Expansion Planning in Distribution Network With DSTATCOM Using Distance-Oriented Grasshopper Optimization Algorithm: An Optimal Model

Adep Sateesh Kumar, Vaagdevi College of Engineering, Warangal, India*
K. Prakash, Vaagdevi College of Engineering, Warangal, India

ABSTRACT

This paper intends to consider a multi-objective problem for expansion planning in power distribution systems (PDS) by focusing on (1) expansion strategy, (2) allocation of circuit breaker (CB), (3) allocation of distribution static compensator (DSTATCOM), (4) contingency load loss index (CLLI), and (5) power loss. Accordingly, the encoding parameters for expansion, circuit breaker (CB) placement, DSTATCOM placement, load of real and reactive powers of expanded bus or node are optimized using grasshopper optimization algorithm (GOA) based on its distance, and hence, the proposed algorithm is termed distance-oriented grasshopper optimization algorithm (DGOA). The proposed expansion planning model is carried out in IEEE 33 test bus system. Moreover, the adopted scheme is compared with conventional algorithms, and the optimal results are obtained.

KEYWORDS

Circuit Breaker, Expansion Planning, Power Distribution System

1. INTRODUCTION

Expansion planning of distribution networks looks for the most excellent reinforcement plans when reducing the overall cost that are subjected to numerous reliability and functioning constraints (Xie, et al., 2018; Kumar & Samantaray, 2016). It exists as a complex problem for numerous decades to find out an improved solution. Distribution Expansion Planning (DEP) (Hosseinnejad, et al., 2018; Kumawat, et al., 2018) is a significant problem in developing countries (Cofini, et al., 2012), where the electricity requirement has been advancing up in current years (Brajula and Prasad, 2018; Chithra and Kumari, 2018). On the other hand, noteworthy efforts in energy management dominion have damped the growing rate of electricity requirement in recent times (Mahdavi, et al., 2018; Humayd & Bhattacharya, 2017). However, the necessitation for a continuous expansion appears unavoidable in the near future. Expansion planning (EP) (Lin & Bie, 2018; Ahmadigorji, et al., 2017) of distribution network comprises of capacity determination, installation of distribution substation units, mounting
Distributed Generation (DG) units (Chen, et al., 2015; Najafi, et al., 2018), and substitution of distribution feeders to deal with upcoming increasing load demand. This is known as Multi-Stage DEP (MDEP) issue (Mauro, et al., 2018) (Emmanuel, et al., 2017; Moradijoz, et al., 2018), which can be manipulated as a nonlinear problem concerning several local optimum solutions. Three phase Distribution Static Compensator (DSTATCOM) (Liu, et al., 2018; Yuvaraj, et al., 2017) is exploited for power factor enhancement, load balancing and harmonic removal in three-phase system with the nonlinear and linear load. The performance of DSTATCOM (Taher & Afsari, 2014; Devabalaji & Ravi, 2016) is based on the assortment of control schemes and models. Numerous algorithms are available for obtaining the reference source currents for controlling the DSTATCOM (Jazebi, et al., 2011; Sundarabalan & Selvi, 2014; Singh & Yadav, 2018).

Nowadays, the distribution networks are implemented with novel control equipments like; DGs. Deployment of local DGs by utility customers directs to avoid needless expansion of distribution networks together with more proficient use of the prevailing networks. In addition, DG (Singh & Mishra, 2018) provides several advantages like, raise in reliability levels (Arachchige and Sathsara, 2020). Moreover, exploitation of DGs can have an effect on the network power losses owing to its proximity to the load centers. As a result, optimal sizing of DG (Gupta & Kumar, 2016a; Gupta & Kumar, 2016b) units have to be involved as a part of the MDEP crisis.

Certain classical schemes for single or multistage modeling issues have been resolved to model an optimal PDS (Gupta & Kumar, 2018). However, the problem formulation only regarded the reduction of an objective function indicating power system expansion costs so as to resolve the optimal locating and sizing problems for the feeder of the Distribution System (DS). In addition, the research work has concerned on simple linear objective function to signify the actual non-linear expansion costs that lead to inappropriate demonstrations of the real costs. Certain heuristics dependent algorithms implemented for these planning issues are Genetic Algorithm (GA), Tabu search, etc. Additional powerful heuristics dependent schemes, effectively exploited in several complex issues, is the Particle Swarm Optimization (PSO). In addition, Multi-Objective Evolutionary Algorithms (MOEAs) have also been deployed that is found appropriate for PDS planning problems (Gupta & Kumar, 2016c; Taher & Karimi, 2014).

The paper contributes a multi-objective problem for expansion planning of DS by concerning on (i) expansion strategy (ii) allocation of CB, (iii) allocation of DSTATCOM (iv) CLLI and power loss. Here, the encoding constraints decides for expansion, CB placement, DSTATCOM placement, load of reactive and real powers of expanded bus or node are optimized by means of proposed DGOA. In addition, the adopted scheme is compared with traditional approaches, and the optimal outcomes are attained. Furthermore, the proposed model is carried out in IEEE 33 test bus system, and it is compared with conventional models such as Artificial Bee Colony (ABC), PSO, FireFly (FF), Grey Wolf Optimization (GWO) and GOA and the results are obtained.

2. LITERATURE REVIEW

2.1 Related Works

Xie, et al., (2018) have introduced a new multi-objective design of active distribution network planning depending on the Uncertain Random Network (URN) concept. The planning design was suggested to discover the last scheme with optimal location, size, alternative and functioning policies. With the intention of attaining the reduction of total cost and assortment of a Minimum Spanning Tree (MST) with random and uncertain weight, a 3-dimensional uncertain space was constructed. Finally, the simulation was carried out, and the outcomes reveal the efficiency of the introduced model.

Kumar & Samantaray (2016) have established a scheme depending on a Multi-objective Seeker-Optimization-Algorithm (MOSOA) for modeling a sophisticated PDS together with DSTATCOM. The established planning method exploits a CLLI for reliability assessment that was independent of
the fault repair duration and failure rate, which is hard to attain in practice. In addition, a qualitative assessment demonstrates the effectiveness of the introduced planning approach. Finally, the simulated results demonstrate the accuracy and effectiveness of the introduced technique.

Hosseinzadeh, et al., (2018) have adopted a comprehensive architecture for optimal day-ahead functional planning of smart DS, taking into account of both emergency and normal circumstances. The introduced process for normal mode reduces the functioning costs and offers sustainability by means of the seamlessness index. The suggested architecture was executed and was analyzed via diverse case studies. Finally, the outcome of case studies reveals noteworthy developments and benefits that were attained by deploying the adopted architecture.

Kumawat, et al., (2018) have presented a Modified Group experience of Teaching Learning Based Optimization approach that can handle with the allotment of DERs in distorted and non-distorted networks. Moreover, the presented algorithm was employed to DER planning in view of harmonics producing loads in certain test systems. Finally, the outcomes with linear and non-linear loads on the entire test systems demonstrate that the presented approach can be a robust model to improve the performance of the system with better loading characteristics.

Mahdavi, et al., (2018) have suggested a two-level planning approach together with long term and short term planning. The long-term planning installs Energy Storage System (ESS) and diesel DGs on the network. The planning optimizes several design parameters simultaneously together with the location and size of diesel DGs and ESSs. At last, the results exhibit that the suggested two-level planning can efficiently decrease losses and cost and it also raises the performance and efficiency of the network.

Humayd & Bhattacharya, (2017) have offered a wide-ranging long-term distribution planning architecture from the viewpoint of Local Distribution Companies (LDCs) regarding substations, DG, feeders, and capacitors. Rather than considering the common demand profile, the offered framework regards controlled and uncontrolled PEV charging demand in addition to Demand Response (DR) choices. It is observed from the analysis that the existence of uncontrolled PEV charging loads consequence in much-increased plan costs when distinguished to the case with no PEVs and therefore, these loads certainly require to be regarded in the planning process.

Lin & Bie (2018) has presented a scheme to enhance the power system resilience. A tri-level Defender-Attacker-Defender (DAD) design was constructed to discover the best consolidating plan under malicious attacks when the available operational restoration and defending resources measures were available for a DS. The DAD issue was created as a tri-level mixed-integer optimization crisis, and the Column Constraint Generation (CCG) technique was offered to attain the optimal solution precisely.

Ahmadigorji, et al., (2017) have introduced a novel scheme for Multiyear Expansion Planning of DS’s (MEPDS). The introduced MEPDS design optimally indicates the expansion schedule of DS’s together with reinforcement design of distribution feeders together with sizing and location of DGs throughout a particular planning perspective. With the intention to resolve the offered MEPDS model as a complex multi-dimensional optimization issue, a novel two-stage solution model was also proposed, and the optimal results were attained.

2.2 Review

Table 1 shows the methods, features, and challenges of conventional techniques based on the planning of DS networks. At first, Mixed-Integer Nonlinear Programming (MINLP) was adopted in (Xie, et al., 2018) that offers reduced energy loss, and it also offers better cost-efficiency. However, there was no contemplation on convergence speed. Similarly, Seeker-Optimization (SO) algorithm was suggested in (Kumar & Samantaray, 2016), which provides improved accuracy and efficiency along with better reliability, but the cost increases with an increase in the number of feeders. Island partitioning was implemented in (Hosseinzadeh, et al., 2018) that solve the uncertainties, and it also offers a reliable supply of power. Anyhow, there were possibilities of an unmanageable optimization
crisis. In addition, teaching learning-based optimization was presented in (Kumawat, et al., 2018) that improve the performance of the system. It was a robust model but, the load scaling factor increases with distortion level. Modified PSO (MPSO) scheme was adopted in (Mahdavi, et al., 2018), which offers minimized cost as well as enhanced efficiency. However, there was no consideration on hybrid ESS. Moreover, MINLP was proposed in (Humayd & Bhattacharya, 2017), which offered better PEV penetration and enhanced charging efficiency, anyhow, there was an increased CPU time per iteration. DAD model was presented in (Lin & Bie, 2018), which improves the capability to respond. Advanced system reliance. However, there was no detailed designing of manmade attacks. Finally, MEPDS was proposed in (Ahmadigorji, et al., 2017), which reduces the total investment cost and satisfies numerous operational parameters, however, the method was more complex. There, these limitations have to be considered for improving the planning of DS networks effectively in the current research work.

### 3. DESIGNING OF DSTATCOM

DSTATCOM is addressed by a synchronous voltage source and its shunt connected transformer. The power flow formulations for the DSTATCOM (Gupta & Kumar, 2018) are attained from initial standards and the bus $k$, voltage source, $E$ is given by Eq. (1):

$$E_{v_R} = V_{v_R} \left( \cos \delta_{v_R} + j \sin \delta_{v_R} \right)$$

(1)

Depending on the shunt connection, Eq. (2) can be formulated:
\[ S_{\text{vR}} = V_{\text{vR}} I_{\text{vR}} = V_{\text{vR}} Y_{\text{vR}} \left( V_{\text{vR}}^* - V^* \right) \]  

(2)

After carrying out certain multifaceted functions, the following reactive and active power equations are obtained for the bus \( k \) and converter, correspondingly:

\[ P_{\text{vR}} = V_{\text{vR}}^2 G_{\text{vR}} + V_{\text{vR}} V_k \left[ G_{\text{vR}} \cos (\delta_{\text{vR}} - \theta_k) + B_{\text{vR}} \sin (\delta_{\text{vR}} - \theta_k) \right] \]  

(3)

\[ Q_{\text{vR}} = -V_{\text{vR}}^2 B_{\text{vR}} + V_{\text{vR}} V_k \left[ G_{\text{vR}} \sin (\delta_{\text{vR}} - \theta_k) - B_{\text{vR}} \cos (\delta_{\text{vR}} - \theta_k) \right] \]  

(4)

\[ P_k = V_k^2 G_{\text{vR}} + V_k V_{\text{vR}} \left[ G_{\text{vR}} \cos (\theta_k - \delta_{\text{vR}}) + B_{\text{vR}} \sin (\theta_k - \delta_{\text{vR}}) \right] \]  

(5)

\[ Q_k = -V_k^2 B_{\text{vR}} + V_k V_{\text{vR}} \left[ G_{\text{vR}} \sin (\theta_k - \delta_{\text{vR}}) - B_{\text{vR}} \cos (\theta_k - \delta_{\text{vR}}) \right] \]  

(6)

By exploiting these power formulations, the linearized DSTATCOM design is depicted here, in which the phase angle \( \delta_{\text{vR}} \) and voltage magnitude \( V_{\text{vR}} \) are considered as the state constraints. The entire Jacobian constituent in Eq. (7) (Acha, et al., 2014), where, \( \theta_k \) refers to the voltage bus angle at bus \( k \), \( vR \) indicates the variable source, \( \delta_{\text{vR}} \) denotes the voltage angle of DSTATCOM and \( V_{\text{vR}} \) points out the fundamental output voltage of DSTATCOM. Also, \( V_k \) refers to the voltage magnitude at bus \( k \), \( P_{\text{vR}} (Q_{\text{vR}}) \) denotes the reactive and active power generation by DSTATCOM at bus \( k \) and \( Z_{\text{vR}} \) indicates the impedance of shunt connected transformer at bus \( k \):

\[
\begin{bmatrix}
\Delta P_k \\
\Delta Q_k \\
\Delta P_{\text{vR}} \\
\Delta Q_{\text{vR}}
\end{bmatrix} =
\begin{bmatrix}
\frac{\partial P_k}{\partial \theta_k} V_k & \frac{\partial P_k}{\partial V_k} & \frac{\partial P_k}{\partial \delta_{\text{vR}}} V_{\text{vR}} & \frac{\partial P_k}{\partial V_{\text{vR}}} V_{\text{vR}} \\
\frac{\partial Q_k}{\partial \theta_k} V_k & \frac{\partial Q_k}{\partial V_k} & \frac{\partial Q_k}{\partial \delta_{\text{vR}}} V_{\text{vR}} & \frac{\partial Q_k}{\partial V_{\text{vR}}} V_{\text{vR}} \\
\frac{\partial P_{\text{vR}}}{\partial \theta_k} V_k & \frac{\partial P_{\text{vR}}}{\partial V_k} & \frac{\partial P_{\text{vR}}}{\partial \delta_{\text{vR}}} V_{\text{vR}} & \frac{\partial P_{\text{vR}}}{\partial V_{\text{vR}}} V_{\text{vR}} \\
\frac{\partial Q_{\text{vR}}}{\partial \theta_k} V_k & \frac{\partial Q_{\text{vR}}}{\partial V_k} & \frac{\partial Q_{\text{vR}}}{\partial \delta_{\text{vR}}} V_{\text{vR}} & \frac{\partial Q_{\text{vR}}}{\partial V_{\text{vR}}} V_{\text{vR}}
\end{bmatrix}
\begin{bmatrix}
\Delta \theta_k \\
\Delta V_k \\
\Delta \delta_{\text{vR}} \\
\Delta V_{\text{vR}}
\end{bmatrix}
\]  

(7)

3.1 Problem Formulation

The problem formulation for expansion of bus or node in power system considers five constraints namely, expansion, CB, DSTATCOM, load of real and reactive power of expanded node.

- **Expansion Strategy**: The expansion planning is exploited for determining the type, capacity and location of novel equipments, which have to be expanded or added to the system, for e.g.
33 conductors (additional) for IEEE 33 test bus system. The expansion configuration involves issues of minimizing cost that is subject to technical factors. The specification of conductor sizes is given in Table 2. Here, six types of conductors are exploited, namely, turkey, swan, sparrow, raven, pigeon, and penguin. The conductors are connected from each bus, for instance, each bus or node is expanded from IEEE 33 test bus system.

- **Circuit Breaker:** CB is a switching device, which breaks off the abnormal fault or current. It is a mechanical tool, which interrupts the flow of high fault current and moreover, it carries out the operations of a switch. The CB is chiefly modeled for the opening or closing of an electrical circuit. Therefore it looks after the electrical system from spoilage. Here, three types of CB’s are exploited as shown in Table 3. The first type of CB includes a short circuit current rating of 25kA with a cost of 20000$; the second type of CB includes a short circuit current rating of 35kA with a cost of 40000$ and the third type of CB includes a short circuit current rating of 50kA with a cost of 60000$. The allocation CB can be in line of expanded nodes in addition to the existed nodes.

- **DSTATCOM:** A D-STATCOM is exploited to control the voltage on a distribution network. It is a compensating device that is deployed to regulate the reactive power flow in the DS. DSTATCOM can be efficiently exploited to develop the supremacy of power distributed to the customers. Here, the number of possible DSTATCOM’s ($N_D$) are three, i.e. $N_D = 3$. The DSTATCOM can be located based on the expansion of the DS, i.e., in line of expanded nodes in addition to the existed nodes similar to the placement of CB.

- **Load of expanded real power ($P$):** The portion of power flow, which outcomes in net transfer of energy in a certain direction is termed as real power. The limits of the load of real power for the expanded nodes should ranges from $P_{\text{min}}$ to $P_{\text{max}}$, i.e. $P \in (P_{\text{min}}, P_{\text{max}})$.

- **Load of expanded reactive power ($Q$):** It prevails in an AC circuit when the voltage and current were not in phase. The limits of a load of real power for the expanded node ranges from $Q_{\text{min}}$ to $Q_{\text{max}}$, i.e. $Q \in (Q_{\text{min}}, Q_{\text{max}})$.

![Table 2. Types of conductors, its size and current rating](image)

| Type of conductor | Size (kcmil) | Current rating (A) |
|-------------------|--------------|--------------------|
| Turkey            | 6            | 105                |
| Swan              | 4            | 140                |
| Sparrow           | 2            | 184                |
| Raven             | 1/0          | 242                |
| Pigeon            | 3/0          | 315                |
| Penguin           | 4/0          | 357                |

![Table 3. Types of circuit breaker with short current rating and cost](image)

| CB type | Short circuit current rating (kA) | Cost for installation ($) |
|---------|----------------------------------|---------------------------|
| 1       | 25                               | 20000                     |
| 2       | 35                               | 40000                     |
| 3       | 50                               | 60000                     |
3.2 Reliability Index

The proposed model comprises of a CLLI-dependent reliability index that could be described as “the ratio of the average of non-delivered load due to failure of all branches, taken one at a time, to the total load”. The benefit of CLLI is that the data concerning the failure rate and the duration for fault repair of the feeder branches are not necessary to calculate CLLI, while the majority of the system performance indices are computed as the weighted averages of the fundamental load point indices (fault repair interval and failure rate). CLLI is evaluated on considering the entire single contingency events.

The CLLI can be evaluated based on the steps given below:

**Step 1:** Let \( i = 1 \) (branch number).

**Step 2:** Get from bus and to bus for the \( i^{th} \) line.

\[
U \left[ U \quad P(to\ bus) \right] \text{// Real power of to bus}
\]

**Step 3:** Determine all lines, where to bus become from bus.

**Step 4:** Get all those “to buses”.

**Step 5:** Follow step 3 till no “to bus become from bus”.

**Step 6:** \( UDL_i \leftarrow \text{sum}(U) \).

**Step 7:** If \( i \leftarrow i + 1 \), go to step 2.

\[
CLLI = \frac{\sum_{i=1}^{N_f} UDL_i / N_f}{L_{Total}}
\]

(8)

where, \( UDL_i \) indicates the non delivered load owing to a fault in the branch \( i \), \( N_f \) indicates the number of feeders, \( UDL_{avg} \) denotes average non delivered load, and \( L_{Total} \) refers to the total load in kVA. The happening of concurrent contingencies, such as concurrent faults in several branches, are not taken into account in this planning task as the occurrence frequency of such faults are much smaller for any realistic DS.

3.3 Solution Encoding

The constraints such as expansion, CB, DSTATCOM, load of real power and reactive power of expanded bus are given as solutions for encoding. The diagrammatic representation of the solution encoding model is given in Fig. 1. The length of the chromosome is determined by summing the length of five gene sets. The solution with all these constraints is collectively represented as \( O \).

3.4 Solution Decoding

The solution decoding of the considered parameters are depicted in this section.
In gene set 1, i.e. in expansion planning, extra node or bus will be connected to the existing nodes and accordingly, line or branch will be formed for each expanded nodes or buses. For, instance, from Fig. 2, it can be noted that, the first bus has not been expanded, the second bus has been expanded to form the 5th node using 2nd type of semiconductor. Also, the third bus has not been expanded and the fourth bus has been expanded to form the sixth node using 3rd type of semiconductor. The total length of gene set 1 is given by $N_F^E$, which is described as the number of the extended node. For example, 33 for IEEE 33 test bus system.

For gene set 2, the allocation of three types of CB’s are concerned, as given by Fig.3. From Fig. 3, it can be noted that CB of type 1 has been connected to line 1 and CB of type 3 has been connected to line 2 and for 3rd branch, no CB’s are connected, and CB of type 2 has been connected to line 4 and for 5th branch, no CB’s are connected. The length of gene set 2 is $N_F^C$, which is the sum of existed lines and the number of expanded nodes.

The third set of genes, i.e. DSTATCOM has been allocated between the lines is given by Fig. 4. From Fig.4, it can be observed that DSTATCOM of type 1 has been connected to line 1 and DSTATCOM of type 3 has been connected to line 2 and no DSTATCOM has been connected to line 3, DSTATCOM of type 2 has been connected to line 4 no DSTATCOM has been connected to line 5. The length of gene set 2 is $N_F^D$, which is the sum of existed lines and the number of expanded nodes.

Similarly, on considering, gene set 4 and 5, the expanded bus index is considered as given by Fig. 5. The powers such as 50, 10, 10 and 30 are randomly taken within limits as per the description given above. As per gene set 1, only two expansions, i.e. at 2, the expanded node is 5 and at 4, the
expanded node is 6. Hence, $P$ of expanded node 5 is 10 and 6 is 30. The same concept is taken for reactive power. The length of gene set 4 and 5 is $N_F^L$, which is the number of expanded buses.

4.OPTIMIZATION ALGORITHM FOR THE ATTAINMENT OF DESIRED OBJECTIVES

4.1 Objective Function

The objective function includes the minimization of expansion cost, CB cost, DSTATCOM cost as given by Eq. (9), Eq. (10) and Eq. (11), respectively. In Eq. (9), $C_E$ indicates the expansion cost and $g_i$ refers to the $i^{th}$ gene, where $\psi g_i = \begin{cases} 1 & \text{if } g_i > 0 \\ 0 & \text{otherwise} \end{cases}$ and $C(g_i)$ indicates the expansion cost of $g_i$.

In Eq. (10), $C_{CB}$ indicates the CB cost and $C_{cb}(g_i)$ indicates the CB cost of $i^{th}$ gene. Also, in Eq. (11), $C_D$ indicates the DSTATCOM cost, and $C_d(g_i)$ specifies the DSTATCOM cost of $i^{th}$ gene:

$$C_E = C^e(g_i) \times \psi g_i$$  \hspace{1cm} (9)

$$C_{CB} = C^b(g_i) \times \psi g_i$$  \hspace{1cm} (10)

$$C_D = C^d(g_i) \times \psi g_i$$  \hspace{1cm} (11)
The overall fitness function is given by Eq. (12), which has to be maximized from the minimum function. In Eq. (12), $C_{E_{Max}}$, $C_{CB_{Max}}$, $C_{D_{Max}}$, $C_{CLLI_{Max}}$ and $C_{P_{Loss_{Max}}}$ denotes the maximum cost of expansion, CB, DSTATCOM, CLLI and real power loss, respectively. Also, $C_{E_{Min}}$, $C_{CB_{Min}}$, $C_{D_{Min}}$, $C_{CLLI_{Min}}$ and $C_{P_{Loss_{Min}}}$ refers to the minimum cost of expansion, CB, DSTATCOM, CLLI and real power loss, respectively. $P_{Loss}$ is considered after load flow analysis for updated bus data:

$$Max \leftarrow \text{Fit} = \text{Min} \begin{bmatrix}
C_{E_{Max}} - C_{E_{Min}} & C_{CB_{Max}} - C_{CB_{Min}} & C_{D_{Max}} - C_{D_{Min}} \\
C_{CLLI_{Max}} - C_{CLLI_{Min}} & C_{P_{Loss_{Max}}} - C_{P_{Loss_{Min}}}
\end{bmatrix}$$

$$\text{(12)}$$

4.2 Grasshopper Optimization Algorithm

GOA (Saremi, et al., 2017) is a heuristic search and optimization technique enthused by the swarming behaviour of grasshoppers. This technique could be exploited for resolving the optimization issues depending on the performance of grasshopper swarms in nature. There are two major features of the swarm, namely, the seeking of food source and its movement. Usually, the search procedure is separated into two phases namely, the exploration and the exploitation phases. In the exploration phase, the search agents are optimistic to shift suddenly and whilst in the exploitation phase, the search agents shifts locally. As a result, these two operations in addition to the target seeking procedures, are carried out by the grasshoppers in nature. Therefore on the basis of this behaviour, a novel nature-inspired algorithm recognized as GOA is implemented (Saremi, et al., 2017).

The arithmetical representation to reveal the swarming behaviour of the grasshopper is revealed in Eq. (13), in which $O_i$ indicates the $i^{th}$ grasshopper position, $I_i$ signifies the social interaction, $F_i$ denotes the gravity force on the $i^{th}$ grasshopper, and $W_i$ points out the wind advection:

$$P_i = I_i + F_i + W_i$$

For generating an arbitrary behaviour, Eq. (3) can be modified as shown in Eq. (14), in which $n_1$, $n_2$, $n_3$ are the arbitrary numbers that lies in the interval $[0, 1]$:

$$O_i = n_1I_i + n_2F_i + n_3W_i$$

$$\text{(14)}$$

Eq. (15) depicts the social interactions, in which $a_{ij}$ denotes the distance among $i^{th}$ and $j^{th}$ grasshopper, and it can be evaluated as $a_{ij} = |y_j - y_i|$, and $\hat{a}_{ij} = \frac{y_j - y_i}{a_{ij}}$ indicates a unit vector from the $i^{th}$ grasshopper to the $j^{th}$ grasshopper:

$$I_i = \sum_{j=1}^{M} r(a_{ij})\hat{a}_{ij}$$

$$\text{(15)}$$
Eq. (16) portrays the strength of social forces \( r \), in which \( g \) indicates the attraction intensity and \( l \) indicates the attractiveness concerning the length scale:

\[
r(q) = ge^{-\frac{q}{l}} - e^{-q}
\]  

The distance between the two grasshoppers is assigned in the range \([1, 4] \). Therefore the \( F \) factor in Eq. (13) could be evaluated as revealed in Eq. (17), in which \( g \) denotes the gravitational constant and \( \hat{e}_u \) reveals a unity vector towards the centre of the earth:

\[
F_i = -g \hat{e}_u
\]  

The \( W \) factor in Eq. (13) could be evaluated as revealed in Eq. (18), in which \( v \) denotes a constant drift and \( \hat{e}_w \) signifies a unity vector in the wind direction:

\[
W_i = v \hat{e}_w
\]  

On replacing the values of \( I \), \( W \) and \( F \) in Eq. (13), it can be extended as in Eq. (19), in which \( M \) indicates the grasshopper count:

\[
O_{ij} = \sum_{j=1}^{M} r\left(y_j - y_i\right) \frac{y_j - y_i}{a_{ij}} - g \hat{e}_u + v \hat{e}_w
\]  

Anyhow, this representation could not be exploited directly to resolve the optimization issues, as the grasshoppers arrive at the comfort zone very rapidly and therefore, the swarm will not join to a certain point. Therefore Eq. (19) could be adapted so as to resolve the optimization issue as given in Eq. (20), in which \( lb \) and \( ub \) denotes the lower and upper bound in the \( A^b \) dimension. \( T_a \) denotes the value of \( A^b \) dimension in the target and \( c \) indicates the lessening coefficient to minimize the repulsion zone, attraction zone and comfort zone. Eq. (20) indicates the subsequent position of the grasshopper depending on its current position, the target position and all other grasshoppers.

\[
O_i^a = c \left( \sum_{j=1}^{M} e \frac{ub - lb}{2} r\left(y_j^a - y_i^a\right) \frac{y_j - y_i}{a_{ij}} \right) + T_a
\]  

Accordingly, for balancing the exploitation and the exploration phase, the constraint \( c \) has to be minimized with regards to the count of iteration and it can be portrayed in Eq. (21), in which \( cmx \) is the utmost value and \( cmn \) denotes the least value, \( t \) denotes the present iteration, and \( L \) indicates the highest count of iterations:

\[
c = cmx - t \frac{cmx - cmn}{L}
\]
Here, the major target is the optimum global value and therefore in every step of optimization, the target for grasshopper has to be established. The value with the finest objective function is regarded as the target value in GOA. Moreover, the more precise target is selected as the optimum global value in the search space.

4.3 Proposed DGOA Algorithm

Despite of the interesting facts of the GOA approach, it includes certain disadvantages such as slow rate of convergence and low precision. Hence to overcome such limitations, the position update of the proposed DGOA is modified in distance computation using a variable as shown in Eq. (22), where \( Q \) is a random variable. Initially, the average position and fitness are determined based on taking mean of position and fitness of all solutions. If the average fitness is greater than the current fitness, \( Q \) will be updated based on the Eq. (23), in which \( U_b \) indicates the upper bound and if average fitness is lesser than the current fitness, \( Q \) will be updated based on the Eq. (24):

\[
O_i^e = c \left( \sum_{j=1}^{u} \frac{ub_j - lb_j}{2} r \left( y_i^e - y_i^e \right) \frac{y_j^e - y_i^e}{a_q + Q} \right) + \hat{T}_a
\]

\[
Q = \text{Abs}(\text{Average position} - U_b) / 8
\]

\[
Q = \text{Abs}(\text{Average fitness} - L_b) / 8
\]

5. RESULTS AND DISCUSSION

5.1 Simulation Procedure

The proposed DGOA algorithm for expansion planning was simulated in MATLAB, and the outcomes were attained. The adopted scheme was implemented in the IEEE-33 test bus system, and the corresponding outcomes of the considered parameters (expansion, CB, DSTATCOM, load of real and reactive powers, CLLI) have been achieved. The proposed algorithm was compared with conventional algorithms such as ABC (Gao, et al., 2016), PSO (Zhang & Xia, 2017), FF (Wang, et al., 2017), GWO (Sharma, et al., 2016) and GOA (Saremi, et al., 2017) for analyzing the performance. Initially, the convergence analysis (cost functions) for the considered parameters have been analyzed, and subsequently, the statistical analysis of the proposed and compared algorithms in terms of best, worst, mean, median and standard deviation has been examined and the respective results were checked. Table 4 shows the algorithm parameters and values.

5.2 Convergence Analysis

The convergence analysis of the proposed DGOA model in determining the expansion planning is given by Fig. 6. From the Fig. 6(a), the overall cost of the adopted DGOA scheme is 49.58% superior to ABC, 24.37% superior to PSO, 66.38% superior to FF, 57.98% superior to GWO and 49.58% superior to GOA algorithms. From Fig. 6(b), the proposed DGOA scheme at the 100th iteration for expansion cost is 20.83% better than ABC, 12.5% better than PSO, 25% better than FF, 20.83% better than GWO and 20.83% better than GOA algorithms. Also, from Fig. 6(c), the adopted DGOA scheme at 100th iteration for CB cost is 66.67% better than ABC, 47.62% better than PSO, 72.38% better than FF,
69.52% better than GWO and 66.67% better than GOA algorithms. From Fig. 6(d), the implemented method at 100th iteration for DSTATCOM cost is 90.19% superior to ABC, 87.8% superior to PSO, 88.37% superior to FF, 87.5% superior to GWO and 87.5% superior to GOA algorithms. Moreover, from Fig. 6(e), the CLLI cost of the adopted scheme is 11.65% superior to ABC, 6.38% superior to PSO, 8.93% superior to FF, 13.19% superior to GWO and 11.65% superior to GOA algorithms. Furthermore, from Fig. 6(f), the implemented DGOA scheme for cost of loss at 100th iteration is 88.23% better than ABC, 80% better than PSO, 82.86% better than FF, 82.35% better than GWO and 80% better than GOA techniques. Since, this work utilizes the DGOA for optimization, the proposed method can yield faster convergence rate than other conventional ABC, PSO, FF, GWO, and GOA algorithms. Thus, the enhancement of the proposed DGOA is proved efficiently.

Table 4. Algorithm 1: DGOA algorithm

| Step | Algorithm parameters | Values |
|------|----------------------|--------|
| 1.   | Grasshopper          | cmx    | 1      |
|      |                      | cmn    | 0.00004|
|      |                      | Intensity of attraction g | 0.5 |
|      |                      | Attractive length scale l | 1.5 |

Table 5. Algorithm Parameters and Values
5.3 Statistical Analysis

Since the meta-heuristic algorithms are stochastic in nature, better results cannot be obtained. Hence, all the algorithms have to be simulated for five times, and the best, worst, mean, median, standard deviation results are determined for finding the accurate values. The statistical analysis of the adopted DGOA model in portraying the expansion planning is specified by Table 5. From the Table 5, the overall cost function of the proposed DGOA model in terms of best performance is 52.99% better than ABC, 22.9% better than PSO, 65.81% better than FF, 57.27% better than GWO and 48.72% better than GOA algorithms. Also, the mean performance of the adopted model is 47.57% superior to ABC, 23.79% superior to PSO, 56.03% superior to FF, 50.95% superior to GWO and 49.26% superior to GOA algorithms. Also from Table 6, the statistical analysis for expansion cost for the proposed DGOA model in terms of best performance is 33.33% better than ABC, 33.33% better than FF, 38.09% better than GWO and 38.09% better than GOA algorithms. Accordingly, the mean performance of the implemented DGOA scheme is 21.37% superior to ABC, 25.64% superior to FF, 23.93% superior to GWO and 23.93% superior to GOA algorithms. From Table 7, the statistical analysis for CB cost for

| Measures        | ABC (Gao, et al., 2016) | PSO (Zhang & Xia, 2017) | FF (Wang, et al., 2017) | GWO (Sharma, et al., 2016) | GOA (Saremi, et al., 2017) | DGOA |
|-----------------|-------------------------|--------------------------|-------------------------|---------------------------|-----------------------------|------|
| Best            | 0.55001                 | 0.90209                  | 0.40001                 | 0.50001                   | 0.60001                     | 1.1701|
| Worst           | 0.70001                 | 1.0336                   | 0.80001                 | 0.60001                   | 0.60001                     | 1.1927|
| Mean            | 0.62001                 | 0.95531                  | 0.52001                 | 0.58001                   | 0.60001                     | 1.1826|
| Median          | 0.60001                 | 0.92551                  | 0.40001                 | 0.60001                   | 0.60001                     | 1.1799|
| Standard deviation | 0.057009              | 0.061371                 | 0.17889                 | 0.044721                  | 0                           | 0.0097|
the proposed DGOA model in terms of mean performance is 81.17% better than ABC, 83.26% better than PSO, 81.06% better than FF, 81.28% better than GWO and 81.39% better than GOA algorithms. Moreover, the median performance of the implemented scheme is 81.52% superior to ABC, 83.48% superior to PSO, 81.08% superior to FF, 81.73% superior to GWO and 81.73% superior to GOA algorithms. Similarly, from Table 8, the DSTATCOM cost can be achieved, where the adopted scheme in terms of worst performance is 62.59% better than ABC, 53.54% better than PSO, 20.12% better than FF, 60% better than GWO and 60% better than GOA algorithms. Moreover, the mean performance of the suggested DGOA system is 71.49% superior to ABC, 64.24% superior to PSO, 71.8% superior to FF, 71.62% superior to GWO and 72.11% superior to GOA algorithms. In addition, from Table 9, the CLLI cost of adopted scheme in terms of best performance is 10.67% better than ABC, 8.33% better than PSO, 12.17% better than FF, 13.53% better than GWO and 13.52% better than GOA algorithms. Also, the median performance of the implemented scheme is 7.75% superior to ABC, 5.18% superior to PSO, 9.22% superior to FF, 8.69% superior to GWO and 8.68% superior to GOA algorithms. Finally, from Table 10, the cost of loss constraint is attained, where the presented DGOA scheme with respect to best performance is 72.92% better than ABC, 71.52% better than PSO, 76.62% better than FF, 78.57% better than GWO and 78.57% better than GOA algorithms. Moreover, the standard deviation of the implemented DGOA scheme is 98.92% superior to ABC, 83.75% superior to PSO, 89.73% superior to FF, 75.7% superior to GWO and 63.01% superior to GOA algorithms. Thus the enhancement of the adopted DGOA model with respect to statistical analysis is validated successfully in this section.

Table 7. Statistical analysis of the proposed and conventional models in terms of the expansion cost

| Measures | ABC (Gao, et al., 2016) | PSO (Zhang & Xia, 2017) | FF (Wang, et al., 2017) | GWO (Sharma, et al., 2016) | GOA (Saremi, et al., 2017) | DGOA |
|----------|------------------------|------------------------|------------------------|------------------------|------------------------|-------|
| Best     | 2.80×10^5             | 1.80×10^5             | 2.80×10^5             | 2.90×10^5             | 2.90×10^5             | 2.10×10^5 |
| Worst    | 2.90×10^5             | 2.70×10^5             | 3.00×10^5             | 2.90×10^5             | 2.90×10^5             | 2.40×10^5 |
| Mean     | 2.84×10^5             | 2.08×10^5             | 2.94×10^5             | 2.90×10^5             | 2.90×10^5             | 2.34×10^5 |
| Median   | 2.80×10^5             | 1.90×10^5             | 3.00×10^5             | 2.90×10^5             | 2.90×10^5             | 2.40×10^5 |
| Standard deviation | 5477.2 | 38341 | 8944.3 | 0 | 0 | 13416 |

Table 8. Statistical analysis of the proposed and conventional models in terms of CB cost

| Measures | ABC (Gao, et al., 2016) | PSO (Zhang & Xia, 2017) | FF (Wang, et al., 2017) | GWO (Sharma, et al., 2016) | GOA (Saremi, et al., 2017) | DGOA |
|----------|------------------------|------------------------|------------------------|------------------------|------------------------|-------|
| Best     | 1.68×10^6             | 1.46×10^6             | 1.64×10^6             | 1.68×10^6             | 1.68×10^6             | 7.20 ×10^6 |
| Worst    | 1.74×10^6             | 1.58×10^6             | 1.80×10^6             | 1.76×10^6             | 1.72×10^6             | 1.04 ×10^6 |
| Mean     | 1.71×10^6             | 1.52×10^6             | 1.72×10^6             | 1.70×10^6             | 1.69×10^6             | 9.08 ×10^6 |
| Median   | 1.70×10^6             | 1.52×10^6             | 1.74×10^6             | 1.68×10^6             | 1.68×10^6             | 9.20 ×10^6 |
| Standard deviation | 22804 | 50990 | 58992 | 35777 | 17889 | 1.40 ×10^6 |
5.4 Scalability Analysis

The Scalability analysis of the proposed DGOA model over the conventional model is depicted in Fig. 7. Here, the analysis is done by varying the population size 5, 10, 15, 20 and 25 as well as by setting the iteration count as 50. From the Fig. 7(a), the overall cost of the implemented DGOA model is 44.10%, 8.25%, 54.10%, 59.10% and 59.10% better than ABC, PSO, FF, GWO and GOA algorithms at population size 5. Further, Fig. 7(b), the adopted DGOA model for expansion cost is 7.14%, 30%, 10.34%, 10.34% and 10.34% better than ABC, PSO, GWO and GOA algorithms at population size 20. Moreover, from Fig. 7(c), the proposed DGOA model for CB cost is 19.75%, 15.58%, 26.14%, 24.42% and 24.42% better than ABC, PSO, GWO and GOA algorithms at population size 20. Likewise, from Fig. 7(d), the cost of loss for the presented DGOA model is 32.71%, 29.68%, 22.57%, 22.27% and 12.05% better than ABC, PSO, GWO and GOA algorithms at population size 20.

5.5 Reliability Analysis

The Reliability test is conducted using the T-test and P-test analysis for the adopted DGOA model over the conventional models specified in Table 11 and Table 12. T-test is a kind of inferential measurement employed to decide whether there is a significant distinction among the means of two groups, which might be associated in specific features. Scientifically, the t-test takes an exemplar from every one
of the two sets and set up the problem statement by considering a null hypothesis that the two means are identical. Here, some values are calculated and compared over the standard values on the basis of formulas and accordingly, the considered null hypothesis is accepted or rejected. The P-value, or calculated probability, is the proof against a null hypothesis. If the p-value is lower, the statistical significance of the observed difference is more.
On observing the Table 11 and 12, the T-test and the P-test shows the relevance of the proposed DGOA algorithm, when compared over other conventional algorithms. From Table 11, for Population size =20, the proposed DGOA algorithm is 93.53%, 85.99%, 84.78%, 98.65% and 98.64% better than other the conventional methods like ABC, PSO, FF, GWO, and GOA, respectively. Moreover, on observing the P-test of Table 16, the adopted DGOA model is 1.00e+01%, 5.53e+00% and 1.00e+01%, 1.00e+01% and 1.00e+01% better than conventional methods like ABC, PSO, FF, GWO, and GOA, respectively for Population size =20. Thus, it is evident that the DGOA outperforms with significant statistical reliability based on the T-test and P-test outcome.

### 6. CONCLUSION

This paper has presented the expansion planning model in power distribution by considering a multi-objective problem that includes expansion strategy, allocation of CB, allocation of DSTATCOM and CLLI, and power loss. Consequently, the encoding constraints decide for expansion, CB placement, DSTATCOM placement, load of reactive and real powers of expanded bus or node were optimized by means of modifies GOA based on distance computation and therefore, the presented algorithm was known as DGOA. Also, the proposed model was distinguished with other conventional algorithms, and the optimal outcomes were attained. Here, the adopted scheme was carried out in IEEE 33 test bus system. From the analysis, the implemented method in terms of convergence analysis at 100th iteration for DSTATCOM cost was 90.19% superior to ABC, 87.8% superior to PSO, 88.37% superior to FF, 87.5% superior to GWO and 87.5% superior to GOA algorithms. On considering the statistical analysis, the CLLI cost of the adopted scheme in terms of best performance was 10.67% better than ABC, 8.33% better than PSO, 12.17% better than FF, 13.53% better than GWO and 13.52% better than GOA algorithms. Also, the median performance of the implemented scheme was 7.75% superior to ABC, 5.18% superior to PSO, 9.22% superior to FF, 8.69% superior to GWO and 8.68% superior to GOA algorithms. Thus, the improved performance of the adopted DGOA model has been validated successfully.
REFERENCES

Acha, E., Fuerte-Esquivel, C. R., Ambriz-Pérez, H., & Angeles-Camacho, C. (2014). ACTS, Modelling and simulation in power networks. John Wiley & Sons Ltd.

Ahmadigorji, M., Amjadi, N., & Dehghan, S. (2017). A novel two-stage evolutionary optimization method for multiyear expansion planning of distribution systems in presence of distributed generation. *Applied Soft Computing*, 52, 1098–1115.

Arachchige, S., & Sathsara, K. T. (2020). *The Impact Of Outbound Training (OBT).* International Journal of Scientific & Technology Research.

Brajula, W., & Prasad, M. B. (2018). ODIFF Opposition and Dimension based Firefly for Optimal Reactive Power Dispatch. *Journal of Computational Mechanics, Power System and Control*, 1(1), 1–10.

Chen, H., Wang, Z., Yan, H., Zou, H., & Luo, B. (2015). Integrated Planning of Distribution Systems with Distributed Generation and Demand Side Response. *Energy Procedia*, 75, 981–986.

Chithra, S., & Kumari, R. M. (2018). Economic Emission Dispatch in Renewable Energy Systems using FireFly Algorithm, *Journal of Computational Mechanics*. *Power System and Control*, 1(1), 18–25.

Cofini, V., Giacomo, D., Mascio, T. D., Necozione, S., & Vittorini, P. (2012). Evaluation plan of terence: when the user-centred design meets the evidence-based approach. In *International Workshop on Evidence-Based Technology Enhanced Learning* (pp. 11-18). Springer.

Devabalaji, K. R., & Ravi, K. (2016). Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using Bacterial Foraging Optimization Algorithm. *Ain Shams Engineering Journal*, 7(3), 959–971.

Emmanuel, M., Rayudu, R., & Welch, I. (2017). Grid capacity released analysis and incremental addition computation for distribution system planning. *Electric Power Systems Research*, 152, 105–121.

Gao, K. Z., Suganthan, P. N., Pan, Q. K., Tasgetiren, M. F., & Sadollah, A. (2016). Artificial bee colony algorithm for scheduling and rescheduling fuzzy flexible job shop problem with new job insertion. *Knowledge-Based Systems*, 109, 1–16.

Gupta, A. R., & Kumar, A. (2016a). Energy Saving Using D-STATCOM Placement in Radial Distribution System under Reconfigured Network. *Energy Procedia*, 90, 124–136.

Gupta, A. R., & Kumar, A. (2016b). Impact of D-STATCOM Placement on Improving the Reactive Loading Capability of Unbalanced Radial Distribution System. *Procedia Technology*, 25, 759–766.

Gupta, A. R., & Kumar, A. (2016c). Optimal placement of D-STATCOM using sensitivity approaches in mesh distribution system with time variant load models under load growth. *Ain Shams Engineering Journal*.

Gupta, A. R., & Kumar, A. (2018). Impact of various load models on D-STATCOM allocation in DNO operated distribution network. *Procedia Computer Science*, 125, 862–870.

Hosseinnezhad, V., Rafiee, M., Ahmadian, M., & Siano, P. (2018). A comprehensive framework for optimal day-ahead operational planning of self-healing smart distribution systems. *International Journal of Electrical Power & Energy Systems*, 99, 28–44.

Humayd, A. S. B., & Bhattacharya, K. (2017). Distribution system planning to accommodate distributed energy resources and PEVs. *Electric Power Systems Research*, 145, 1–11.

Jazebi, S., Hosseinian, S. H., & Vahidi, B. (2011). DSTATCOM allocation in distribution networks considering reconfiguration using differential evolution algorithm. *Energy Conversion and Management*, 52(7), 2777–2783.

Kumar, D., & Samantaray, S. R. (2016). Implementation of multi-objective seeker-optimization-algorithm for optimal planning of primary distribution systems including DSTATCOM. *International Journal of Electrical Power & Energy Systems*, 77, 439–449.

Kumawat, M., Gupta, N., Jain, N., & Bansal, R. C. (2018). Optimal planning of distributed energy resources in harmonics polluted distribution system. *Swarm and Evolutionary Computation*, 39, 99–113.
Lin, Y., & Bie, Z. (2018). Tri-level optimal hardening plan for a resilient distribution system considering reconfiguration and DG islanding. *Applied Energy, 210*, 1266–1279.

Liu, J., Cheng, H., Zeng, P., Yao, L., & Tian, Y. (2018). Decentralized stochastic optimization based planning of integrated transmission and distribution networks with distributed generation penetration. *Applied Energy, 220*, 800–813.

Mahdavi, S., Hemmati, R., & Jirdehi, M. A. (2018). Two-level planning for coordination of energy storage systems and wind-solar-diesel units in active distribution networks. *Energy, 151*, 954–965.

Mauro, D., Longo, M., & Postiglione, F. (2018). Availability evaluation of multi-tenant service function chaining infrastructures by multidimensional universal generating function. *IEEE Transactions on Services Computing*.

Moradijooz, M., Moghaddam, M. P., & Haghifam, M. R. (2018). A flexible active distribution system expansion planning model: A risk-based approach. *Energy, 145*, 442–457.

Najafi, J., Peiravi, A., & Guerrero, J. M. (2018). Power distribution system improvement planning under hurricanes based on a new resilience index. *Sustainable Cities and Society, 39*, 592–604.

Saremi, S., Mirjalili, S., & Lewis, A. (2017). Grasshopper Optimisation Algorithm: Theory and application. *Advances in Engineering Software, 105*, 30–47.

Sharma, S., Bhattacharjee, S., & Bhattacharya, A. (2016). Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid. *IET Generation, Transmission & Distribution, 10*(3), 625–637.

Singh, B., & Mishra, D. K. (2018). A survey on enhancement of power system performances by optimally placed DG in distribution networks. *Energy Reports, 4*, 129–158.

Singh, B., Yadav, M. K. (2018). GA for enhancement of system performance by DG incorporated with D-STATCOM in distribution power networks. *Journal of Electrical Systems and Information Technology*.

Sundarabalan, C. K., & Selvi, K. (2014). PEM fuel cell supported distribution static compensator for power quality enhancement in three-phase four-wire distribution system. *International Journal of Hydrogen Energy, 39*(33), 19051–19066.

Taher, S. A., & Afsari, S. A. (2014). Optimal location and sizing of DSTATCOM in distribution systems by immune algorithm. *International Journal of Electrical Power & Energy Systems, 60*, 34–44.

Taher, S. A., & Karimi, M. H. (2014). Optimal reconfiguration and DG allocation in balanced and unbalanced distribution systems. *Ain Shams Engineering Journal, 5*(3), 735–749.

Wang, H., Wang, W., Zhou, X., Sun, H., & Cui, Z. (2017). Firefly algorithm with neighborhood attraction. *Information Sciences, 382–383*, 374–387.

Xie, S., Hu, Z., Zhou, D., Li, Y., & Zheng, Y. (2018). Multi-objective active distribution networks expansion planning by scenario-based stochastic programming considering uncertain and random weight of network. *Applied Energy, 219*, 207–225.

Yuvaraj, T., Ravi, K., & Devabalaji, K. R. (2017). DSTATCOM allocation in distribution networks considering load variations using bat algorithm. *Ain Shams Engineering Journal, 8*(3), 391–403.

Zhang, J., & Xia, P. (2017). An improved PSO algorithm for parameter identification of nonlinear dynamic hysteretic models. *Journal of Sound and Vibration, 389*, 153–167.

---

*Adepu Sateesh Kumar is currently working as Associate Professor in Vaagdevi College of Engineering.*

*K. Prakash is currently working as Professor in Vaagdevi College of Engineering.*