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Congestion Management in IEEE Bus System Using GSA Optimization

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ABSTRACT: Gravitational Search Algorithm (GSA) is a recent algorithm that hasbeen inspired by the Newtonian's law of gravity and motion. Sinceits introduction in 2009, GSA has undergone a lot of changes to thealgorithm itself and has been applied in various applications. Atpresent, there are various variants of GSA which have beendeveloped to enhance and improve the original version. Thealgorithm has also been explored in many areas. Nevertheless, it isstill unknown how much the algorithm has evolved and how far theresearch and development has been done since its introduction.Hence, this paper is intended to dig out the algorithm's current stateof publications, advances, its applications and discover its futurepossibilities. This review is expected to provide an outlook on GSAespecially for those researchers who are keen to explore thealgorithm's capabilities and performances.

KEYWORDS: Gravitational Search Algorithm, Gravitational Constant, Firefly Algorithm etc.

I. INTRODUCTION

GSA is a heuristic optimization algorithm which has been gaining interest amongthe scientific community recently. GSA is a nature inspired algorithm which isbased on the Newton's law of gravity and the law of motion [1]. GSA is groupedunder the population based approach and is reported to be more intuitive [2]. Thealgorithm is intended to improve the performance in the exploration andexploitation capabilities of a population based algorithm, based on gravity rules.However, recently GSA has been criticized for not genuinely based on the law ofgravity [3]. GSA is reported to exclude the distance between masses in its formula,whereas mass and distance are both integral parts of the law of gravity. Despitethe criticism, the algorithm is still being explored and accepted by the scientificcommunity.This paper is intended to explore GSA in order to determine how much thealgorithm has evolved and how far the research and development has been donesince the introduction of the algorithm. The objectives of the paper are to analyzedthe works related to GSA, to review GSA advances and its performances, toreview the applications and finally to bring out the future challenges andpossibilities.The paper is organized as follows. Section 2 presents a brief review on GSA whilesection 3 provides the review methodology for carrying out the literature study.Section 4 summarizes GSA advancements and section 5 presents the algorithm'sapplications. Finally, section 6 presents the discussion and the possible path forfuture research in GSA.

A. GSA: A Brief Review

GSA was introduced by Rashedi et al. in 2009 and is intended to solveoptimization problems. The population-based heuristic algorithm is based on thelaw of gravity and mass interactions. The algorithm is comprised of collection ofsearcher agents that interact with each other through the gravity force [1]. Theagents are considered as objects and their performance is measured by theirmasses. The gravity force causes a global movement where all objects movetowards other objects with heavier masses. The slow movement of heavier massesguarantees the exploitation step of the algorithm and corresponds to goodsolutions. The masses are actually obeying the law of gravity as shown inEquation (1) and the law of motion in Equation (2).

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F = G (M1M2 / R2) (1)

a = F/M(2)

Based on Equation (1), F represents the magnitude of the gravitational force, G isgravitational constant, M1 and M2 are the mass of the first and second objects andR is the distance between the two objects. Equation (1) shows that in the Newtonlaw of gravity, the gravitational force between two objects is directly proportionalto the product of their masses and inversely proportional to the square of thedistance between the objects. While for Equation (2), Newton's second law showsthat when a force, F, is applied to an object, its acceleration, a, depends on theforce and its mass, M.In GSA, the agent has four parameters which are position, inertial mass, active gravitational mass, and passive gravitational mass [1]. The position of the mass represents the solution of the problem, where the gravitational and inertial massesare determined using a fitness function. The algorithm is navigated by adjustingthe gravitational and inertia masses, whereas each mass presents a solution.Masses are attracted by the heaviest mass. Hence, the heaviest mass presents an optimum solution in the search space. The steps of GSA are as follows:

II. SOLUTION METHODOLOGY

Step 1: Agents initialization:
The positions of the N number of agents are initialized randomly.

$$X_i = x_i^1, x_i^d, \ldots . . x_i^n fori = 1,2 \ldots \ldots, N \quad (3)$$

x_i^drepresents the positions of the ith agent in the dth dimension, while n is the space dimension.

Step 2: Fitness evolution and best fitness computation:
For minimization or maximization problems, the fitness evolution is performed by evaluating the best and worst fitness for all agents at each iteration.
Minimization problems:

$$best(t) = \min_{j\epsilon\{1,..N\}} fitj(t) \quad (4)$$

$$worst(t) = \max_{j\epsilon\{1,..N\}} fitj(t)(5)$$

Maximization problems:

$$best(t) = \max_{j\epsilon\{1,..N\}} fitj(t)(6)$$

$$worst(t) = \min_{j\epsilon\{1,..N\}} fitj(t)(7)$$

fit j(t) represents the fitness value of the *jth*agent at iteration *t*, *best(t)* and *worst(t)*represents the best and worst fitness at iteration *t*.

Step 3: Gravitational constant (*G*) computation:
Gravitational constant *G* is computed at iteration *t*

$$G(t) = G_0 e^{-\alpha t/T} \quad (8).$$

G0 and α are initialized at the beginning and will be reduced with time to control the search accuracy. *T* is the total number of iterations.

Step 4: Masses of the agents' calculation:
Gravitational and inertia masses for each agent are calculated at iteration *t*.
Mai = Mpi = Mii = Mi, i = l, 2, ...,N.(9)

$$m_i(t) = \frac{fit(t)-worst(t)}{best(t)-worst(t)} \quad (10)$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (11)$$

Mai and *Mpi*are the active and passive gravitational masses respectively, while *Mii*is the inertia mass of the ith agent.

Step 5: Accelerations of agents' calculation:
Acceleration of the ith agents at iteration *t* is computed.

$$a_i^d(t) = F_i^d(t)/M_{ii}(t) \ (12)$$

$F_i^d(t)$is the total force acting on ith agent calculated as:

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$$F_i^d(t) = \sum_{j \in Kbest, j \neq i} rand_j F_{ij}^d(t)$$

$F_i^d(t) = \sum_{j\epsilon kbest} rand_j F_{ij}^d(t)$(13)

*Kbest*is the set of first *K* agents with the best fitness value and biggest mass. *Kbest*will decrease linearly with time and at the end there will be only one agent applying force to the others.

$F_{ij}^d(t)$can be computed as:

$$F_{ij}^d(t) = G(t).\left(M_{pi}(t) \times \frac{M_{ai}(t)}{R_{ij}(t)} + \varepsilon\right).(x_j^d(t) - x_i^d(t))$$

$F_{ij}^d(t)$is the force acting on agent *i* from agent *j* at *dth*dimension and *tth*iteration. *Rij(t)* is the Euclidian distance between two agents *i* and *j* at iteration *t*. *G(t)* is the computed gravitational constant at the same iteration while ε is a small constant.

Step 6: Velocity and positions of agents:

Velocity and the position of the agents at next iteration (t+1) are computed based on the following equations:

$$v_i^d(t+1) = rand_i x v_i^d(t) + a_i^d(t)$$
$$x_i^d(t+1) = v_i^d(t+1) + x_i^d(t)$$

Step 7: Repeat steps 2 to 6

Steps 2 to 6 are repeated until the iterations reach their maximum limit. The best fitness value at the final iteration is computed as the global fitness while the position of the corresponding agent at specified dimensions is computed as the global solution of that particular problem.

III. Results And Discussion

A. IEEE-30 Bus System Used in GSA(gravitational search algorithm) Optimization

Congestion management is necessary to tackle load demand in power system. The IEEE 30 bus system consists of 6 generators buses, 24 load buses and 41 transmission lines. The real load of the system is 283.4MW and reactive load is 126.2MVAR. The load bus voltages are maintained between 0.9 and 1.1 p.u.IEEE-30 bus system as shown in fig 1.

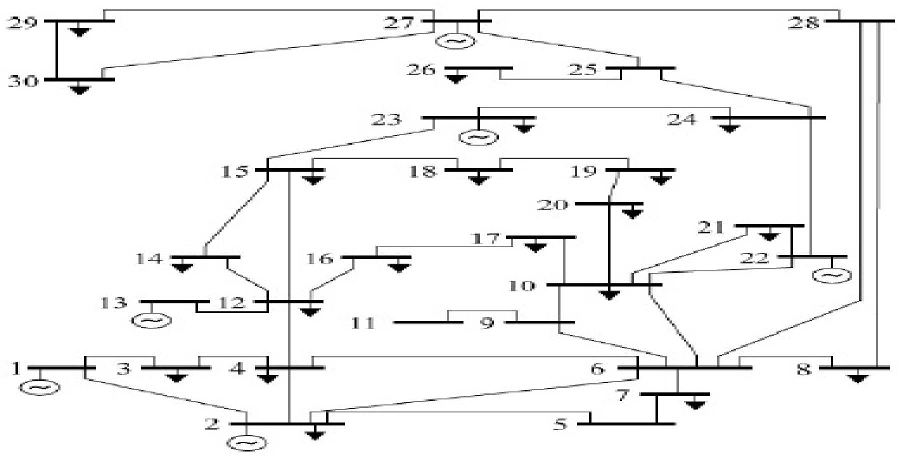

Fig. 1 IEEE-30 bus system

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B. *Total Line Losses After GSA Congestion*

In IEEE-30 bus system,we apply the GSA congestion method.This method reduced the losses in the line due to less losses the cost of the system is not increase.Before the congestion management the line losses is more than as compare to after congestion management.Before congestion management the line losses is 25.4509 and after GSA congestion the losses is 10.8848. The total line loss after and before congestion as shown in table.

Before Congestion Management (MW)	After Congestion Management(MW) by GSA
25.4509	10.8848

C. *Comparison Of Firefly CM And GSA CM*

Firefly congestion management and GSA management both are optimization technique as below given figure show the comparison of firefly optimization and GSA optimization.Figure (a) show the power flow in the IEEE-30 bus system and figure(b) show the line losses in the branch.

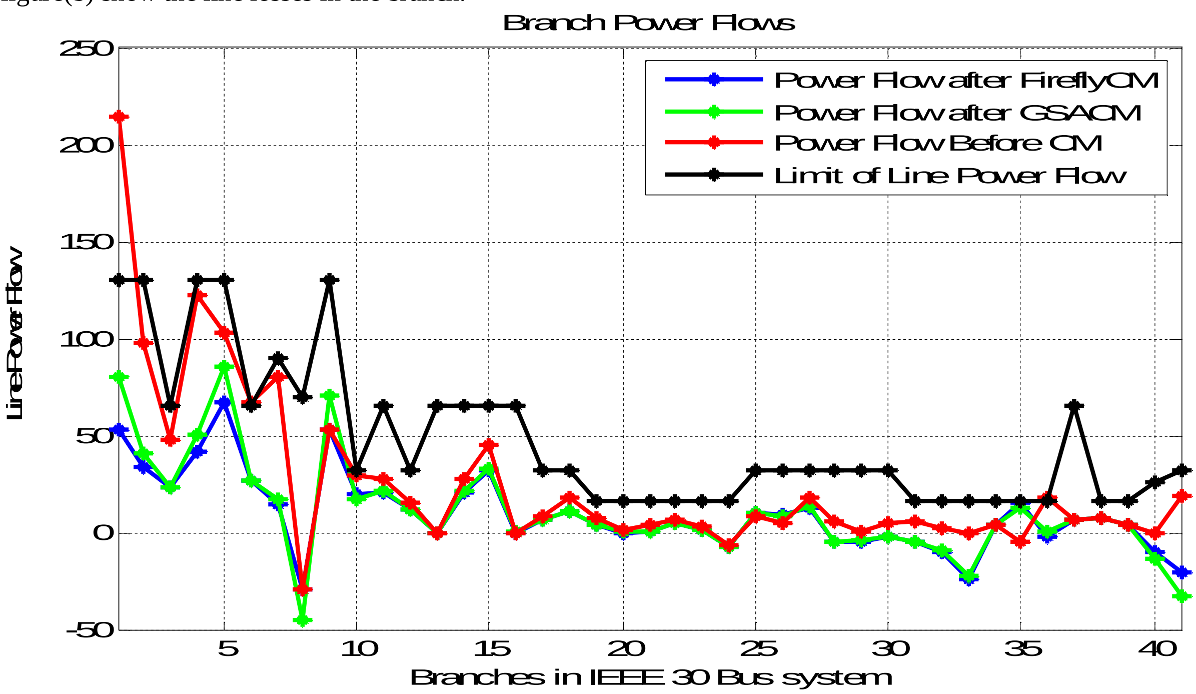

Fig. (a)

In the fig (a) firstly we set the limit of line power flow represent in black line. Red line represents the power flow before congestion management. Green line shows the power flow after GSA congestion management. Blue line shows power flow after firefly congestion management.

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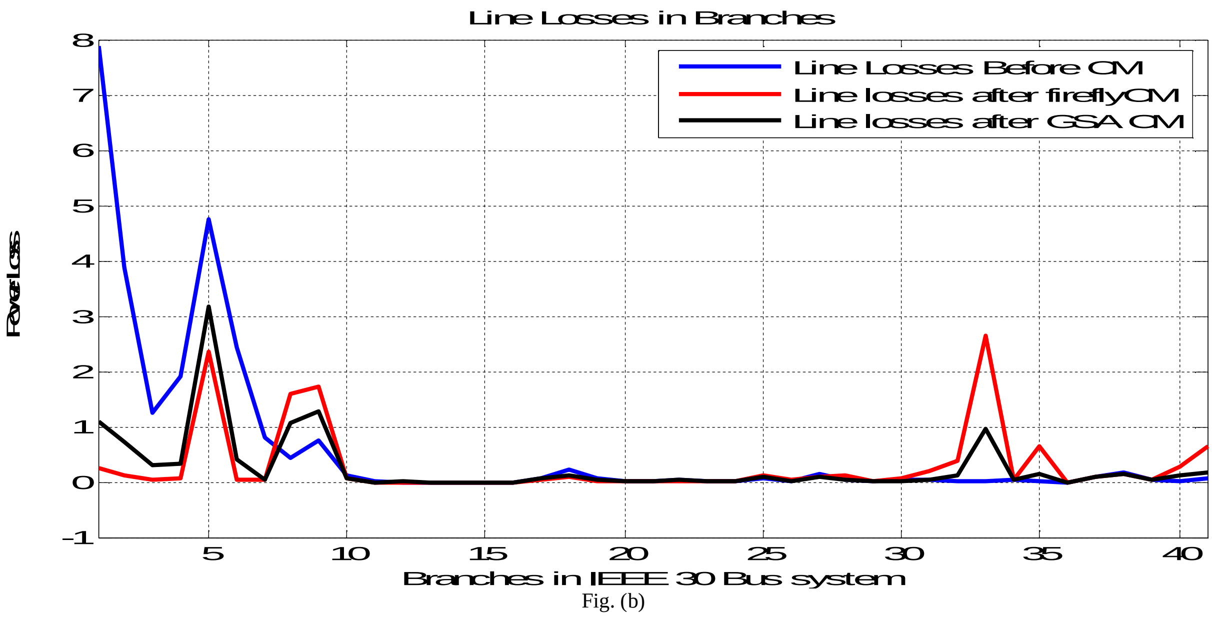

Fig. (b)

In figure (b) the total line losses show. In this figure blue, red and black represent the line losses before CM,line losses after firefly CM and line losses after GSA CM respectively.
An improvement of 98.9860% in line losses is visible by our proposed congestion management scheme which is shown in bar graph form in figure ©.

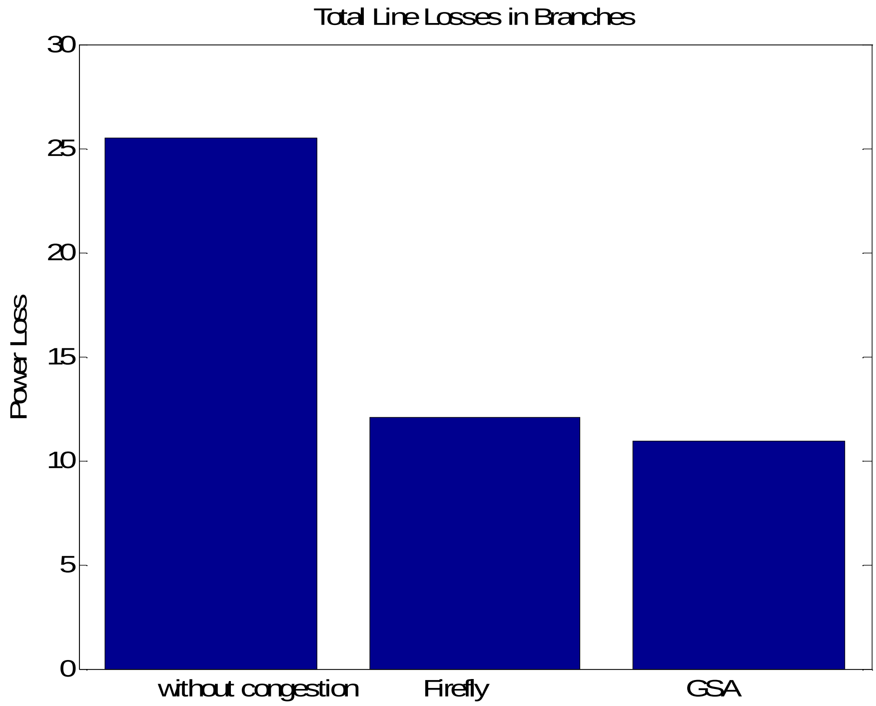

Figure (c): Line loss comparison for congested lines and without congested lines

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IV. CONCLUSION

The objective of this project is to minimize or alleviate power congestion of the network by rescheduling of active power of generators at minimum cost satisfying the operational constraints. The method proposed here using GSA optimization separately has been implemented on IEEE 30 bus system. The congestion is knowingly introduced by increasing the outage in line 2-3 for the test purpose and has been successfully managed with minimum cost and maintaining system constraints. The results obtained are quite satisfactory and checked on the ground of power losses and voltage profile improvement after congestion management. The comparative analysis of results showed that GSA performs better to reduce the line losses than firefly algorithm. Thus it can be said that rescheduling of generators for congestion management is fruitful process as it maintained the supplied quality, security of the grid and also taking care of the interest of the consumers without shedding any load.

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