ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

Locating and sizing reactive power compensation devices for voltage control ancillary services optimally using the HFPSO-TOPSIS technique

Dr. N.V.Subba Rao[1], Dr. B. Ravi[2]
[1]Professor, Department of EEE
[2]Associate Professor, Department of Mechanical Engineering
Anu Bose Institute of Technology for Women's, Paloncha, Telangana, India
Email: nvsubbaraonv@gmail.com, bravi1234@gmail.com

ABSTRACT: The correct size and placement of reactive power supports are of the utmost importance in today's power systems that include renewable energy sources into the distribution network. In order to increase the overall performance and dependability of the system, as well as to minimise power loss and enhance the voltage profile, it is necessary to optimise the location and size of reactive power support resources. This will maximise the techno-economic advantages to both consumers and system operators. Nevertheless, a MOMCDM strategy is necessary for the optimum position and size of the reactive power supporting device (OLRPSD) for voltage control auxiliary service, which is a multi-objective issue. Reducing power losses has been the stated goal of reactive power support in the literature. More than one goal, however, is dependent on the gadget that supports reactive power. Equally crucial for all parties involved is taking into account the monetary gain from reactive power assistance. This paper presents OLRPSD, a newly developed MOMCDM technique called Hybrid Firefly Particle Swarm Optimisation with TOPSIS approach (HFPSO-TOPSIS), which is applied with the goal of minimising reactive power cost and other objectives such as reducing power loss, maximising the stability margin of voltage, and minimising the deviation of voltage. The objective is to minimise financial benefit. The "modified IEEE 33 bus" radial distribution network is used to carry this out. The following reactive power balancing devices are being considered: electric car charging stations, batteries, capacitors, and distributed generation (DG). The results validate the superiority of this approach compared to the alternatives.

Keywords: Hybrid Firefly Particle Swarm Optimization, TOPSIS, multi-objective, reactive power support, voltage control ancillary service.

1. INTRODUCTION

Reactive power support is now essential in modern restructured power systems that use distributed generation (DGs) with bidirectional power flow. In order to maintain stable voltage levels and a reliable network, this assistance is necessary in the form of reactive power reserves. An important auxiliary function for grid operations, ensuring a steady flow of electricity from generators to consumers, is reactive power compensation. New systems for transmission and distribution level reactive power assistance have been made possible by smart grid technology.

By incorporating renewable energy into its generating mix and putting its smart grid road plan into action, India is not lagging behind in decreasing carbon emissions. India has invested much in the development of smart cities and intends to build 100 of them. Australia, Sweden, the United Kingdom, the United States of America, and Denmark are just a few of the nations that have recently amended their legislation to include renewable energy sources in their electricity generating mix. India is no exception. As a matter of strategy, 450 GW of power generated by renewable sources till 2030 [1]. Keeping the voltage at the distribution level within limitations has become more important due to all these factors. As a result, reactive power will support the market in India more heavily by 2020. Roughly twenty million people have seen it.

This market sizing is done on three different bases [2]

1. Customer basis i.e. industries, utilities, railways, NTPC and big manufacturing industries [2].
2. Type of load: slow varying loads such as servers, escalators, distribution transformers, fast changing loads like traction system, elevators and industrial loads, very fast changing loads like spot welding, arc furnaces, rolling mills etc.
3. Reactive power compensating devices: D-STATCOM, dynamic voltage restorer, DVR's, fixed or variable Capacitors etc.

Uncertainty of generation from renewable sources and irregular demand causes increase or decrease in power factor and therefore reactive power support becomes necessity. Any change in voltage level is controlled by efficient and effective use of reactive power compensating devices. By optimal location of reactive power supporting devices in the network, voltage stability is also enhanced.

- The introduction should briefly place the study in a broad context and highlight why it is important. It should

International Journal of applied

ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

define the purpose of the work and its significance. The current state of the research field should be reviewed carefully and key publications cited. Please highlight controversial and diverging hypotheses when necessary. Finally, briefly mention the main aim of the work and highlight the principal conclusions. As far as possible, please keep the introduction comprehensible to scientists outside your particular field of research. References should be numbered in order of appearance and indicated by a numeral or numerals in square brackets, e.g., [1] or [2-3], or [4–6]. See the end of the document for further details on references.

2. LITERATURE

(OLRPSD) at the level of distribution is a difficult challenge because of the many aspects that must be taken into account [3]. The first factor is the location of the resources, which affects the cost of reactive power. The second thing is to determine where the reactive power comes from from devices like D-STATCOM, DVRs, capacitors, batteries, DGs, and so on, that aren't synchronous condensers. New research shows that EV chargers are crucial for distribution-level reactive power supply as well. Finding the best answer to this issue requires taking into account a number of restrictions. However, modifications at the policy level are also necessary for the correct deployment of reactive power supporting for voltage control ancillary services. The third component that exacerbates the OLRPSD issue is the evolution of traditional methods used by reactive power suppliers, such as load flow analysis, to ascertain the need for these services.

A number of operational restrictions of the system in question affect the OLRPSD issue. Through the use of analytical and heuristic methodologies in conjunction with linear programming, the OLRPSD issue at the transmission level has been resolved. Due to its speed, robustness, and convergence nature, heuristic approaches are determined to be the most appropriate for this search issue. A few examples of these techniques include ant colony optimisation, genetic algorithms, particle swarm algorithms, etc. [4]. This is an increasingly difficult issue in distribution systems, made worse by topological changes brought about by the widespread use of renewable energy. Due to the impending transformation of distribution grids into networks of multi-micro-grids, which will include bidirectional power flows and voltage management as key issues, this study focusses on OLRPSD in these systems. Essential parts of micro-grids are distributed generation (DG) and energy storage (ES). To minimise loss, enhance power factor, mitigate harmonics, and move active power from production to load to the highest extent possible, reactive power assistance is crucial.

.

Optimal placement of distributed generators is taken into account in particle swarm optimisation (PSO) [5]. Using loss minimisation functions with a single goal, hybrid PSO and whale optimisation are used in [6] and [7]. The best place to put capacitors is the subject of current research. Similarly, the authors of [8] have thought about the goal of voltage enhancement by taking into account the smallest number of capacitors needed, operational limits for capacitors, and loss sensitivity indices. Using direct load flow (DLF), D-STATCOM is best positioned in [9]. [10] Harmony search algorithms like MOGA and [11] try to keep costs down while minimising voltage variation, losses, and harmonic distortion. Likewise with batteries page in reference [12] In order to minimise losses, PSO and GA are used in [13]. Electric vehicles also have the capability to supply reactive power. A teaching learning algorithm handles the optimum placement of chargers in [14] and PSO handles it in [15], both of which are crucial for sustaining reactive power.

1. Nevertheless, the ideal placement of various reactive power supporting devices, such as those included in this study, has been the subject of relatively few investigations. For this reason, while performing OLRPSD at maximum load conditions, it is important to optimise reactive power holding costs in addition to minimising losses, reducing voltage deviation, and maximising the voltage stability index for voltage control auxiliary service. The outcome is a more favourable voltage profile and lower operating costs for the financial sector as a whole.

2. A method that maximises several, equally weighted goals is necessary for this kind of issue. So, we'll approach this issue as a MOMCDM, or problems with multiple objectives and criteria. A "Technique for Order of Preferences by Similarity to Ideal Solution (TOPSIS)" [21] technique might be useful for setting order of preference in order to identify the perfect answer.

We do OLRPSD with the goal of minimising reactive power cost for economic advantage, along with other equally essential goals such as minimising losses, maximising voltage stability, and minimising voltage variation. Hybrid Firefly Particle Swarm Optimisation with TOPSIS method (HFPSO-TOPSIS) is a newly designed MOMCDM technology.

In its quest for a worldwide optimum, this algorithm takes into account the benefits of Particle Swarm Optimisation and Firefly for rapid convergence. In addition, the solution is ranked using the goal function's priorities using the TOPSIS technique

Five different reactive power compensating devices which are considered in this study are:

1. Capacitors
2. D-STATCOM with and without DG
3. Distributed generation (DG's)
4. Battery
5. Electric Vehicle Charging station

Organization of this paper is as follows: Section I gives introduction, section 2 discusses related literature section 3, explains the methodology used, section 3 discusses in detail HFPSO-TOPSIS for solving OLRPSD problem, section 4, explains base case in this study, section 5, discusses the test results of OLRPSD and section 6, gives conclusion with future scope.

3. METHODOLOGY

3.1. Formulation of Problem with Objectives considered
The multi-objective function for this OLRPSD problem is given as follows:

3.1.1. Voltage deviation minimization:
The system voltage quality is measured by the node voltage deviation [6]. Therefore, utilities require to maintain the node voltage in a regulated level. In the OLRPCD integration model, minimization voltage deviation at a node is considered and is expressed as

$$\text{minimize } f_1 = \sum_{d=1}^{Nd}(V_d - 1)^2 \quad (1)$$

Where, voltage at node 'd' is V_d, total number of nodes 'Nd' in network.

3.1.2. Minimization of losses:
In distribution network maximum power loss occurs due to during power delivery that causes maximum revenue losses to the utility. If losses are less than power delivery with good voltage levels is possible [5, 6] Second objective is power loss minimization for OLRPSD, which may be expressed as

$$\min f_2 = \sum_{i=1}^{Nd}\sum_{j=1}^{Nd} \gamma_{ij}\left(P_i P_j + Q_i Q_j\right) + \rho_{ij}\left(Q_i P_j + P_i Q_j\right) \quad (2)$$

Where

$$\gamma_{ij} = R_{ij}\, cos\left(\delta_i - \delta_j\right)/V_i V_j$$
$$\rho_{ij} = R_{ij}\, sin\left(\delta_i - \delta_j\right)/V_i V_j$$

'Nd' is number of nodes in total, P_i is active and Q_i, is reactive power injections at the 'i' node, resistance R_{ij} is between node 'i' and node 'j', 'V_i' is voltage magnitude and δ_i is angle of the i^{th} node and at node 'j', 'P_j' is active and 'Q_j' is reactive power injections.

3.1.3 Reactive power supporting Cost minimization:
The reactive power cost from reactive power supporting devices is minimized [16].

For reactive power cost from capacitor and D-STATCOM reactive power costing:

$$Cost\left(Q_{React\,Gi}\right) = Cost\left(SA_{Gmax}\right) - \sqrt{Cost\left(SA_{Gmax}^2 - Q_{React\,Gi}^{\,2}\right) * k} \quad (4)$$

Where,
$Q_{ReactGi}$ = reactive power,
SA_{Gmax}= Maximum Nominal Apparent Power, K= rate of benefit from active power generation, k is considered as 10% in the paper work.

The reactive power cost from DGs i.e. its cost function, for the reactive power support, becomes:

$$C\left(P_{DG}, Q_{DG}\right) = C_{DG}^{Q}\left(P_{DG}, Q_{DG}\right) + C_{DG}^{0} \times Q_{DG}^{max} \quad (5)$$

Where C_{PV}^{0} is the fixed cost in per unit that the DG will spend on change in size of converter for incorporating reactive power supporting feature and Q_{PV}^{max} is the maximum capacity of the converter [17].

$$C_{PV}^{Q}\left(P_{DG}, Q_{DG}\right) = FeedIT_{DG} \times \Delta Loss_{DG}\left(P_{DG}, Q_{DG}\right) \quad (6)$$

Where $FeedIT_{DG}$ is the rate of feed-in tariff for any DG power produced by renewable source and its payment in per kWh and

$\Delta Loss\left(P_{DG}, Q_{DG}\right) =$ converter losses. (7)

3.1.4. Voltage stability margin (VSM) Maximization:
The voltage stability Margin (VSM) is maximized to keep the system stable. This is achieved by minimizing the Voltage stability indices (VSI). VSI is a level of device protection that describes a node's ability to keep its voltage profile within acceptable bounds under a variety of high loading scenarios The VSIs of the branch connecting nodes a and by [6], [20].

$$VSI_{ab} = V_b^4 - 4(P_a r_{ab} + Q_a x_{ab})V_b^2 - 4(P_a x_{ab} - Q_a r_{ab})^2$$

International journal of applied exercise physiology
ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

$$\min f_3 = \sum_{i=1}^{n} Cost\,|Q_d| \geq 0 \quad (3)$$

This cost covers the device's purchase price as well as installation and maintenance charges. The reactive power supporting value in MVAr at node 'd' is 'Q_d', and 'n' is number of network nodes.[17] gives the costing of reactive power from Capacitors, D-STATCOM, DG's, batteries and EV charging stations. While considering the fourth objective function the cost per MVAr for each device depends upon installation and maintenance cost for devices like capacitor, D- STATCOM etc. For cost calculations from DG opportunity cost has to be considered along with investment and maintenance cost. The investment and maintenance cost for reactive power supporting devices are considered as in [17] when installed in distribution grids, which must be analysed together with the saving of revenue gained by energy loss reduction. Costing of reactive power from devices providing reactive power support is considered in f_3 objective function.

(8)

Where impedance x_{abj} is that of branch connecting nodes **a** and **b**. The objective function for can be expressed as:

(9)

$$\text{maximize } f_4 = \min\langle VSI_{ij}\rangle \quad \forall_{i,j.}$$

3.2. Basic Constraints

The following constraints are considered along with some special constraints that vary as per the devices. The fundamental power flow equality and inequality constraints followed while solving this problem are:

- Power Balance Constraint: power balance equations at node 'a'. P_a is the active power and Q_a is the reactive power at node 'a' [6].

$$Q_a = -V_a \sum_{b=1}^{Nd} V_b Y_{ab} \sin(\theta_{ab} + \delta_b - \delta_a) \quad \forall\, a \quad (11)$$

3.2.1. Bus voltage constraint [6]:

At each bus, if the voltage is (Va) it must be within their minimum voltage and maximum voltage limits as:

$$V_a^{min} \leq V_a \leq V_a^{max} \quad (12)$$

3.2.2. Constraint for Power flow [5] [6]:

In each line, the power flow in (PF_K) should be lesser than the line's maximum limit of power flow (PF_K^{max}) as:

$$|PF_K| \leq PF_K^{max} \quad (13)$$

3.2.3. Overall power factor constraint [6, 8, 10, 12]:

The power factor of the system (pf_{sys}) must be greater than (pf_{sys}^{min}) i.e. the minimum of its value as:

$$|pf_{sys}| \geq pf_{sys}^{min} \quad (14)$$

More device specific constraints that are followed for optimal capacitor, D-STATCOM, and DG's.

3.3. Device specific constraints

3.3.1. Capacitor constraints:

Along with General operational constraints these constraints are followed for optimal capacitor location [8].

3.3.2. Number of Capacitor Constraint:

'N_{Cap}' is the number of capacitors that must be equal to or lesser than the highest number of potential locations (Nl_{cap}^{max}), this will reduce cost significantly.

$$N_{cap} \leq Nl_{cap}^{max} \quad (15)$$

$$P_a = V_a \sum_{b=1}^{Nd} V_b Y_{ab} \cos(\theta_{ab} + \delta_b - \delta_a) \quad \forall\, a \quad (10)$$

Minimum limit of reactive power supporting is $Q_{Dstatmin}(t)$ at bus 't' and $Q_{Dstatmax}(t)$ is the maximum limit of reactive power supporting at bus 't'.

3.3.6. Constraints for DGs:

Along with General operational constraints these constraints are followed for DG Location [5] [6][7]:

$$DG_i^{min} \leq DG_i \leq DG_i^{max} \quad \forall\, i \quad (18)$$

International journal of applied exercise physiology

ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

(19)

Where, DG_i^{min}, DG_i^{max} is the smallest and largest size of DG located on one node, DG installation decision variable is α_i at node i, and D_{Peak} is the network peak demand.

3.3.7. Constraints for batteries:

For optimal Battery location along with general operational constraints [12, 13].At instant *'t'* the battery bank should satisfy following constraints:

(20)

(21)

3.3.3. Constraint on size of Capacitor:
Size of capacitor for reactive power injections in the system must be limited by bounds.

$$Q_{C_j}^{min} \leq Q_{C_j} \leq Q_{C_j}^{max} \quad (16)$$

Where, reactive power injection at node j is Q_{C_j}.

3.3.4 Constraint for reactive power support from capacitor:
Reactive power from load (Q_{Load}^{Total}) should be greater than Q_{Cap}^{Total} i.e. reactive power contribution from capacitor

$$Q_{Cap}^{Total} < Q_{Load}^{Total} \quad (17)$$

3.3.5. Constraints for D-STATCOM:
Along with General operational constraints these constraints are for D-STATCOM location and sizing [9] [10] [11].

$$\sum_{j=1}^{N} \alpha_i DG_i \leq D_{Peak} \quad \forall i$$

Where $E_{Battmax}(t)$ is battery's maximum charge quantity, $E_{Battmin}(t)$ is battery's minimum charge quantity and S_{Batt} is battery's capacity. *DOD* is battery's depth of discharge and σ is rate of Self- discharge of battery.

3.3.8. Constraints for EV charging stations:

Along with General operational constraints these constraints are followed for number 'n' of EV charging station (ChS) consisting of Charging points (ChP) location subject to following constraints:

$$E_{Battmin}(t) = (1 - DOD) * S_{Batt}$$

$$E_{Battmin}(t) \leq E_{Batt}(t) \leq E_{Battmax}(t)$$

$$nChP_{min} \leq nChP \leq nChP_{max} \quad (22)$$

$$nChS_{min} \leq nChS \leq nChS_{max} \quad (23)$$

4. HFPSO-TOPSIS METHOD

4.1. Particle swarm Optimization

In "Particle Swarm Optimization (PSO) algorithm", the particles are possible solution to the problem. Best particle, showing fitness value that is best in the solution search space and all particles are oriented towards it. The velocity of each particle (VL) is updated in each iteration, also the position is changed according to the orientation towards the best fitted particle. Equation (18) gives the position and velocity of individual particles. New changed Velocity for each particle $'j'$, is calculated by equation (20) with past iteration position Z_j based on its past iteration velocity VL_j .Iteratively ,

International journal of applied exercise physiology
ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

particle's local best fitness (P_{Best}) and the global best particle among the neighboring particles is (G_{Best}) is calculated by equation (20). The weights are updated as in equation (19) iteratively to get the global best solution. The 'co_1' and 'co_2' are the constants for acceleration that change the velocity of a particle towards P_{Best} and G_{Best} and $random_1$, $random_2$ are uniformly distributed random numbers in [16].

$$VL_j^{itr+1} = \omega . VL_j^{itr} + co_1 . random_1 . (P_{Best,j}^{itr} - Z_j^{itr}) + co_2 . random_2 . (G_{Best}^{itr} - Z_j^{itr}) \quad (24)$$

$$Z_j^{itr+1} = Z_j^{itr} + VL_j^{itr+1} \quad (25)$$

$$WT.^{itr} = WT_{max} - [(WT_{max} - WT_{min})/itr_{max}] * itr \quad (26)$$

4.2. Firefly Algorithm

"Firefly algorithm (FA)" works on fireflies' behavior of bioluminescence. Depending upon the brightness of each firefly they are attracted towards each other. The attractiveness of the fireflies is 'β_0'. If brightness is more the distance between the fireflies will be less. Let 'i' and 'j' be the two fireflies with distance between the two fireflies is 'r_{ij}' and position is 'Z'. The by the scaling factor α is between and ∈ (0,1) controls the movement as well as randomization of fireflies. The luminance of a firefly depends on objective function. Visibility is controlled by 'γ' and is between (0, ∞). This process goes on iteratively, till the best solution is reached or maximum number of iteration are reached. $\in i$ is random variables vector.

$$Z_i^{itr+1} = Z_i^{itr} + \beta_0 e^{-\gamma r_{ij}^2} (Z_j^{itr} - Z_i^{itr}) + \alpha \epsilon_i^{itr} \quad (27)$$

4.3. Hybrid Firefly-Particle Swarm Optimization

Ibrahim Berkan designed "Hybrid firefly and particle swarm optimization (HFPSO)." This algorithm maintains balance between global level optimal solution as well as local level optimal solution taking into account strong points and advantageous features of both "Firefly algorithm (FA) and Particle Swarm Optimization algorithm". There is no velocity parameter in firefly algorithm or no recorded individual best position (P_{Best}). PSO is commonly utilized in the global search in these two algorithms because it converges rapidly in exploration and FA is also commonly employed in local search i.e exploitation. The HFPSO takes initial input parameters, these parameters are used as per requirement by both the algorithm. Further randomly uniform particle vectors are generated in the search space which is pre-defined along with predefined velocity ranges. Particles for the global best (G_{Best})) and personal best (P_{Best}) are calculated and allocated. Current G_{Best} value is compared with the previous one and is checked whether the particle's fitness value has improved from the previous iteration or not. After that, in a temp variable (Z_{jtemp}) the current position is kept in record and new position and velocity are computed using this current position.

$$f(i, itr) = \begin{cases} false, if\ particle\ is\ having\ fitness\ > G_{Best}^{itr-1} \\ true, if\ particle\ is\ having\ fitness\ \leq G_{Best}^{itr-1} \end{cases} \quad (28)$$

$$Z_i^{itr+1} = Z_i^{itr} + \beta_0 e^{-\gamma r_{ij}^2} (Z_j^{itr} - G_{Best}^{itr-1}) + \alpha \epsilon_i^{itr} \quad (29)$$

$$VL_j^{itr+1} = Z_j^{itr+1} - Z_{jtemp} \quad (30)$$

If a particle has an equal or better value of fitness then local search is initiated using FA loop, otherwise, the particle PSO loop is initiated, and PSO works with regular operations for this particle as described in (24) and (25). After this, all particles are evaluated for fitness function and range constraints are examined. If number of iterations are maximum, it ends the hybrid algorithm and the result will be G_{Best} and its fitness value of the proposed algorithm.

4.4. TOPSIS Approach

This problem has many Objectives

$$optimize\ [f_1(X), f_2(X), f_3(X), \dots, f_n\ (X)] \quad (31)$$

Subjected to $X \in SS$, where $f_j(x) : R^n \rightarrow R$ is the jth objective function, $j = 1, 2, \dots, n, n > 1$, and SS is the search space. As in [6, 7], this problem with many objectives is solved by TOPSIS approach for prioritizing the objective functions. The best solution is found without compromising the quality of solution by weighting the objective function. In TOPSIS approach the best solution is 'POIS' and 'NOIS' is the worst solution and are based on Euclidean geometry which is further discussed in step 3. If there are many objectives, individual finest solutions can be found to be present around the best solution without compromising the quality of solution. Improvement in the quality of solution is achieved by TOPSIS approach.

This approach use following steps to find the most appropriate problem solution having many objectives to be satisfied:

1st Step: To convert all dimensional qualities to non-dimensional attributes, create a normalized decision matrix (D.M.).

The matrix elements are given as:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{n_1} f_{ij}^2}} \ \forall\ i \epsilon\ n_1 \text{ and } j\ \epsilon\ n \quad (32)$$

International Journal of applied exercise physiology
ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

Where n_1 is number of feasible solutions and for jth objective, with 'ith' alternate, the value is f_{ij} and 'n' is number of objective functions.

2nd Step: If weights for the objectives are required, a normalized decision matrix with weight can be built. If all objectives are equally essential, this phase can be skipped. The matrix's components are written as

$$IO_{ij} = \omega_j \times r_{ij} \; \forall \, i \epsilon \, n_1 \text{ and } j \, \epsilon \, n \qquad (33)$$

Where ω_j is the weight of the jth and $\sum_{i=1}^{n} \omega_j = 1$.

3rd Step: In this step, best solution is POIS and NOIS is worst solution of each objective individually individual objective, respectively, explained as

$$POIS = \{IO_1^+, IO_2^+, IO_3^+, \dots, IO_n^+\} \qquad (34)$$

$$NOIS = \{IO_1^-, IO_2^-, IO_3^-, \dots, IO_n^-\} \qquad (35)$$

Where,

$$IO_j^+ = \begin{cases} \max\langle I.O._{ij} \rangle \; \forall \, i, \\ \text{if benefit is represented by individual objectivepresents a benefit} \\ \min\langle I.O._{ij} \rangle \; \forall \, i, \\ \text{if cost is prepresented by individual objective ve sents a cost} \end{cases} \qquad (36)$$

4th Step: d_{j+} and d_{j-} are Euclidean distances calculated in this step for each possible solution from POIS and NOIS, respectively:

$$d_i^+ = \sqrt{\sum_{j=1}^{n_2} \left(v_{ij} - v_j^+\right)^2}$$

and

$$d_i^- = \sqrt{\sum_{j=1}^{n_2} \left(v_{ij} - v_j^-\right)^2} \qquad (37)$$

5th Step: The relatively close index (RCI) is computed for each viable solution calculated as:

$$RCI_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \qquad (38)$$

The most competent solution is possible solution with the highest RCI value and Ranking is carried out according highest value to lowest value.

4.5. OLRPSD by HFPSO-TOPSIS

Applying HFPSO to get the objective function's global best solution is the first step of two-stage optimisation. In order to begin, the provided test system undergoes load flow analysis using the backward/forward sweep technique [10]. Losses, in addition to voltage magnitude and power flows are computed. The primary information is derived from the outcomes of the fundamental power flow. There is a random orientation of sizes and locations inside the bottom and upper boundaries of a population of reactive power supporting devices (RPSDs). The optimal solutions for placements and sizes are obtained via the power flow, both on an individual and a global scale. This answer is compared to the one from the previous iteration. The optimisation cycle of Particle Swarm starts if it isn't again. If the solution is found to be better, the Firefly Algorithm Loop is used to do a local search. This procedure continues until either a global optimum is reached or the maximum number of iterations have been accomplished. The input for Stage II, where the TOPSIS technique is used to prioritise the goal function, is the globally optimal solution for position and size RPSD for each objective function. In this problem, equal importance is given to each aim. Equation 25 is used to generate the choice matrix. To determine which solution is the best, we first compute the POIS and NOIS for the best and worst cases, and then we rank the solutions using the relative proximity index and separation metrics. The answer could vary depending on whether goal function is given more weight. The process is shown in Figure 1 by a flow diagram. The HFPSO-TOPSIS model as it pertains to OLRPSD

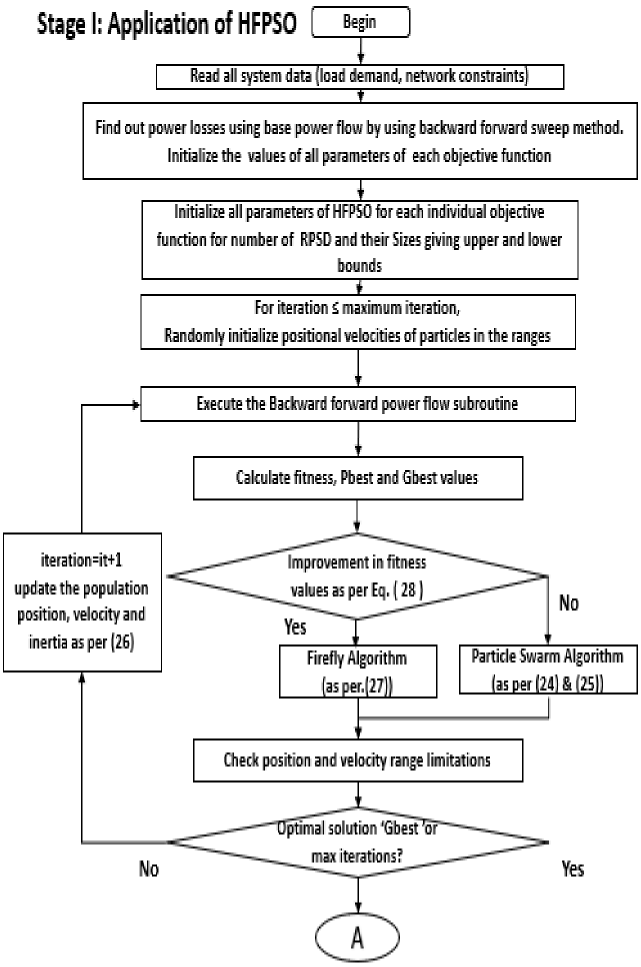

Figure 1. (a): Stage I of Implementation of HFPSO-TOPSIS for OLRPSD

International journal of applied exercise physiology
ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

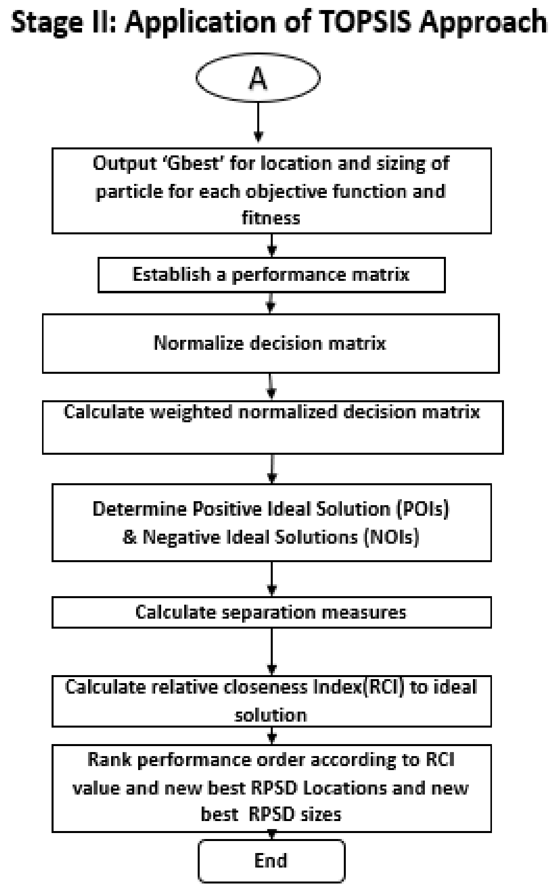

Figure 1. (b): Stage II of Implementation of HFPSO-TOPSIS for OLRPSD

5. CASE STUDY

The "modified radial distribution system IEEE 33 bus system" [23] as shown in Figure 2, having voltage level of 12.66 kV. 3.715 MW and 2.3 MVAr is the maximum active and reactive power at maximum load condition [23, 24]. Load flow using Backward/forward sweep method at maximum load is carried out for this system. The real power loss obtained is as "210.0897 kW"and reactive power losses are "143.027 kVAr" [23, 24] respectively.

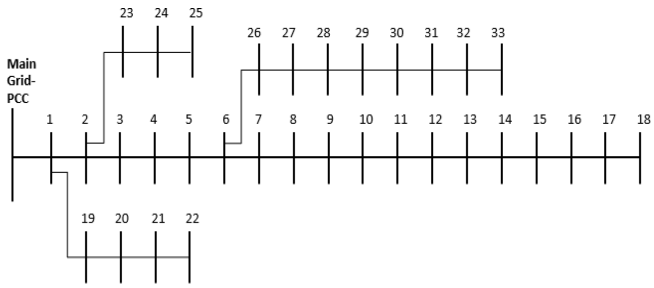

Figure 2. Modified "IEEE 33 bus system" radial distribution network

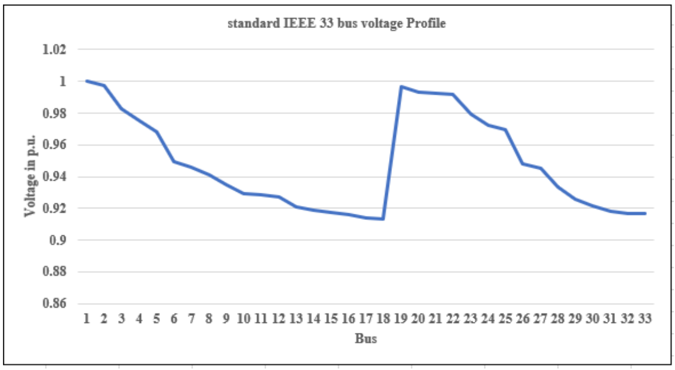

Figure 3. Voltage profile of standard IEEE 33 bus radial distribution system (base case).

As can be seen in Figure. 3. The magnitude of the voltage is determined by load flow. The lowest voltage level is 0.910 p.u. is at bus 18, and the minimum voltage stability index is 0.6686 at the same location

6. RESULTS AND DISCUSSION

The proposed algorithm was implemented and evaluated using MATLAB® programming on a PC with an Intel ® CORE TM i5-7200U CPU running at 2.50 GHz and 8.00 GB of RAM. The simulations are run under maximum load using IEEE standard 33-bus RDS test system.

6.1 Optimal Location of Capacitors:

In Table 1. Results are tabulated, for optimal location of capacitors considering all objectives.

Table 1: optimal location for fixed capacitors.

RPSD	Algo	@ Bus	Size kVAr	*f1*	*f2*	*f3* *$/MVArh*	*f4*
Base case	NA	NA	NA	*0.11*	*210*	*17.92*	*0.67*
Fixed Capacitors	ACO[8]	9,22,25	645, 719, 665	0.05	162	NA	0.79
	HFPSO-TOPSIS	6,9,13	1200, 542 264	0.05	140	2.64	0.88

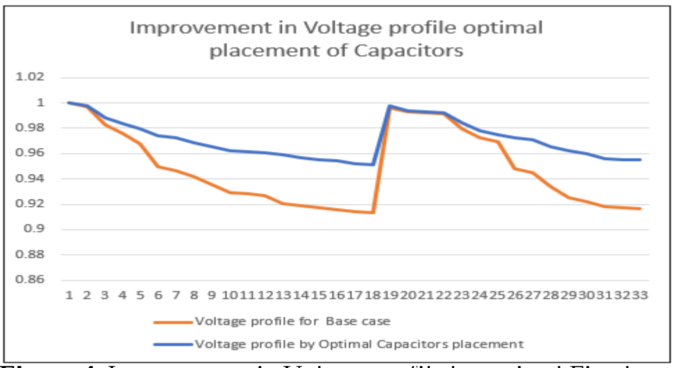

Figure 4. Improvement in Voltage profile by optimal Fixed capacitor location

International journal of applied exercise physiology
ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

As seen from Figure.4. Voltage profile is improved as observed minimum voltage is 0.95 p.u.

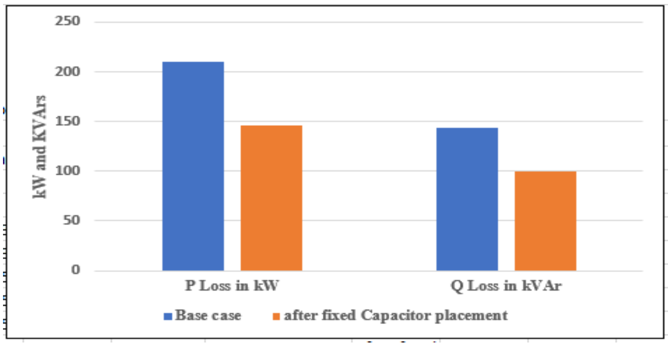

Figure 5. Comparison with base case, minimization of Power loss by optimal capacitor location.

As evident form Figureure.5. By optimal location of Capacitors by HFPSO-TOPSIS, Losses are also reduced by 32 % as compared to 27% by ACO.

6.2. Optimal Location of only D-STATCOM and PV- D-STATCOM system:

By working with a distributed generator, D-STATCOM is able to both produce and consume reactive power while keeping the voltage at 1.0 p.u. The evaluation of all goals, operational factors, and restrictions is carried out to determine the correct position of D-STATCOM with DG at bus.no.30. It has been noted that the voltage profile is much better after installing D-STATCOM with DG at this site. Tabulated in Table 2 are the HFPSO-TOPSIS outcomes for OPRPCD. Figure 7 shows voltage profile improvement using both D-STATCOM and DG, while Figure 6 shows voltage profile improvement using just D-STATCOM. Figure.8 shows the loss minimisation achieved by locating D-STATCOM ideally alone and by locating it in conjunction with DG.When D-STATCOM is linked to DG and placed appropriately, losses are minimised even further.

Table 2: Results for optimal location of D-STATCOM

RPSD	Algo	@ Bus	Size kVAr	*f1*	*f2*	*f3* $/MVArh	*f4*
Base case	NA	NA	NA	0.11	210	17.92	0.67
only DSTATCOM	HSA[11]	12	1150	NA	143	NA	NA
	HFPSO-TOPSIS	30	962	NA	148	8.32	0.7
D-STATCOM with DG 1500 kW	DLF [9]	30	1,000	0.08	86	NA	0.68
	HFPSO-TOPSIS	30	1,000	0.08	78	5.19	0.8

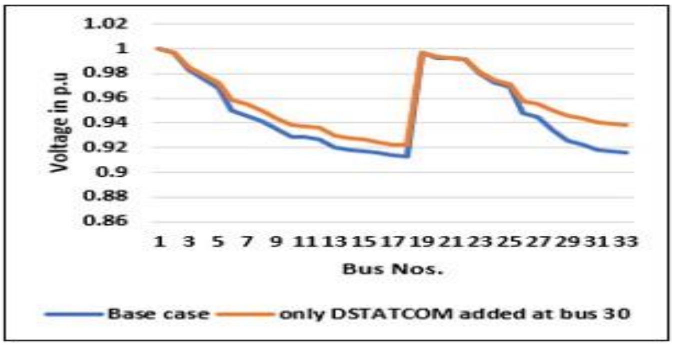

Figure 6. Voltage profile improvement with optimal location of only D-STATCOM at bus.no.30 for reactive power supporting.

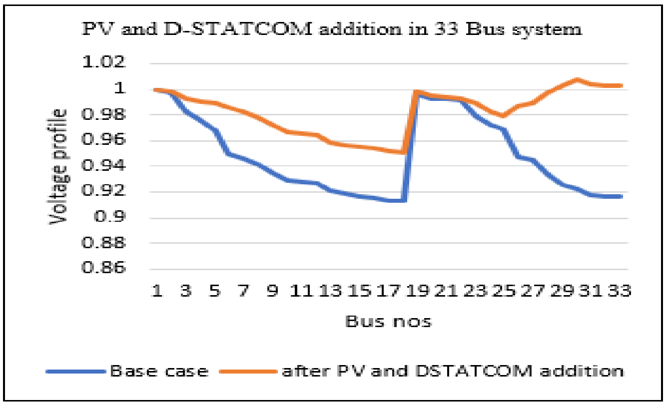

Figure 7. Improvement in Voltage profile of IEEE 33 Bus radial system after optimally placing PV-D-STATCOM at bus no.30.

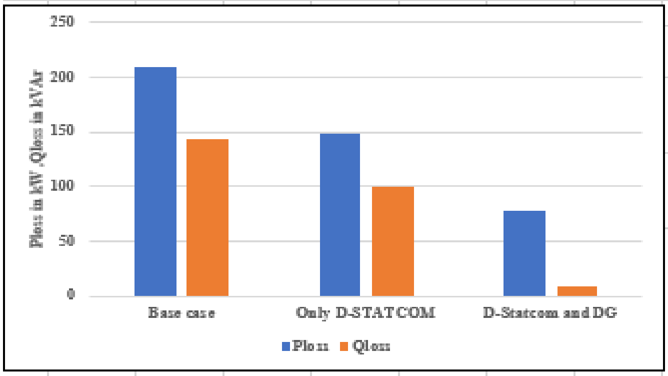

Figure 8. Minimization of losses by Optimally placing D-STATCOM and of D-STATCOM with DG.

6.3. Optimal Location of DGs:

Table 3 below gives results of objective functions attained values for optimal location of DGs. Optimization using HFPSO-TOPSIS is carried out and objectives are considered simultaneously for DG location and sizing for getting a more practical, realistic and economical solution.

ISSN: 2322-3537
Vol-13 Issue-02 Sep 2024

Table 3: Optimal Location of Distributed generation

RPSD	Algo	@ Bus location of DG	DG Size kW	f1	f2 in kW	f3 $/MVArh	f4
DG	NA	NA	NA	0.11	210	17.92	0.67
	GA[ ]	6,13,24,30	643, 857, 857,738	0.0115	71	NA	0.87
	HFPSO-TOPSIS	12,17,24,31	1200, 900, 600, 1300	0.06	70	5.19	0.93

The sizes of DGs considered are 1200 kW, 900kW, 600kW, 1300kW. It is observed that there is improvement in voltage profile as compared to base case as seen in Figure.9 with voltage level of 0.947 p.u to be minimum. The power losses are reduced to 65% as is observed from Figure.10.

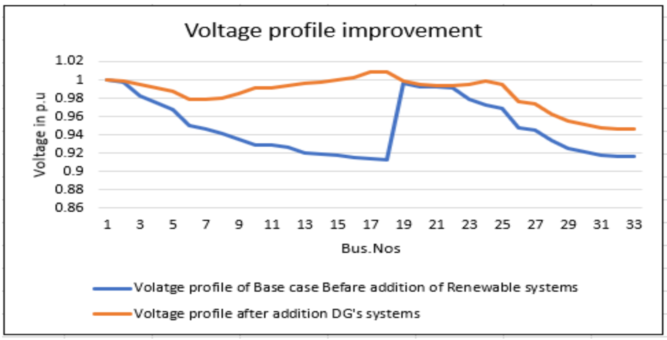

Figure 9. Voltage profile improvement by optimally Placing Distributed generation sources.

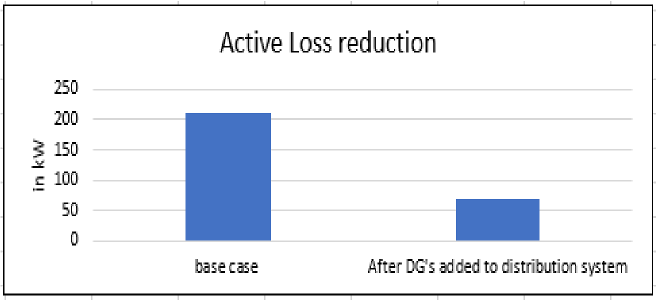

Figure 10. Minimization of losses by optimal Location of Distributed generation for reactive power support.

6.4. Optimal location of batteries

If Battery Energy storage system (BESS) is not properly sized and located in power system than it can cause system disturbances like over voltages, low voltages and also high-power losses. All objectives along with constraints are considered. High voltage sensitivity shows that the large change in voltage at that bus may occur for even small change in voltage. When energy storage is placed at this optimum location then it avoids major change in voltages due to small changes in load. Table 4 shows the results of OPRPCD (Batteries and DG). The modified topology of IEEE 33 bus radial system after DG and Batteries are placed is depicted in Figure 11. Improved voltage profile is as seen in Figure.12. The optimal bus location is found to be at bus.no. 14,18,24,32.

Table 4: Results for optimal location of Batteries

RPCD	Algo	@ Bus	Size kVAr	*f1*	*f2*	*f3* $/MVArh	*f4*
Base case	NA	NA	NA	*0.11*	*210*	*17.92*	*0.67*
Battery with DG	GAMS [25]	7,8,24,25	DG in kW 1350.2, 1499 446.73, 418.68 and 1300 kWh battery at each location	*0.04*	*NA*	*NA*	*NA*
	HFPSO-TOPSIS	14,18,24,32	DG in kW 1200,900,600 and Battery of SOC Max=800 kWh	0.03	17	0.93	0.9

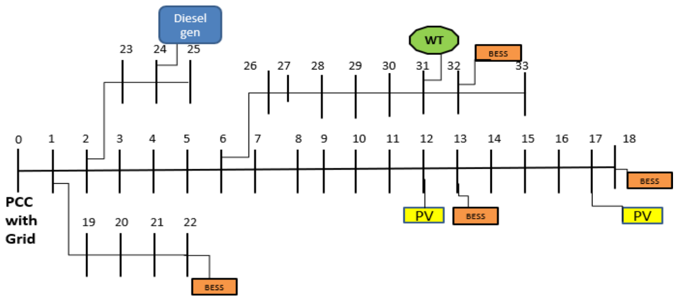

Figure 11. DG's sources and BESS optimally placed in ithe test system for reactive power support.

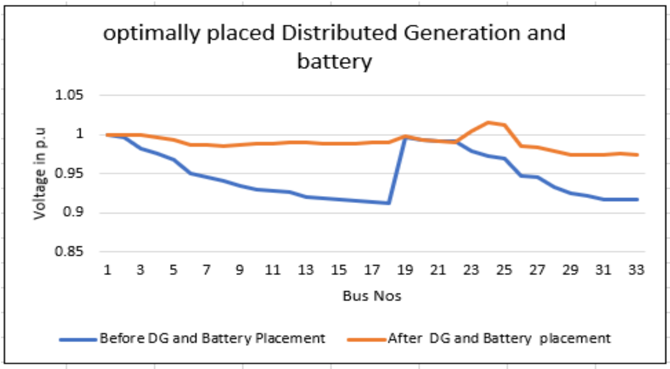

Figure 12. Volatge profile improvement as compared to base case by optimal location of DG's and Batteries.

6.5. Optimal Location of EV charging points

If there are any voltage violations into the grid, instead of dumb charging through active power absorption only, electric vehicle can inject reactive power into the grid to maintain the voltage and this is called as power factor control mode of charging. The voltage in the system is improved when Electric Vehicles are charged in power factor control mode. Therefore, the Charging stations have to be optimally positioned in system. Table 5 gives the data considered for EV charging stations optimal location in the test system. All 4 objective functions considered. Base case without any Charging stations (ChS's) and Charging Points (ChP's) is considered as 'Case A'. Three charging stations one in each sub-feeder is optimally placed with minimum number of ChP's. This increases the real power load to from3715kW to 6640kW and losses also increase from 203 kw to 576kW. This condition is considered as 'case B' and When Optimization Tool is used and EV charging stations are optimally placed the scenario is considered as 'case C'. Table 6 gives the results for optimal location of EV ChS's using HFPSO-TOPSIS method are compared with results obtained from Teaching Learning algorithm (TLBO) and Particle Swarm Optimization (PSO) [26].

Table 5: Data considered for EV charging stations

EV Type	EV Power Rating (kW)	No of ChPs		Rating of ChS (kW)	
		Min	Max	Min	Max
Chevrolet VOLT	2.2	25	35	55	77
CHANG AN YIDONG	3.75	20	30	75	112.5
Tesla Model X	12	15	25	195	325
BMW i3	44	10	20	440	880
SAE J1772 Standard	7	30	40	210	280
Total Power Rating of ChS (kW)				**975**	**1674.5**

Table 6: Optimal location of EV ChS's by HFPSO-TOPSIS.

Case	Algorithm	EV CS's location	Ploss	VSI min	Vmin (p.u)
A	-	-	203	0.666	0.903
B	-	-	576	0.496	0.840
C	TLBO	2/19/25	295.6	0.649	0.898
	PSO	2/19/25	292	0.649	0.898
	HFPSO-TOPSIS	2/19/21	248	0.69	0.90

Table 6, shows that, apllication of HFPSO-TOPSIS, gives the optimal location of EV ChS's that minimizes the active power losses in the system. It is observed that by implementing HFPSO-TOPSIS approach these losses are reduced by 57% whereas losses are reduced by only 50% by other methods.

7. CONCLUSION AND FUTURE SCOPE

According to the findings, OLRPSD is crucial at the distribution system level, since it reduces losses, improves the voltage profile, and maximises the techno-economic advantages to thereby enhancing the overall dependability and performance of the system, benefiting both the user and the operator. Given the complexity and number of objectives involved, a MOMCDM technique, such as HFPSO- TOPSIS, is necessary to solve this issue.

This study makes good use of the strengths of "Firefly and particle swarm optimisation." The "HFPSO-TOPSIS" method is effectively used to size OLRPSD. This method is capable of optimising several goals all at once. One notable advantage of this technique is the reduction in reactive power support costs and the increase in power quality, which may lead to financial gains. It has been noted that reactive power assistance greatly improves both the voltage profile and power quality. The correct placement and sizing of reactive power supporting devices, such as capacitors, D-STATCOM-PV systems, distributed generators (e.g., wind energy conversion systems, PV systems, diesel generators), and batteries, are ensured. This research also suggests using HFPSO-TOPSIS for newly developed reactive power compensating devices, such as electric vehicle charging stations.

Optimal placement of transformers in distribution systems, optimal bidding, and optimal scheduling are all examples of more complicated problems that can benefit from this approach, which takes into account multiple objective functions simultaneously while giving preference to or prioritising certain objective functions.

REFERENCES

[1] https://energy.economictimes.indiatimes.com/news/renewable/india-to-have-450-gw-renewable-energy-by-2030-president.
[2] https://energy.economictimes.indiatimes.com
[3] Kavitha K and Neela R, "Optimal allocation of multi-type FACTS devices and its effect in enhancing system security using BBO', Journal of electrical systems and Information technology, 2018. Pp777-783.
[4] Dipesh Gaur and Lini Mathew, "Optimal location of FACTS devices using optimization techniques: A review" IOP Conf. Ser.: Mater. Sci. Eng. 331(2018) 012023.2018.
[5] D. Sattianadan , M. Sudhakaran, S.S. Dash, K. Vijayakumar and Bishnupriya Biswal, "Power Loss Minimization by the Location of DG in Distribution System Using PSO", Proc. of Int. Conf. on Front. of Intell. Comput., AISC 199, pp. 497–504.springer-verlag Berlin Heidelberg 2013.
[6] M.M. Aman, G.B. Jasmon, A.H.A. Bakar, H. Mokhlis, "A new approach for optimum DG location and sizing based on voltage stability maximization and minimization of power losses", Energy Conversion and Management 70 (2013) 202–210.
[7] Dinakara Prasasd Reddy P, V.C. Veera Reddy, T. Gowri Manohar, "Optimal renewable resources placement in distribution networks by combined power loss index and whale optimization algorithm", Journal of Electrical Systems and Information Technology, (2017), pp. 175-191
[8] Adel Ali Abou El-Ela, Ragab A. El-Sehiemy, Abdel-Mohsen Kinawy, Mohamed Taha Mouwafi "Optimal capacitor location in distribution systems for power loss reduction and voltage profile improvement", IET Generation, Transmission & Distribution,2016, Vol. 10, Iss. 5, pp. 1209–1221

[9] T.Yuvaraja, ,K.R.Devabalajia, K.Ravia, "Optimal location and sizing of DSTATCOM using Harmony Search algorithm", International Conference on Alternative Energy in Developing Countries and Emerging Economies,2015,Elsevier, Energy Procedia 79 (2015)pp. 759 – 765.

[10] Srinivas Bhaskar Karanki, David Xu and Bala Venkatesh, Birendra N. Singh, "Optimal Location of Battery Energy Storage Systems in Power Distribution Network for Integrating Renewable Energy Sources", IEEE2013.

[11] Ahmed Alzahrani, Hussain Alharthi and Muhammad Khalid, "Minimization of Power Losses through Optimal Battery Location in a Distributed Network with High Penetration of Photovoltaics" Energies 2020, 13, 140.

[12] Ponnam Venkata K Babu*‡, K. Swarnasri, "Multi-Objective Optimal Allocation of Electric Vehicle Charging Stations in Radial Distribution System Using Teaching Learning Based Optimization" International Journal of Renewable Energy Research, Vol.10, No.1, March, 2020.

[13] Moupuri Satish Kumar Reddy, K.Selvajyothi "Optimal Location of Electric Vehicle Charging Stations in Radial Distribution System along with Reconfiguration", 1st International Conference on Energy, Systems and Information, 2019, IEEE.

[14] A. Aguila Tellez, G. Lopez, I. Isaac,J. W. Gonz alez,"Optimal reactive power supporting in electrical distribution systems with distributed resources" Review. Heliyon (2018).

[15] H. Haghighat and S. Kennedy, "A Model for Reactive Power Pricing and Dispatch of Distributed Generation ", IEEE PES General Meeting, Minneapolis, MN, USA, 2010.

[16] Ruoyang Li, Qiuwei Wu and Shmuel S. Oren," Distribution Locational Marginal Pricing for Optimal Electric Vehicle Charging Management" IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 29, NO. 1, JANUARY 2014 203.

[17] Chitransh Shrivastava, Manoj Gupta, Dr. Atul Koshti, "Review of Forward & Backward Sweep Method for Load Flow Analysis of Radial Distribution System" International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 4, Issue 6, June 2015.

[18] Gai-Ge Wang; Suash Deb; Leandro dos S. Coelho, "Elephant Herding Optimization",3rd International Symposium on Computational and Business Intelligence (ISCBI),Bali,Indonesia,18 January 2016

[19] Nand Kishor Meena, Sonam Parashar, Anil Swarnkar,Nikhil Gupta and Khaleequr Rehman Niazi,"Improved Elephant Herding Optimization for Multiobjective DER Accommodation in Distribution Systems" ,IEEE Transactions On Industrial Informatics, Vol. 14, No. 3, March 2018.

[20] Pushpendra Singh, Nand K. Meena Jin Yang∗, Eduardo Vega-Fuentes, Shree Krishna Bishnoi, "Multi-criteria decision making monarch butterfly optimization for optimal distributed energy resources mix in distribution networks", Applied Energy 278 (2020).

[21] Mesut E. Baran and Felix F. Wu ‘’Network reconfiguration in distribution systems for loss reduction and load balancing’, presented at IEEE /PES 1988 Summer meeting, Portland, Oregon, July 24-29,1988,Printed in 1989.

[22] M. A. Kashem, V. Ganapathy, G. B. Jasmon & M. Buhari, "A novel method for loss minimization in distribution networks," in International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT 2000), 2000.

[23] Bharat Singh, Satyaveer Singh Rawat, "Optimal Location of DG with Battery Energy Storage in Distribution Network for Power loss Minimization using Combined Dispatch & Combined PLS Strategy "International Journal of Engineering and Advanced Technology (IJEAT), Volume-9 Issue-5, June 2020.

[24] P. V. K. Babu and K. Swarnasri,"Multi-Objective Optimal Allocation of Electric Vehicle Charging Stations in Radial Distribution System Using Teaching Learning Based Optimization "International Journal of Renewable Energy research, Vol.10, No.1, March, 2020.

[25] M. H. Moradi and M. Abedinie, “A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems,” in Proc. Conf. Proc. IPEC, Singapore, 2010, pp. 858–862.

[26] K.Divya , S.Srinivasan, "Placing And Sizing of DG In Radial Distribution System And Identifying Fault Location In Distribution System Integrated With Distributed Generation" International Research Journal of Engineering and Technology, Volume: 02 Issue: 09,pp:440-449,Dec-2015.

[27] Jose L. Mart´ınez-Ramos, Alejandro Marano-Marcolini, Francisco P. Garc´ıa-L´opez, Fernando Almagro-Yravedra, Ahmet Oneny, Yeliz Yoldasy, Mounir Khiatz, Leila Ghomriz, Nunziatina Fragalex,"Provision of Ancillary Services by a Smart Microgrid: An OPF Approach", 2018 International Conference on Smart Energy Systems and Technologies, IEEE, (SEST),Sevilla, Spain,10-12 Sept. 2018.