GWO OPTIMIZATION BASED LOCATION SELECTION OF D-STATCOM

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ABSTRACT

Reactive power compensation in radial distribution systems (RDS) is an important requirement for improving the system power quality and security. Grey wolf optimization (GWO) technique is a modern technique based on updating the positions of populations around the best solutions. Grey Wolf Optimizer (GWO) inspired by grey wolves (Canis lupus). The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. This work presented and applied for determine the optimal locations and sizes of Distribution Static Synchronous Compensator (DSTATCOM) in RDS as a reactive power source. The considered objective function is a multi-objective function which includes minimizing the real power losses, enhancing the voltage profile and improving the system stability, concurrently. To show the efficiency of the proposed technique it is applied on the stranded IEEE85-bus system and the captured results are compared to the founded results of the basic SCA techniques. The simulation reveals to that the proposed algorithm is more superior compared to the other reported algorithms.

I - INTRODUCTION

The distribution systems play an important role in the failure statistics or unavailability of power at consumer's disposal. Consequently, the competitive markets increase the demand of plans or techniques which can improve the total condition of the distribution systems. Therefore, in order to maximize the obtained efficiency and profit, any plan should be examined precisely. In this regard, new methods are under investigation by the utilities to improve the total system electrical services from both operation and planning standpoints. The most renowned and popular methods can be identified as: the optimal management of the shunt capacitors, shunt reactors, automatic voltage regulator, series capacitors or recently distribution network flexible AC transmission system (DFACTS) technologies such as distribution static compensator (DSTATCOM).

In the dynamic studies, switching in the system causes several operational issues such as resonance or transient harmonics in some popular reactive power compensations methods like shunt capacitor placement strategy or series capacitors while the DSTATCOM does not have these kinds of operational issues. In the power quality, DSTATCOM will improve the quality of the electrical services by improving the flicker suppression, voltage regulation and voltage balancing. Moreover, the ability of cleaning up the voltage from any unbalance or harmonic distortion is one of the functional characteristics of the DSTATCOM. Other useful properties such as low harmonic production, low power losses, high regulatory ability and small size make DSTATCOM a special device among other reactive power compensation devices. Actually, as the load demand varies in the system, the DSTATCOM is capable to compensate the load demand locally and it is regulated automatically. As time goes by, with increase of the total load consumption in power systems, the effectiveness of the DSTATCOM to maximize the power system load ability, stability and reactive power compensation is more characterized too.

It can be easily deduced from the above discussion that the DSTATCOM device has a major role in the optimal operation and management of the future distribution networks. One of the most significant issues in the utility area is to reduce the amount of MW power losses by reducing the resistive losses. By improving the voltage of the buses, we can obtain an improvement in the network power quality which can result in improvement of the electrical services by reducing the cost of damaging sensitive electrical devices and also reducing the number of interruptions in the system. In spite of the above observation, there is very little works available in the area of DSTATCOM allocation to demonstrate its effect on the distribution network from various points of view. In, by taking the objective functions of active power losses and voltage profile into consideration simultaneously, the author assessed the DSTATCOM allocation problem. However, decrease in the dependability of the final results is a big deficiency of the analysis which is the consequence of forgetting the uncertainty with the active and reactive loads. In, the optimal DSTATCOM allocation and sizing is under investigation to lessen the impact of the voltage fluctuations in the network.

Radial distribution network (RDN) is an important part in electric system where it delivers the required power from transmission networks (TN) to utilities or consumers. The R/X ration is high in RDS compared to TN. Thus, RDS suffer from power quality including high power loss and voltage droop. Moreover, suffer from some instability problems. Reactive power compensation is an elegant solution for the power quality enhancement of RDN. The capacitors and distributed Flexible AC transmission system (D-FACTS) devices are employed for reactive power compensation. DSTATCOM is a powerful controller that can regulate the bus voltage by injection or absorption a reactive power at this bus. D-STATCOM constructed of voltage source converter (VSC) linked to DC bus which is coupled by a transformer and a harmonic filter.

Existing several algorithms have been employed to find the best placement and rating of D-STATCOM in RDS such as immune algorithm (IA), differential evolution (DE) algorithm, bat algorithm (BA), bacterial foraging optimization (PFA) algorithm, PSO algorithm, firefly algorithm (FA), using binary gravitational search algorithm (BGSA) etc.

II - LITERATURE SURVEY

Hung, et. al., (2013) presents three alternative analytical expressions, including two new expressions, to determine the optimum sizes and operating strategy of distributed generation (DG) units considering power loss minimization and a methodology to identify the best location. These expressions can be easily adapted to consider the renewable DG units (i.e., biomass, wind and photovoltaic) for minimizing energy losses. By considering time-varying demand and possible operating conditions of DG units. Its obtained on a 69-bus distribution test system demonstrate that the proposed approaches can be adequate to determine the location, size and power factor of DG unit for minimizing energy losses.

Eldery, et. al., (2007) presents, the dynamic models for adjustable speed drive (ASD) and distribution-static compensator (DSTATCOM). An eigen domain approach to the transient response investigation is formulated by means of variable in synchronously rotating reference frame to study the dynamic interactions between ASDs and DSTATCOM. Two inverter topologies of ASD, current source inverter and voltage source inverter, are included in the study as well as two control techniques of the DSTATCOM, namely voltage and current control.

H. Masdi, et. al., (2004) presents the design of a prototype distribution static compensator (D-STATCOM) for voltage sag mitigation in an unbalanced distribution system. The D-STATCOM is intended to replace the widely used static Var compensator (SVC). For fast response requirement, the feedforward compensation scheme is employed to enable the D-STATCOM to mitigate voltage sag and at the same time correct the power factor, thus acting as a load compensator.

III - SYSTEM IMPLEMENTATION

A. PROPOSED SYSTEM

The GWO algorithm imitates the leadership hierarchy and hunting mechanism of grey wolves in nature proposed, a random populations are produced then their positions are updated in path around the best obtained position. The process of GWO a three main steps of hunting, searching for prey, encircling prey and attacking prey are implemented. This work describes on grey wolf optimization for optimum allocation of STATCOM devices on power system grid to minimized load buses voltage deviations and system power losses. In this work, the best position of D-STATCOM is determined optimally in RDS using GWO. D-STATCOM is incorporated in RDS for real power losses reduction the voltage profile enhancement and the voltage stability improvement.

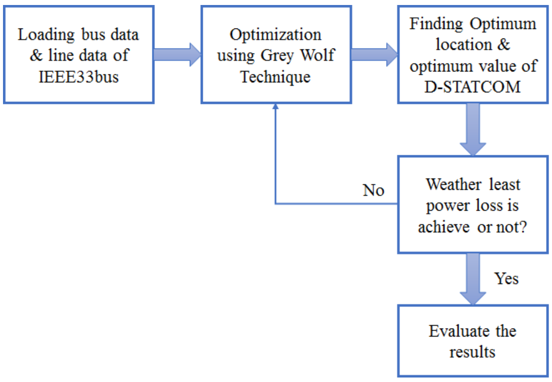

Fig .1 Proposed block diagram

B. SYSTEM CONSTRAINTS

The system constraints are categorized as follows:

1. Equality constraints

The active and reactive powers flow in RDS are considered the system equality constraints which can be represented as follows:

$$P_s = \sum_{h=1}^{n} P_D(h) + \sum_{j=1}^{nl} P_{loss}(j) \quad (1)$$

$$Q_s + \sum_{i=1}^{nc} Q_{DSTATCOM}(i) = \sum_{h=1}^{n} Q_D(h) + \sum_{j=1}^{n_l} Q_{loss}(j) \quad (2)$$

where, P_s is the supplied active power of the substation while Q_s denoted the supplied reactive powers at substation, respectively. P_D denoted the active load while Q_D denoted the reactive load, respectively. n_l represents number of transmission branches in RDS. *ns* is number of DSTATCOMs.

2. Inequality constraints

***a)* Bust voltage**

$$V_{min} \le V_i \le V_{max} \quad (3)$$

where, V_{min} denoted the lower voltage limit while V_{max} denoted the upper voltage limits.

***b)* D-STATCOM's reactive power**

The D-STATCOM's reactive power should equal or less than the reactive demand.

$$\sum_{i=1}^{nc} Q_{DSTATCOM}(i) \le \sum_{i=1}^{n} Q_D(i) \quad (4)$$

where, Q_D denoted the reactive load and $Q_{D-STATCOM}$ denoted the D-STATCOM's reactive power.

***c)* Transmission line loading**

$$I_k \le I_{max,k} \quad k = 1,2,3\ldots,Nb \quad (5)$$

C. SINE COSINE ALGORITHM (SCA)

SCA is a new population-based algorithm. The main concept of the optimization is generating set of populations randomly in iterative process around the best solution. The stochastic process is performed for exploration of SCA technique where the positions of populations are updated based on sine cosine functions around the best solution as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + C_1 \times \sin(C_2) \times |C_3 X_{best}^t - X_i^t| C_4 < 0.5 \\ X_i^t + C_1 \times \cos(C_2) \times |C_3 X_{best}^t - X_i^t| C_4 > 0.5 \end{cases} \quad (6)$$

where, t is the iteration x_i^{t+1} and x_i^t is the population positions at t^{th} and $(t+1)^{th}$ iteration at the i^{th} dimension, respectively. x_{best}^t is the best obtained position. C_2,C_3 and C_4 are random numbers in range [0, 1]. C_1 is adaptive parameter which is calculated as follows:

$$C_1 = k - t \times \frac{K}{T_{max}} \quad (7)$$

where, k represents a constant value. T_{max} denoted the maximum number of iterations. It should point out that Eq. (6) describes the main features of SCA as depicted in Fig. 3.2 which illustrates variation of position of populations around the best position based on variation of magnitude and phase angle in sine and cosine functions. C_1 adjusts the new followed position to move outward or inward the best position as shown in Fig. 3.3.

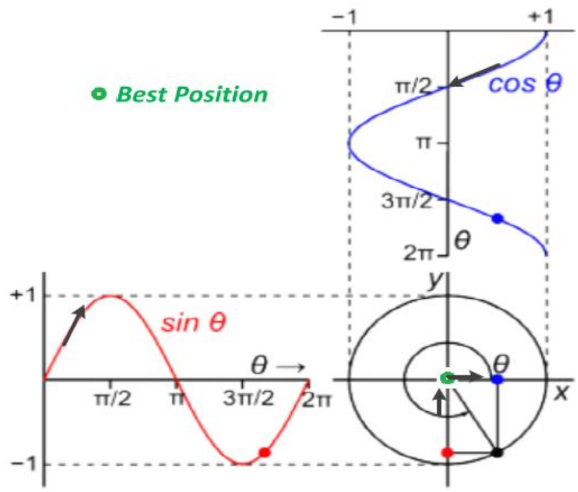

Fig .2 Motion of population around the best solution based on Sine Cosine functions.

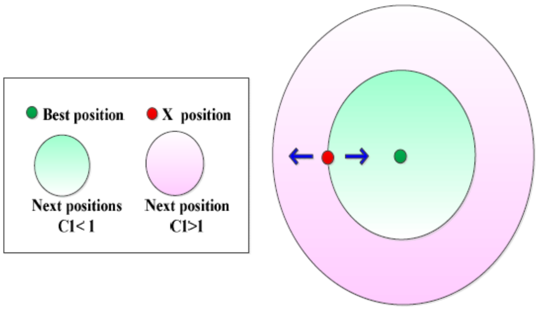

Fig .3 Direction of the next positions around the best positions based on C_1.

D. GREY WOLF OPTIMIZATION (GWO)

The GWO algorithm imitates the leadership hierarchy and hunting mechanism of grey wolves in nature proposed by Mirjalili et al. [14]. Grey wolves are considered to be at the top of food chain and they prefer to live in a pack. Four types of grey wolves such as alpha (α), beta (β), delta (δ), and omega (ω) are employed for simulating the leadership hierarchy. In order to mathematically model the social hierarchy of wolves while designing GWO, we consider the fittest solution as the alpha (α). Consequently, the second and third best solutions are named as beta (β) and delta (δ), respectively. The rest of the candidate solutions are assumed to be omega (ω). Fig. 3 shows three main steps of GWO algorithm, namely hunting, chasing and tracking for prey, encircling prey, and attacking prey which is implemented to design GWO for performing optimization.

In this section the inspiration of the proposed method is first discussed. Then, the mathematical model is provided.

i) Inspiration

Grey wolf (Canis lupus) belongs to Canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. The group size is 5–12 on average. Of particular interest is that they have a very strict social dominant hierarchy as shown in Figure 3.3.The leaders are a male and a female, called alphas. The alpha is mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alpha's decisions are dictated to the pack.

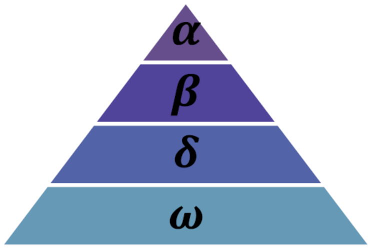

Figure .4 Hierarchy of grey wolf (dominance decreases from top down).

However, some kind of democratic behavior has also been observed, in which an alpha follows the other wolves in the pack. In gatherings, the entire pack acknowledges the alpha by holding their tails down. The alpha wolf is also called the dominant wolf since his/her orders should be followed by the pack [46]. The alpha wolves are only allowed to mate in the pack. Interestingly, the alpha is not necessarily the strongest member of the pack but the best in terms of managing the pack. This shows that the organization and discipline of a pack is much more important than its strength.

The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities. The beta wolf can be either male or female, and he/she is probably the best candidate to be the alpha in case one of the alpha wolves passes away or becomes very old. The beta wolf should respect the alpha, but commands the other lower-level wolves as well. It plays the role of an advisor to the alpha and discipliner for the pack. The beta reinforces the alpha's commands throughout the pack and gives feedback to the alpha.

The lowest ranking grey wolf is omega. The omega plays the role of scapegoat. Omega wolves always have to submit to all the other dominant wolves. They are the last wolves that are allowed to eat. It may seem the omega is not an important individual in the pack, but it has been observed that the whole pack face internal fighting and problems in case of losing the omega. This is due to the venting of violence and frustration of all wolves by the omega(s). This assists satisfying the entire pack and maintaining the dominance structure. In some cases the omega is also the baby sitters in the pack.

If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category. Scouts are responsible for watching the boundaries of the territory and warning the pack in case of any danger. Sentinels protect and guarantee the safety of the pack. Elders are the experienced wolves who used to be alpha or beta. Hunters help the alphas and betas when hunting prey and providing food for the pack. Finally, the caretakers are responsible for caring for the weak, ill, and wounded wolves in the pack.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. According to Muro et al. [47] the main phases of grey wolf hunting are as follows:

Tracking, chasing, and approaching the prey.

Pursuing, encircling, and harassing the prey until it stops moving.

Attack towards the prey.

These steps are shown in Figure 3.4 In this work this hunting technique and the social hierarchy of grey wolves are mathematically modeled in order to design GWO and perform optimization

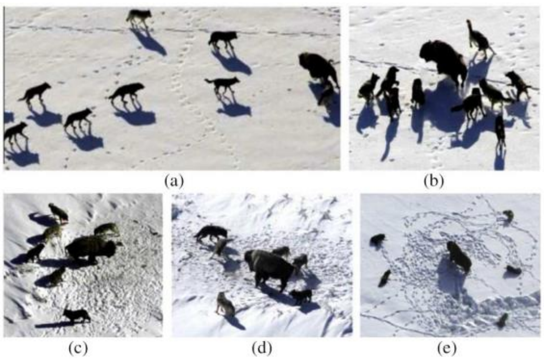

Figure .5 Hunting behavior of grey wolves: (a)–(c) chasing and tracking prey; (d) encircling prey; and (e) attacking prey.

ii) Mathematical Equations:

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha (a). Consequently, the second and third best solutions are named beta (b) and delta (d) respectively. The rest of the candidate solutions are assumed to be omega (x). In the GWO algorithm the hunting (optimization) is guided by a, b, and d. The x wolves follow these three wolves.

Grey wolves encircle a prey during the hunt and the encircling behavior can be modeled by the following equations:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \overrightarrow{X_p}(t)\right|$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D}$$

Where t denotes the current iteration, D, A, and C denote coefficient vectors, Xp is the position vector of the prey, and X indicates the position vector of grey wolf. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a}$$

$$\vec{C} = 2.\overrightarrow{r_2}$$

Where components of a linearly decreases from 2 to 0 during the course of iterations and r1, r2 are random vectors in [0, 1]. The hunt is usually guided by alpha called leaders followed by beta and delta which might also participate in hunting occasionally.

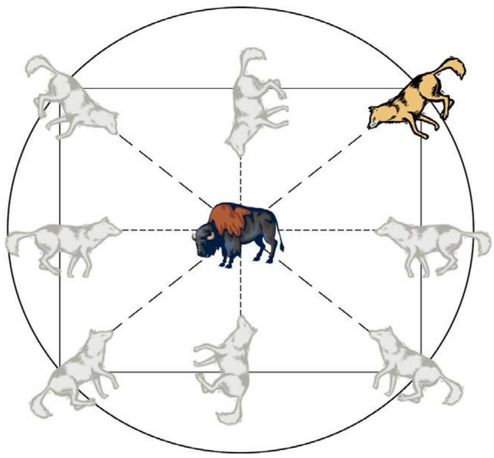

Figure .6 2D position vectors and their possible next locations

The pseudo code of the GWO algorithm is presented in Figure 3.6 To see how GWO is theoretically able to solve optimization problems, some points may be noted:

- The proposed social hierarchy assists GWO to save the best solutions obtained so far over the course of iteration.
- The proposed encircling mechanism defines a circle-shaped neighborhood around the solutions which can be extended to higher dimensions as a hyper-sphere.

- The random parameters A and C assist candidate solutions to have hyper-spheres with different random radii.
- The proposed hunting method allows candidate solutions to locate the probable position of the prey.
- Exploration and exploitation are guaranteed by the adaptive values of a and A.
- The adaptive values of parameters a and A allow GWO to smoothly transition between exploration and exploitation.
- With decreasing A, half of the iterations are devoted to exploration (|A|P1) and the other half are dedicated to exploitation (|A| < 1).
- The GWO has only two main parameters to be adjusted (a and C).

```
Initialize the grey wolf population Xi (i = 1, 2, ..., n)
Initialize a, A, and C
Calculate the fitness of each search agent
Xα=the best search agent
Xβ=the second best search agent
Xδ=the third best search agent
while (t < Max number of iterations)
    for each search agent
            Update the position of the current search agent by equation (3.7)
    end for
    Update a, A, and C
    Calculate the fitness of all search agents
    Update Xα, Xβ, and Xδ
    t=t+1
end while
return Xα
```

Figure 3.6 Pseudo code of the GWO algorithm

There are possibilities to integrate mutation and other evolutionary operators to mimic the whole life cycle of grey wolves. However, we have kept the GWO algorithm as simple as possible with the fewest operators to be adjusted. Such mechanisms are recommended for future work.

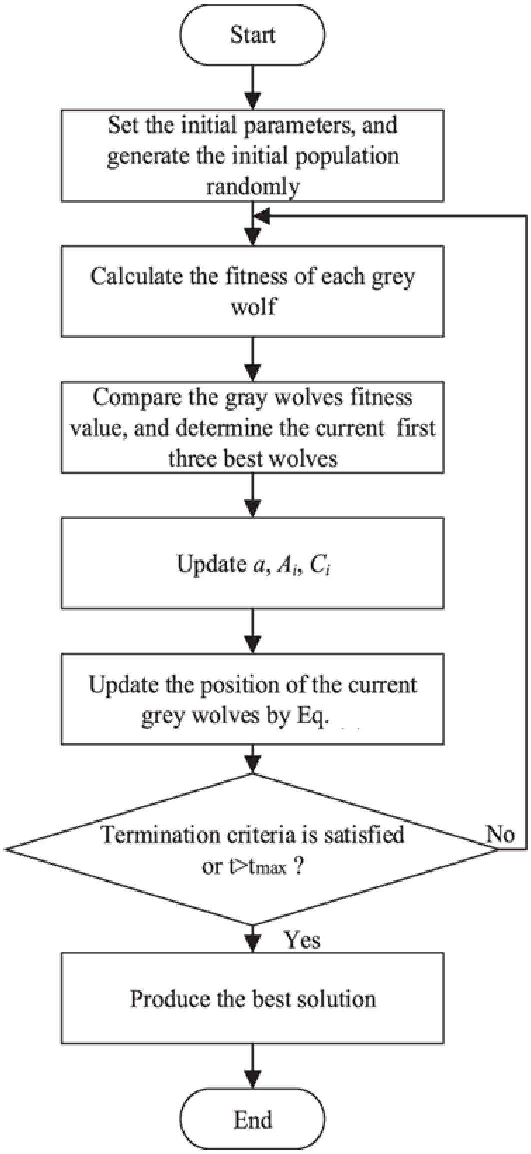

Fig .7 Flow chart of GWO

IV - RESULTS AND DISCUSSION

In this project, the numerical results are presented to realize the impact of incorporating of D-STATCOM optimally by the proposed algorithm. The program code was written by MATLAB 2014a software platform. The GWO is applied on IEEE85-bus system.

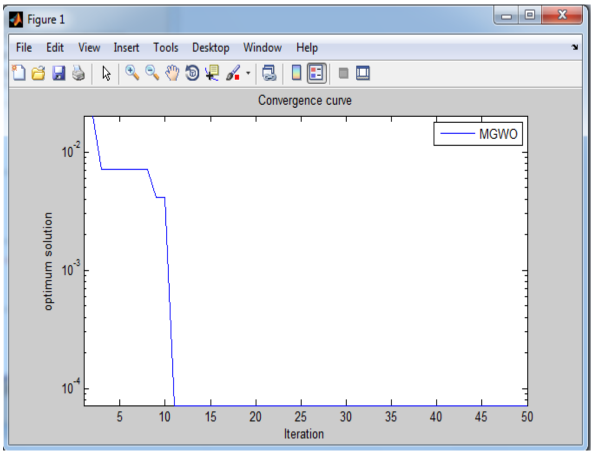

Fig .8 Convergence curve of MSCA

The following figure 4.2 represents the bus voltage in per unit with MSCA based D-statcom and with MGWO based D-statcom. In this figure x-axis takes bus number and y-axis takes bus voltage.

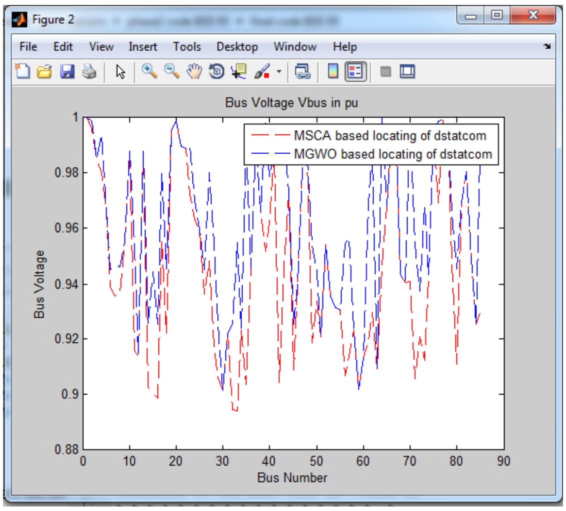

Fig .9 Bus voltage

The following figures 4.3 & 4.4 shows the comparison of real and reactive power losses with D-statcom and without D-statcom. In this figures red color indicate the real and reactive power loss with dstatcom. Green color indicates real and reactive power losses without dstatcom. Dark Blue color indicates MSCA based real and reactive power locating of dstatcom. Sky Blue color indicates MGWO based real and reactive power locating of dstatcom.

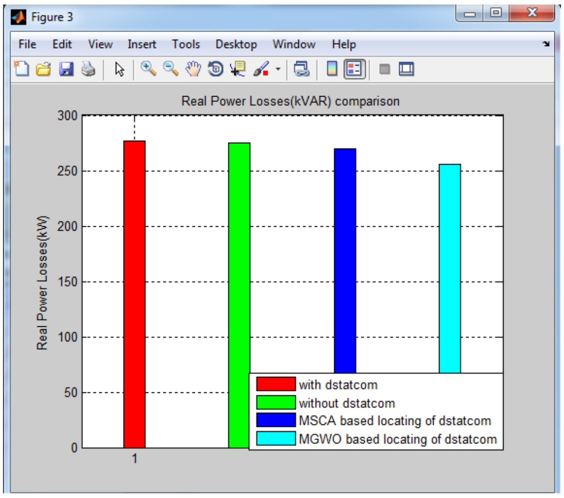

Fig .10 Comparison of real power losses (kVAR)

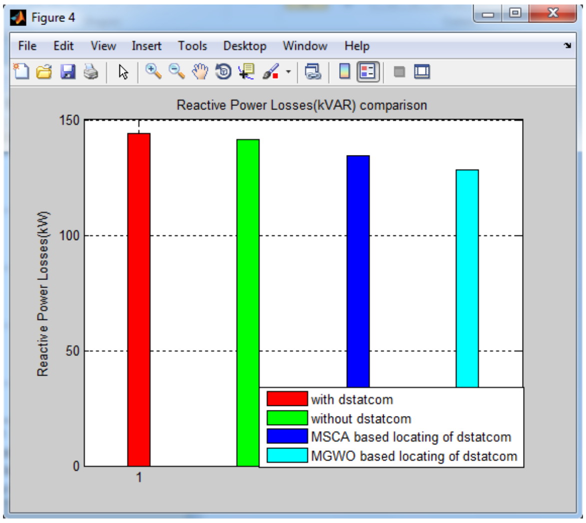

Fig .11 Comparison of Reactive power losses (kVAR)

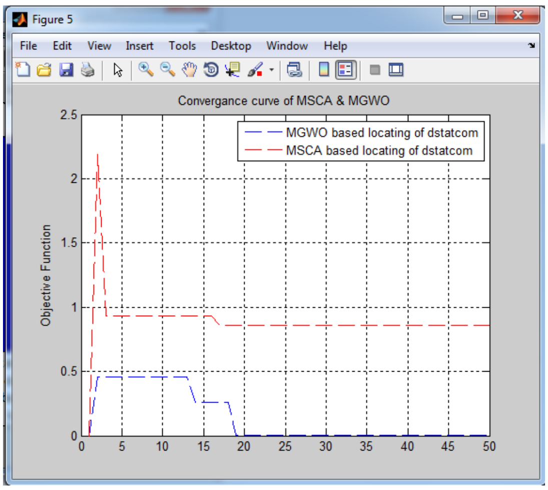

Fig .12 Convergence curve of MSCA & MGWO

The above figure 4.5 shows the convergence curve of MSCA (Modify Sine cosine algorithm) and

MGWO (Modified Grey Wolf Optimization). In this figure x-axis represents the no. of iteration and y-axis represents the objective function. The objective function of MSCA based locating dstatcom is 2.2. The objective function of MGWO based locating of dstatcom is 0.45.

V - CONCLUSION

The optimal integration of D-STATCOMs in RDS has been solved using a GWO technique. GWO algorithm is based on the leadership hierarchy and hunting mechanism of grey wolves. This work describes on grey wolf optimization for optimum allocation of STATCOM devices on power system grid to minimized load buses voltage deviations and system power losses. The GWO is tested on IEEE85-bus system. The results showed that incorporating DSTATCOM optimally can diminishes the active power losses, enhance the voltage profile and improve the voltage stability, considerably. Moreover, GWO was better than SCA for optimal integration of the D-STATCOM in term of objective function and its convergence characteristic.

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