Grasshopper Optimization Algorithm Applied for Economic Load Dispatch Problem and Benchmark Function

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Abstract: **A large number of algorithms have been evolved on account of natural phenomenon's and swarm behavior. Natural phenomenon's and swarms behavior are the warm area of research among the researchers. These algorithms have been executed on the different computational problems for the sake of solutions and gave critical outcomes than conventional system yet there is no such algorithm which can be connected for the greater part of the computational problems. This paper proposes an optimisation algorithm called Grasshopper Optimisation Algorithm (GOA) and applies it to challenging problems in structural optimisation. The proposed algorithm mathematically models and mimics the behaviour of grasshopper swarms in nature for solving optimisation problems. The GOA algorithm is first benchmarked on a set of test problems to test and verify its performance qualitatively and quantitatively. The results show that the pro- posed algorithm is able to provide superior results compared to well-known and recent algorithms in the literature. The results of the real applications also prove the merits of GOA in solving real problems with unknown search spaces.**

Keywords: Grasshopper Optimisation Algorithm (GOA), Nature Inspired Algorithm, Thermal generators, Economic load dispatch.

I. INTRODUCTION

In recent years, different heuristic optimization methods have been created. Many of these methods are inspired by swarm behavior in nature. Nature has dependably been a nonstop wellspring of motivation for scientists and researchers. A large number of algorithms have been produced in view of the characteristic procedure of development, laws, swarms conduct and so forth. Nature inspired algorithms are the most recent condition of art algorithms & works well with improvement problems and different problems than the traditional methods since established techniques are resolute in nature. Over the last decades, there has been a growing interest in algorithms inspired by the behaviors of natural phenomena [5,8,17,19,21,28]. It is appeared by many researchers that these algorithms are appropriate to settle complex computational problems, for example, optimization of objective functions [6,31], pattern recognition [24,27], control objectives [2,16,20], image processing [4,26], filter modeling [15,23], and so forth. etc. Various heuristic approaches have been adopted by researches so far, for example Genetic Algorithm [28], Simulated Annealing [21], Ant Colony Search Algorithm [5], Particle Swarm Optimization [17], etc. These algorithms are progressively analyzed or powered by researchers in many different areas [1,3,7,12,25,29]. These algorithms solve different optimization problems. However, there is no specific algorithm to achieve the best solution for all optimization problems. Some algorithms give a better solution for some particular problems than others. Hence, searching for new heuristic optimization algorithms is an open problem [30].

The economic dispatch problem (EDP) is one of the fundamental issues in power systems to solve keeping in mind the end goal to acquire benefits as stability, reliability and security. Its objective is to allocate the power demand among committed generators in the most efficient way, while all physical and operational limitations are fulfilled. The cost of power generation, especially in fossil fuel plants, is high and economic dispatch helps in saving a significant amount of revenue [7]. Different algorithms have been adopted in order to find the rate of optimum product for each power generation unit. The effective and economic operation and management of electrical power generating system has always been an important concern in the electrical power industry. The developing size of energy networks, tremendous request and emergency of vitality over the world, continuous rise in cost of fossil fuel require the ideal mix of generation level of power generating units. The exemplary issue of Economic Load Dispatch (ELD) is to limit the aggregate cost of energy era (counting fuel utilization and operational cost) from differently found power plants while fulfilling loads and losses in the power transmission framework. The goal is to distribute the total load demand and total loss among the generating plants while at the same time limiting generation costs and fulfilling the operational limitations.

In this review, Grasshopper Optimization Algorithm (GOA) method based on fuzzy logic optimization algorithm is presented to search global optimum solution in the 23 benchmark test functions and well-known ELD problem which is one of the important optimization problems in power systems.

Table-1: Unimodal test functions

Test function	*Dim.*	*Range*
$f_1(x) = \sum_{i=1}^{n} x_i^2$	5	[-100,100]
$f_2(x) = \sum_{i=1}^{n} (i \times x_i^2)$	5	[-100,100]
$f_3(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$	5	[-30,30]
$f_4(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	5	[-10,10]
$f_5(x) = \max_{i\{\lvert x_i \rvert, 1 \le i \le n\}}$	5	[-100,100]
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	5	[-100,100]
$f_7(x) = \sum_{i=1}^{n} i x_i^4 + \text{random}[0,1)$	5	[-1.28,1.28]

Table -2: Multimodal test function

Test function	*Dim.*	*Range*
$f_8(x) = \sum_{i=1}^{n} [-x_1 \sin(\sqrt{\lvert x_i \rvert})]$	5	[-500,500]
$f_9(x) = 10n + \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i)]$	5	[-5.12,5.12]
$f_{10}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	5	[-600,600]
$f_{11}(x) = -20\exp\left(-0.2\sqrt{\frac{1}{\pi}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$ *xp(1)*	5	[-32,32]
$f_{12}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	[-2,2]
$f_{13}(x) = \left\{0.002 + \sum_{i=1}^{n}\left[[J + (x_1 - a_{1j})^6] + (x_2 - a_{2j})^6\right]^{-1}\right\}^{-1}$	2	[-65.536,65.536]
$f_{14}(x) = \left(4 - 2.1{x_1}^2 + \frac{{x_1}^4}{3}\right){x_1}^2 + x_1x_2 + (4{x_2}^2 - 4){x_2}^2$	2	[-5,5]
$f_{15}(x) = 1\left(x_2 - \frac{5.1}{4\pi^2} + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos(x_1) + 10$	2	lb=[-5,0] ub=[10,15]

The Grasshopper Optimisation Algorithm is proposed in Section 3 . Section 4 presents and discusses the results on the optimisation test beds and inspects the behaviour of the proposed algorithm. Finally, Section 5 concludes the work and suggests several directions for future studies

II. PROBLEM FORMULATION

Economic dispatch is the technique for deciding the most proficient, minimal effort and reliable operation of a power system by dispatching the available electricity generation resources to supply the load on the system. The primary objective of economic load dispatch problem is to limit the aggregate cost of generation while fulfilling the operational limitations of the available generation resources .The ELD problem can be conceived as an optimization problem of minimizing the total fuel cost of all generating units while satisfying the demand and losses. Consider a system with n power generating units. The objective function is to minimize the total fuel cost (F) given by the following expression:

$$\boldsymbol{Min\ F} = \sum_{i=1}^{N_g}\left(a_i + b_i P_{g_i} + c_i P_{g_i}^2\right) \ \$/h \qquad (1)$$

Here n is the total number of generation units a_i , b_i and c_i are the cost coefficients of i^{th} power generation unit, P_{g_i} is the output of i^{th} power generation unit, and c_i is the cost function of i^{th} generating unit. i = 1, 2 … n. The operational constraints are given by:

(a)Power Balance Equation: In ELD of energy, the aggregate power generated ought to precisely coordinate with the load demand and losses which is represented by the taking after condition. It is a sort of equality constraint.

$$\sum_{i=1}^{N_g} P_{g_i} = P_D - P_L \qquad (2)$$

Here P_{g_i} is the power output from i^{th} generating unit, N_g is the number of generating units, P_L is the Transmission Loss, and P_D is the Load Demand. P_L is calculated using B-coefficient as:

$$P_L = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{N_g} B_{0i} P_{gi} + B_{00}$$
(3)

(b) Generator Constraints: The output power of each generating unit is restricted by its upper $P_{g_i}^{max}$ and lower $P_{g_i}^{min}$ limits of actual power generation and is given by:

$$P_{g_i}^{min} \le P_{g_i} \le P_{g_i}^{max} \qquad (4)$$

$P_{g_i}^{min}$ and $P_{g_i}^{max}$ are, the output of the minimum and maximum operation of the generating unit i (in MW) In the case studies presented here with 6 thermal generators.

III. Grasshopper Optimisation Algorithm (GOA)

Grasshopper are insects. They are considered a pest due to their damage to crop production and agriculture. The life cycle of grasshoppers is shown in Fig. 1 . Although grasshoppers are usually seen individually in nature, they join in one of the largest swarm of all creatures [9] . The size of the swarm may be of continental scale and a nightmare for farmers. The unique aspect of the grasshopper swarm is that the swarming behaviour is found in both nymph and adulthood [10] . Millions of nymph grasshoppers jump and move like rolling cylinders. In their path, they eat almost all vegetation. After this behaviour, when they become adult, they form a swarm in the air. This is how grasshoppers migrate over large distances. The main characteristic of the

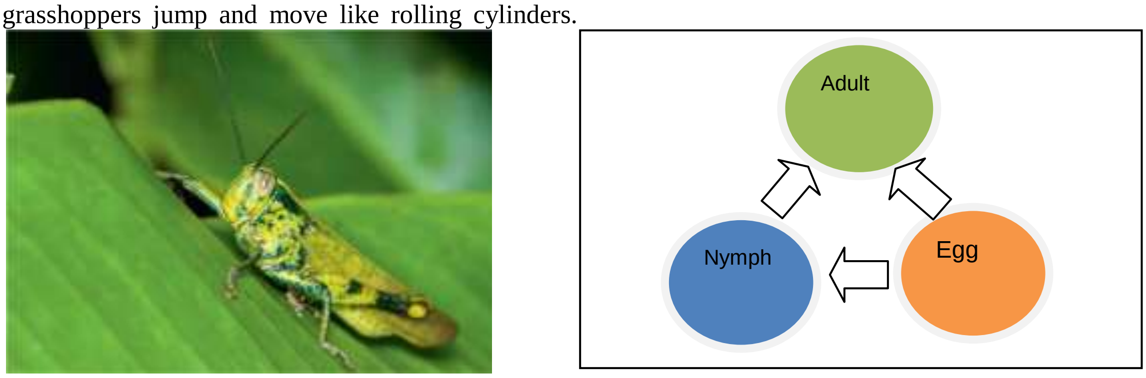
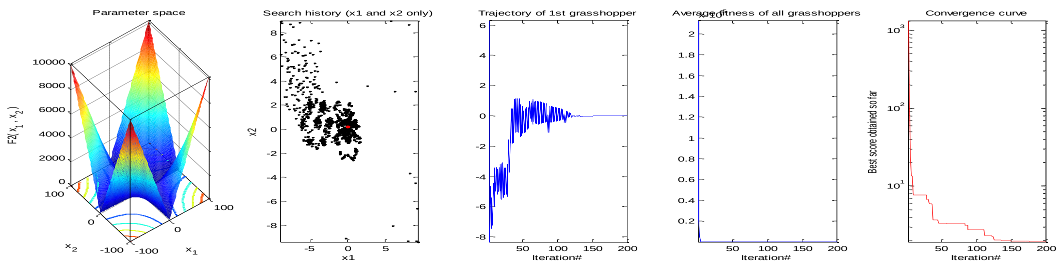


Fig. 1. (a) Real grasshopper (b) Life cycle of grasshoppers (left image courtesy of Mehrdad Momeny).

Benchmark function: F2



Benchmark function:F3

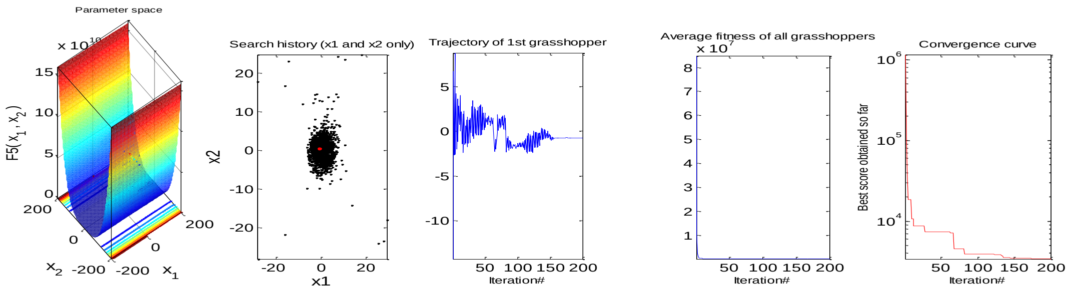
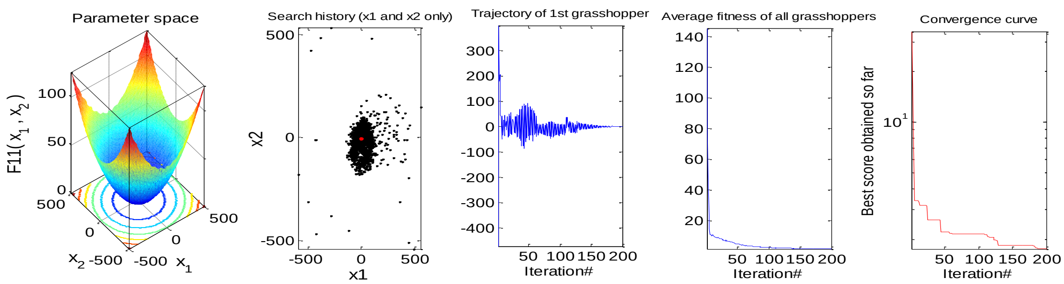
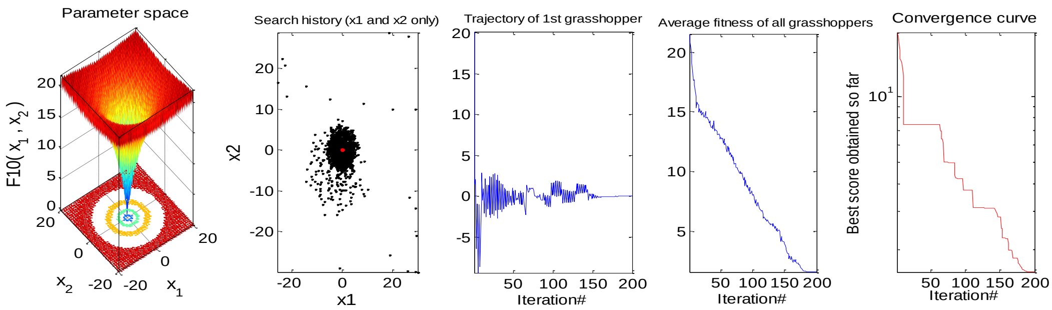


Fig.2 Convergence profiles of the selected unimodal test functions

Benchmark function:F6



Benchmark function:F7



Benchmark function:F8

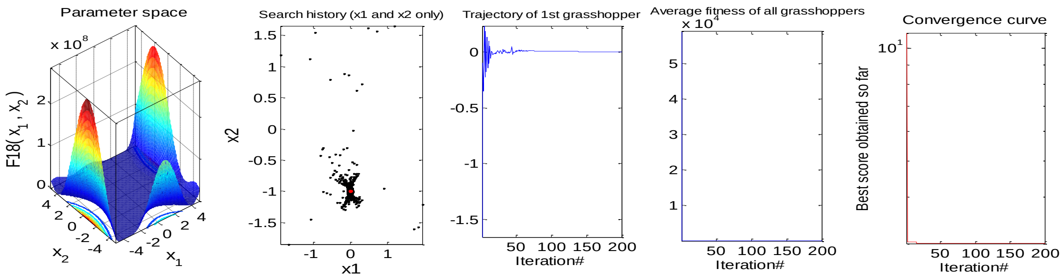


Fig.3 Convergence profiles of the selected multimodal test functions.

TABLE -3: Generating Unit Capacity and Coefficients

Unit	$P_{g_i}^{min}$	$P_{g_i}^{max}$	a_i ($)	b_i ($/MW)	c_i ($/MW^2)
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

TABLE-4: Transmission loss coefficients

$$B_{ij}=\begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$B_{0i} = 1.0e^{-03}*[-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635]$,

$B_{00} = 0.056$.

in the larval phase is slow movement and small steps of the grasshoppers. In contrast, long- range and abrupt movement is the essential feature of the swarm in adulthood. Food source seeking is another important characteristic of the swarming of grasshoppers. As discussed in the introduction, nature-inspired algorithms logically divide the search process into two tendencies: exploration and exploitation. In exploration, the search agents are encouraged to move abruptly, while they tend to move locally during exploitation. These two functions, as well as target seeking, are performed by grasshoppers naturally. Therefore, if we find a way to mathematically model this behaviour, we can design a new nature-inspired algorithm. The proposed mathematical formulations are able to explore and exploit the search space. However, there should be a mechanism to require the search agents to tune the level of exploration to exploitation. In nature, grasshoppers first move and search for foods locally because in larvae they have no wing. They then move freely in air and explore a much larger scale region. In stochastic optimisation algorithms, however, exploration comes first due to the need for finding promising regions of the search space. After finding promising regions, exploitation obliges search agents to search locally to find an accurate approximation of the global optimum

IV. CASE STUDIES AND SIMULATION RESULTS

This section presents a description of the three case studies of EDPs and the optimization results. First, the case study with Benchmark function is presented. After, the case studies with 6 generators are solved.

(a) Test case I: Benchmark function

With a particular ultimate objective to demonstrate the viability and quality of the proposed GOA approach, it is associated with 15 standard benchmark test limits which are taken from Ref. [11]. Tables 1-2 speak to the benchmark capacities utilized as a part of this paper. The base esteem (fopt) of the elements of Tables 1-2 are zero, with the exception of F4 which has a base estimation of - 418.9829× n. n is characterized as measurement of the benchmark test capacities.

Unimodal high-dimensional test functions:
Functions F1 to F7 are unimodal functions. In this case the convergence rate of search algorithm is more important for unimodal functions than the final results because there are other methods which are specifically designed to optimize unimodal functions. Functions F1 to F7 are unimodal capacities which are appeared in Table 1. The outcomes are arrived at the midpoint of more than 500 runs and contrasted with past outcomes revealed in the writing [13]. The joining of the proposed GOA calculation for the chose unimodal test capacities is appeared in Fig 2.

Multimodal high-dimensional test functions:
Functions F8 to F15 are multimodal test Functions which are appeared in Table 2. These test capacities have numerous nearby minima and defined as difficult problems to be optimized.. The outcomes are found the middle value of more than 500 runs and contrasted with beforehand revealed outcomes in the writing [13]. The merging of the proposed GOA calculation for the chose multimodal test capacities is appeared in Fig 3.

(b) Test case II: Six unit system
The system contains six thermal units, 26 buses, and 46 transmission lines [14]. The load demand is 1263MW. The characteristics of the six thermal units are given in Tables 3 and 4. In normal operation of the system, the loss coefficients **B** with the 100 MVA base capacity power outputs, such as $\boldsymbol{P_{G1}}, \boldsymbol{P_{G2}}, \boldsymbol{P_{G3}}, \boldsymbol{P_{G4}}, \boldsymbol{P_{G5}}$ and $\boldsymbol{P_{G6}}$, which are generated randomly. The dimension of the population is equal to 6×100. Through the evolutionary process of the proposed methods, their best solutions are shown in Table 5, respectively, that satisfy the system constraints. The result got from the proposed approach is 15276.1591\$/h. From Table 6, it can be seen that the GOA has less aggregate fuel cost than the other evolutionary algorithms in the literature. Table 4 shows the Transmission loss coefficients for test systems [18].Table- 5 demonstrates the minimum results of the GOA technique for this test system.

Units	GOA
P_{G1}	448.4841
P_{G2}	170.181
P_{G5}	265.4511
P_{G8}	125.7546
P_{G11}	173.9889
P_{G13}	79.14027
Total power output (MW)	**1263**
Ploss(MW)	**11.9583**
Total fuel cost (\$/h)	**15276.1591**

Table 5:- The results obtained from the proposed approach for case II in (\$/h)

V.CONCLUSION
In this paper, we have successfully employed the GOA method to solve the ELD problem with the generator constraints. This paper proposes an optimisation algorithm called Grasshopper Optimisation Algorithm (GOA) and applies it to challenging problems in structural optimisation. The proposed algorithm mathematically models and mimics the behaviour of grasshopper swarms in nature for solving optimisation problems[22]. The effectiveness of the developed program is tested for

Units Power output	PSO Method	GA Method	GOA Method
P_{G1} (MW)	447.4970	474.8066	448.4841
P_{G2} (MW)	173.3221	178.6363	170.181
P_{G5} (MW)	263.4745	262.2089	265.4511
P_{G8} (MW)	139.0594	134.2826	125.7546
P_{G11} (MW)	165.4761	151.9039	173.9889
P_{G13} (MW)	87.1280	74.1812	79.14027
Total power output (MW)	**1276.01**	**1276.03**	**1263**
Ploss(MW)	**12.9584**	**13.0217**	**11.9583**
Total fuel cost (\$/h)	**15450**	**15459**	**15276.1591**

Table 6:- Comparison of the results obtained from the proposed approach for case II.

test function and for different generator set systems i.e. for 6-generator electrical power system. The electrical power systems were taken considering without valve point loading. It is found that GOA gives better solution on comparison with the Particle swarm optimisation method, and Genetic algorithm method.

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