermal units in comparison of generation cost as given in Table 3.

Table 3: *Comparison between different methods taken after 50 trials (140-generators system) Load Demand-49342MW.*

Methods	Costs($/h)	Time (s)	No. of hits
KMVO[36]	1568,450.94	-	-
MVMOS[37]	1557461.803	-	-
HHE[38]	1 655 679.4116	-	-
OGWO[28]	1559709.97	-	-
DEHS[39]	1655679	-	-
SDE [32]	1,560,236.85	-	-
OIWO[23]	1559405.4669	46.8	46
CTPSO[40]	1655685	50.1	-
DEL[24]	1657962.7166	-	30
CSA[25]	1559547.4708	26.37	-
CCPSO [41]	1655685	42.9	-
KMVO [37]	1577607	-	-
Proposed GSA	1557461.7934	22	50

Case Study 4: 160 generator test system
In Table 4, system consists of 160 generator systems with valve point loading effect and multi-fuel options. The load demand is considered as 43200 MW. The input data of 10 units are replicated up to 160 units and are taken from [23]. The generating level of each generator is not given in Table due to page limitation. Transmission loss is not considered in this case study. The best generating cost using proposed algorithm is 9978.8593 $/hour and this result is quite better than the result obtained other algorithm shown in Table 4.

Table 4: *Comparison between different methods taken after 50 trials (160-generators system).*

Methods	Best Cost ($/h)	Time (s)	No. of hits
OIWO[23]	9981.9834	17.3	46
ORCCRO [31]	10,004.20	19	48
BBO [2]	10,008.71	44	40
DE/BBO [34]	10,007.05	35	42
ED-DE [42]	10,012.68	-	-
CGA-MU [10]	10,143.73	-	-
IGA-MU [10]	10,042.47	-	-
CSA [25]	9982.085	29.97	-
Proposed GSA	9978.8593	15.3	50

Case Study 5: 320 generator test system
320 thermal units are considered with valve point loading effect and the load demand is set up to 86400 MW. The input data of 10 units are replicated up to 160 units and 320 units [23].The transmission loss is not considered in the cost function. The cheapest generating cost using proposed method is 19925.4291$/hr. The result is quite better than result obtained by using CSA [25] shown in Table 5.

Table 5: *Comparison between different methods taken after 50 trials (320-generators system).*

Methods	Best Cost ($/h)	Time (s)	No. of hits
CSA[25]	19964.171	59.82	-
Proposed GSA	19925.4291	40	15

CONCLUSION

GSA algorithm has been proposed for solving ELD problems. In the proposed algorithm, GSA avoids the divergence of the agents in the search space. The GSA algorithm is used to explore the search and tunes the control variables in order to find global optimal solution. The results obtained show the effectiveness of the proposed algorithm over other well established optimization techniques applied in modern power system. This comparison results reveal the effectiveness, robustness, high quality solution, feasibility, stable convergence characteristics and good computation efficiency of the proposed GSA technique.

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