International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Optimal Allocation of Capacitor Banks and DSTATCOMs in Radial Distribution System Considering Electric Vehicle Load Growth

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Abstract: In this paper, an improved variant of nature-inspired meta-heuristic algorithm inspired by the pollination process of flowering plants called improved flower pollination algorithm (IFPA) is utilized for solving the optimal allocation of capacitor banks (CBs) and distribution-static synchronous compensator (DSTATCOM) problem considering electric vehicle (EV) load growth. In IFPA, a new double-direction learning strategy to advance local searching capacity, a novel dynamic switching probability method to balance global and local searching, and a new greedy technique to increase population diversity. A multi-objective function is formulated for minimizing the real power loss and installation cost of CBs/DSTATCOM. The search space of the multiple CBs/DSTATCOMs is primarily reduced using voltage stability index (VSI) and later the best locations and sizes of CBs/DSTATCOMs are determined by implementing IFPA. The proposed hybrid VSI-FPA approach is applied to solve the DSTATCOM allocation problem in standard IEEE 33-bus radial distribution systems (RDS). The effectiveness of the proposed approach is compared with the similar types of heuristic approaches in the literature. The comparative results shown that the IFPA is outperformed than other algorithms by providing minimum losses, reduced installation cost, and consequently improved voltage profile as well as voltage stability irrespective of EV load growth via allocating the CBs/DSTATCOM optimally in the RDS. The basic network profited from CBs and DSTATCOMs by a loss reduction of 34.71% and 29.50%, respectively, according to the results. The loss, on the other hand, increases to 88.69 percent when the network is filled with 50% EV load. With CBs and DSTATCOMs, however, the higher losses are just 37.07% and 37.26%, respectively.

Keywords: Improved flower pollination algorithm, Capacitor bank, DSTATCOM, Radial distribution system, Loss minimization, Voltage stability index, Electric vehicle load.

1. Introduction

Optimization of distribution system performance is always an important criterion in power system operation and control. Network reconfiguration, installation of capacitor banks (CBs) and distribution-static synchronous compensators (DSTATCOMs), and integration of distribution generation (DGs) are some of the remedial ways for some extent to improve the radial distribution system (RDS) performance without curtailing the load. The major objective of optimal allocation of CBs/DSTATCOMs problem is to improve the distribution system performance and maximization of economic benefits to the utilities. In literature, many researchers have been contributed for this OAC problem using various heuristic algorithms. In [1], Grey wolf optimization (GWO), dragonfly optimization (DFO), moth–flame optimization (MFO), and particle swarm optimization (PSO) are used solved the CBs allocation problem considering minimization of loss cost and CBs cost. Loss sensitivity factors (LSFs) and voltage sensitivity factors (VSFs) have used to identify the potential candidates and then GWO, DFO, MFO and PSO are used to optimize locations and sizes. In [2], flower pollination algorithm (FPA) and power loss index

(PLI) have been used for operating cost minimization and thus, maximization of net savings by installing CBs in RDS optimally. In [3], clonal selection algorithm (CSA) is proposed for CBs allocation towards loss minimization and voltage profile improvement. In [4], LSFs and voltage stability indices (VSIs) are used to determine candidate locations and then improved bacterial foraging optimization algorithm (IBFOA) is utilized to deduct the optimal locations and sizes of CBs considering loss minimization and voltage stability enhancement under different loading conditions. In [5], techno-economic-environmental aspects have been optimized by installing CBs and DGs optimally in RDS using salp swarm algorithm (SSA). In [6], loss reduction, annual savings, and optimization of VSI and load balancing indices are focused in CBs allocation using brain storm optimization algorithm (BSOA). In [7], water cycle algorithm (WCA) is introduced for integrating CBs and DGs considering various techno-economic-environmental aspects in RDS operation and control. Similarly, a comprehensive literature survey on various meta-heuristic approaches for optimal integration of CBs can be seen in [8].

On the other hand, optimal integration of DSTATCOMs in RDS is also attained high attention for its versatile operation and applications. However, the targeted benefits of DSTATCOM can be attained when they integrate optimally in the network. In [9], new voltage stability index (NVSI) is proposed for identifying DSTATCOM location and then the optimal sizes are determined for loss reduction considering different load models. In [10], loss reduction, voltage profile improvement, and maximizing net savings are aimed via optimally integration DSTATCOM using gravitational search algorithm (GSA). In [11], DSTATCOM and unified power quality conditioner (UPQC) are used for reactive power cost savings considering different load growth scenarios. PLIs are used for identifying the candidate locations. For different loading conditions, the RDS performance is optimized for both technical and economical aspects by optimizing the DSTATCOMs using bat algorithm (BAT) [12]. In [13], improved bald eagle search (IBES) is introduced for optimal location and sizing the DSTATCOM for different types of load modelling. DE [14], immune algorithm (IA) and genetic algorithm (GA) [15], and Voltage Stability Indicator (VSI) [16] are such approaches for DSTATCOM allocation. Similarly, a comprehensive review on different meta-heuristic approaches for optimal allocation of DSTATCOMs in RDS can be found in [17].

From the literature, the following are the major observations and motivations to this research work. Many of these works are solved in two stages. In stage 1, the potential candidate locations for CBs/DSTATCOMs are predetermined by sensitivity analysis. In stage 2, algorithms are used to determine optimal locations and sizes of CBs. Limited works only are used directly to determine both locations and sizes of CBs/DSTATCOMs using algorithms. On the other side, the technical benefits aimed to achieve via CBs/DSTATCOMs allocation are mainly loss reduction, voltage profile improvement, voltage stability enhancement and annual net savings. These objectives are handled either single or multi-objective functions. The sizing of CBs/DSTATCOMs are determined for either 100% load level as given in the standard test system details or multiple loading levels like 50%, 75%, 100%, 125% and 160% etc. Majority of the works have handled with constant power (CP) load model, in which the power rating of any location is independent of its associated bus voltage magnitude. In reality, this may not be correct. Hence these is a need to address this CBs/DSTATCOMs allocation problem considering emerging loads like electric vehicles (EVs), which are highly dependent on voltage profile.

In these aspects, the following are the major contributions:

- The objective of optimal allocation of CBs/DSTATCOMs problem in RDS is reframed considering technical and economical benefits under electric vehicle (EV) load growth.
- In order to reduce the search space of CB/DSTATCOM locations, VSIs are used. Later, a recent powerful and efficient nature-inspired heuristic algorithm called flower pollination algorithm (FPA) [18] is proposed for deducing the optimal locations and their sizes towards minimizing the objective function.
- In order to avoid local optima, improvements in terms of double-direction learning strategy at the global searching process, greedy strategy at local searching process and dynamically switching probability strategy for balancing between global search and local search and termed as improved flower pollination algorithm (IFPA) [19].
- Initially the efficiency of proposed methodology is compared with existing type of works without considering EV load growth. Later, the simulations are extended for different for EV load growth scenarios considering different EV load penetration levels in the network.

Received: April 11, 2022. Revised: July 7, 2022.

The remainder of the paper is structured out as follows: The mathematical modelling of EV load development is described in Section 2. In Section 3, you'll find a problem formulation with several equal and unequal limits. The updated enhanced flower pollination algorithm, as well as its modelling, is explained in Section 4. The simulation results on IEEE 33-bus RDN are explained in Section 5. The important contributions of this study are summarised in Section 6 at the conclusion.

2. Modelling of EV load growth

For the system operator, it is essential to know the load growth of a particular load type for planning studies and control operations. Here, it is assumed here that all types of Electric Vehicle (EV) are integrated to utility via AC/DC converter or charging port. Since EV is basically powered by batteries, its corresponding load is modeled by considering voltage dependent load modeling [20]. The following Eqs. (1) and (2) represents the real and reactive power demand at bus-*n* after EV integration respectively.

$$P_{d(n)}^{t} = P_{d(n)}^{0} + \rho_{ev} P_{d(n)}^{0} \left(\frac{|V_{(n)}|}{|V_{(r)}|}\right)^{\alpha_{ev}} \quad (1)$$

$$Q_{d(n)}^{t} = Q_{d(n)}^{0} + \rho_{ev} P_{d(n)}^{0} tan(\emptyset_{ev}) \left(\frac{|V_{(n)}|}{|V_{(r)}|}\right)^{\beta_{ev}} \quad (2)$$

where$P_{d(n)}^{0}$and $Q_{d(n)}^{0}$ are nominal real and reactive power loads at bus-*n* respectively; $P_{d(n)}^{t}$and $Q_{d(n)}^{t}$ are modified real and reactive powers at location *n* after integration of EV load respectively; $\rho_{ev}$is the scaling factor to define EV load penetration, $|V_{(n)}|$ and $|V_r|$ are the voltage magnitude of bus-*n* at nominal and reference voltage, respectively; $\emptyset_{ev}$ is the is the operating power factor (p.f.) angle of AC/DC converter, α_{ev} and β_{ev} are the exponents of EV's real and VAr loads respectively [21].

3. Problem formulation

Minimization of total real power loss cost, installation cost of CBs and consequently maximization of net savings is considered as the objective function.

$$OF = k_p\left[P_{ls(b)} - P_{ls(c)}\right] - \sum_{i}^{nc} k_{c(i)} Q_{c(i)} \quad (3)$$

where $P_{ls(b)}$ and$P_{ls(c)}$ are the total real power losses before and after installation of CBs/DSTATCOMs in distribution system, are determined using NR load flow [22]; k_p is the cost of power in \$/kW; $k_{c(i)}$ is the cost of CBs [23] or DSTATCOMs in \$/kVAr [11]; $Q_{c(i)}$ is the reactive power compensation or size of CBs/DSTATCOMs in kVAr.

The OF is subjected to the following equal and unequal constraints such as (i) supply-demand balance, (ii) voltage limits, (iii) branch current/MVA limits, and (iv) reactive power compensation limit, which are expressed in Eqs. (4) to (8) respectively.

$$P_{eff(sub)} = P_{ls} + \sum_{i}^{nbus} P_{d(i)} \quad (4)$$

$$Q_{eff(sub)} = Q_{ls} + \sum_{i}^{nbus} Q_{d(i)} \quad (5)$$

$$\left|V_{(n)}\right|_{min} \le \left|V_{(n)}\right| \le \left|V_{(n)}\right|_{max} \quad (6)$$

$$\left|I_{(k)}\right| \le \left|I_{(k)}\right|_{max} \quad (7)$$

$$\sum_{i}^{nc} Q_{c(i)} \le \sum_{i=1}^{nbus} Q_{d(i)} \quad (8)$$

where $P_{eff(sub)}$ and $Q_{eff(sub)}$ are the active and reactive powers of substation, respectively; P_{ls} and Q_{ls} are the active and reactive power losses, respectively; $P_{d(i)}$ and $Q_{d(i)}$ are the active and reactive power loads at bus-*i*, respectively; $\left|V_{(n)}\right|_{min}$ and $\left|V_{(n)}\right|_{max}$ are the voltage magnitude minimum and maximum limits, respectively; $\left|I_{(k)}\right|$ and $\left|I_{(k)}\right|_{max}$ are the branch current and its maximum limit, respectively; $nbus$ and nc are the number of buses and number of compensators (either CBs or DSTATCOMs), respectively.

4. Improved flower pollination algorithm

From the last two decades, nature–inspired meta–heuristic optimization algorithms got high attention in all engineering optimization problems due to their easiness in adoptability and computational efficiency. With their stochastic nature, a set of random solutions may generate at first stage and improves the solution based on mechanism of the algorithm at second stage. The second stage continues by mimicking the nature of an element and stops when stopping criterion reaches. A comprehensive literature survey on different heuristic algorithms can be found in [24]. One of such recent algorithms, Flower Pollination Algorithm (FPA), introduced by Yang, X. S in 2012 [18], is so simple and easy to implement by having a small number of parameters and works efficiently as compared with similar type of algorithms.

4.1 Modeling of flower pollination algorithm

Basically, FPA works with the process of transferring flowers' pollens. Generally, bees, birds, bats, butterflies, insects, other animals and some extend even wind play a key role to transfer these pollens. Nature had also created some extended bond between some specified flowers and insects so called 'flower–pollinator partnership'. The basic mode of pollination in flowering plants can take place by either biotic/cross–pollination or abiotic/self–pollination. Around 90% of flowering plants depend on biotic/cross–pollination, in which bees, birds, bats, butterflies, insects and other animals act like pollinators. On the other side, around 10% of flowering plants may do pollination by self using wind and diffusion. In biotic, the motion of pollinators can be considered as global search where as in abiotic, they are called as local search due to their limited boundary. Sometimes, it is also possible to have flower–pollinator partnership for constancy. Under this behaviour, the pollinators like humming birds visit only a specific type of flowering plants which may offer sufficient nectar reward to the pollinators so as to encourage frequent visits and consequently there is a guarantee for constancy and successful reproduction rate with energy saving.

Using this naturist relation between flowering plants and pollinators, the main characteristics of pollinators and corresponding components of FPA are reframed and summarized here. The pollinators (insects, butterflies and birds) are represented as variables and pollen/flowers as solution vector in the optimization problem. In case, there are similar solutions in the vector, it can be treated as flower constancy. The biotic pollination represents global search and where as abiotic pollination is represented as local search. The initial random solution vector can be corrected using a step size with Lévy flight, and the evolution of new flowers can be represented as a new solution vector in each iteration. Lastly, the best solution found after the most iterations can be thought of as the best way for a flower to reproduce.

As described in [15], the biotic pollination for global search or *rule 1* is represented as:

$$v_i^{k+1} = v_i^k + \gamma L\left(v_{best}^k - v_i^k\right) \tag{9}$$

where v_i^k is pollen i or solution vector i at iteration k; v_{best}^k is the best pollen found among all pollens at iteration k; L is a step size, essentially used to represents strength of pollination. It can be obtained using Lévy flight as given in Eq. (10),

$$L \sim \frac{\mu\Gamma(\mu)sin\left(\frac{\pi\mu}{2}\right)}{\pi}\frac{1}{s^{1+\mu}}, (s \geq 0) \tag{10}$$

where $\Gamma(\mu)$ ddenotes the standard gamma function and this distribution is valid for large steps $s \geq 0$; $\mu = 1.5$ and $s = u/v^{1/\mu}$. Here v is a random number with standard normal distribution and u is Gaussian distribution with variance δ^2.

Similarly, abiotic pollination or *rule 2* is represented as:

$$v_i^{k+1} = v_i^k + \varepsilon\left(v_l^k - v_m^k\right) \tag{11}$$

where v_i^k and v_m^k are the pollens from different flowers of the same plant type at iteration k; ε is a random distribution in [0, 1].

This step ensures the exploration or global search space from exploitation or local search space. For each population/flower, the type of pollination is defined by a switching parameter p *and* its best value is 0.8 after testing by Yang. If the random number generated for ε is greater than *p*, then local pollination carried out and that provides exploitation property to the algorithm else it follows global pollination, which provides exploration property to the algorithm. This process continues until the convergence criterion satisfies i.e., number of maximum iterations.

4.2 Improved flower pollination algorithm

Despite of its simple and easy way to implement for any optimization problem, the basic FPA has been suffered with local minima while solving some complex and high-dimensional optimization problems. To overcome this, various improvements have been introduced and a comprehensive literature survey on various variant of PFA for improving its performance can be found in [25]. As presented in [19], the following are the basic steps involved in the Improved Flower Pollination Algorithm (IFPA) for solving the CBs/DSTATCOMs problem.

St. 1) Read system bus data, branch data and the annual EV load growth, number of CBs/DSTATCOMs locations with their minimum and maximum range, CBs/DSTATCOMs sizes with their minimum and maximum range. Also FPA controlling parameters such as number of flowers (n_f), switching probability limits $\left[p_{a,min}, p_{a,max}\right]$, and maximum iterations (k_{max}).

St. 2) Generate initial random population vector or pollinators consists of the vector of locations and sizes of CBs/DSTATCOMs.

St. 3) Using all the control variables generated at step 2, determine total loss using load flow [22] and VSI given in [21], and corresponding function value. Repeat step 3 for all populations and find the current best fitness value (v_{best}^{k}) over the initial population.

St. 4) Set iteration count $k = 1$. Update switching probability dynamically as given by:

$$p_a^k = p_{a,min} + exp\left(-10\frac{k}{k_{max}}\right)\left(p_{a,max} - p_{a,min}\right) \quad (12)$$

St. 5) Run the *for* loop n_f times: if $rand < p_a^k$, search for global pollinators using Eq. (9) and also a greedy solution as defined by Eq. (13).

$$v_i'^{k+1} = v_i^k + \gamma L\left(v_m^k - v_i^k\right) \quad (13)$$

Here, v_m^k is a random individual from the population. Find the best among greedy solution $v_i'^{k+1}$ and v_i^{k+1}, else, search for local best using Eqs. (14) and (15), and end the loop.

$$v_i^{k+1} = v_i^k + \varepsilon\left(v_j^k - v_i^k\right) + S \quad (13)$$

$$S = \alpha\left\{\omega\left(v_{best}^k - v_i^k\right) + (1-\omega)\left(v_{best}^{k-1} - v_i^k\right)\right\} \quad (14)$$

where v_{best}^k andv_{best}^{k-1} are the best solutions of k and (k-1) iterations respectively; ω is a weighting coefficient for obtaining the proportion of $\left(v_{best}^k - v_i^k\right)$ and $\left(v_{best}^{k-1} - v_i^k\right)$; $\alpha \in (0,1)$ is the scaling factor for adjusting the step size.

St. 6) Evaluate the new fitness value with the pollinators determined at step 5 and set iteration count $k = 1 + 1$.

St. 7) Repeat step 4 and step 6 until $k = k_{max}$. At each iteration, compare the new fitness value with the global fitness so far. If current fitness is better than global fitness, then replace global fitness by current fitness and current pollinators as global solution vector.

St. 8) Display the global fitness and global solution vector and stop.

5. Results and discussion

The simulations are performed in a PC with specification of 4 GB, 64-bit OS and Intel® Core™ i5-2410M CPU @ 2.30 GHz processor using MATLAB program. Simulations are performed for two scenarios. In Scenario-1, the simulations are performed without considering EV load penetrations. And in Scenario-2, EV load penetration is considered. Again, in each scenario, two cases are considered. Case-1, network performance optimization using CBs allocation and in Case-2, network performance optimization using DSTATCOM allocation. The cost of real power loss is selected as 168 \$/kWh/year and practically available capacitor sizes in kVAr and their prices in \$/kVAr taken from [23]. The cost of DSTATCOM and annual savings are estimated as given in [12]. Simulations are done on standard IEEE 33-bus test system [26].

This test system consists of 33 buses interconnected by 32 branches, and total real and reactive power demands of 3.715 MW and 2.30 MVAr respectively. The NR load flow [21] is performed by choosing the base values of 100 MVA and 12.66 kV. The uncompensated system has suffering with 202.6706 kW of real power loss and 135.1366 kVAr of reactive power loss. It has lowest voltage of 0.9131 p.u. at bus-18. By computing the VSI as defined in [18], it has 0.694 and system is said to be low voltage stability. Under this case, the overall operating cost is 34048.66 \$.

5.1 Scenario – 1: without EV load

In this section, optimal allocation of CBs problem is performed for two cases. Case-1 represents the results for without considering EV load growth and Case-2 represents results for with EV load growth.

5.1.1. Case-1: allocation of CBs

In this Case-1, optimal allocation of CBs problem is handled without considering EV load growth and compared the results obtained via proposed IFPA with existing literature works.

The search space for IFPA is defined as follows. The number of CB locations is 3. The minimum and maximum limits for the CB locations are [2, 33]. Since, the system has 2.3 MVAr reactive load, the compensation using standard sizes can be done between 150 kVAr and 2.25 MVAr, which can be found in [20]. Hence, the minimum and maximum limits for CB locations [bus-2, bus-33] and the sizes

Table 1. The optimal allocation of CBs and comparison with literature

Algorithm	IBFOA [4]	SSA [5]	MFO, GWO, DFO, PSO [1]	CSA [3]	WCA [7]	IFPA
CB Sizes (kVAr) and locations	695 (18) 525 (25) 850 (30)	450 (10) 450 (23) 1050 (29)	450 (8) 300 (13) 900 (30)	400 (12) 550 (24) 600 (30)	397.3 (14) 451.1 (24) 1000 (30)	390 (14) 600 (24) 1000 (30)
% kVAr Comp.	86.52	95.25	89.11	88.60	79.80	88.37
CB Cost ($/kVAr)$_A$	0.205	0.177	0.180	0.185	0.181	0.185
CB Cost ($)	471.500	436.703	472.673	513.677	528.451	565.236
P_{loss} (kW)	147.8886	135.814	134.1471	132.8662	132.4272	132.3156
Q_{loss} (kVAr)	102.4581	90.4472	89.5245	88.7456	88.4819	88.4727
V_{min} (p.u.)	0.945	0.936	0.9395	0.9341	0.9397	0.9397
VSI	0.7968	0.7663	0.7778	0.7602	0.7786	0.7787
P_{loss} Cost ($)$_B$	24845.28	22816.75	22536.71	22321.52	22247.77	22229.02
Total Cost ($)$_{A+B}$	25316.78	23253.46	23009.39	22835.20	22776.22	22794.26
% Savings	25.65	31.71	32.42	32.93	33.11	33.05
% P_{loss} Reduction	27.03	32.99	33.81	34.44	34.66	34.71

Table 2. The optimal allocation of DSTATCOM and comparison with literature

Algorithm	VSI [16]	IA [15]	GA [15]	DE [14]	BA [12]	IFPA
DSTATCOM (kVAr) and location	3386 (30)	962.49 (12)	1114.2 (12)	1252.7 (30)	1150 (30)	1278.7 (30)
% kVAr Comp.	147.217	41.847	48.443	54.465	50.000	55.596
DSTATCOM Cost ($)$_A$	169300	48124.5	55710	62635	57500	63935
P_{loss} (kW)	280.174	169.513	171.101	142.902	143.446	142.879
Q_{loss} (kVAr)	196.913	113.698	114.986	95.917	96.076	95.957
V_{min} (p.u.)	0.9458	0.9264	0.9279	0.9260	0.9250	0.9262
VSI	0.8002	0.7366	0.7414	0.7352	0.7319	0.7360
Annual savings ($)	-58694.75	12322.83	10683.47	24770.12	25029.07	24644.29
% P_{loss} Reduction	-38.24	16.36	15.58	29.49	29.22	29.50

are chosen correspondingly between [1, 46], considering 50 kVAr as step size of CB.

In Table 1, the results obtained with IFPA are compared with the existing works. The methodologies using IBFOA [4], SSA [5], MFO [1], GWO [1], DFO [1], PSO [1], CSA [3] and WCA [7] are taken in to consideration for comparison. In order to maintain uniformity in comparison, the results presented are given based on our load flow program and hence the reader may observe slightly deviation when compared with the actual works.

By implementing the proposed IFPA, the best locations for CBs are bus-14. 24 and 30. The sizes are 390, 600 and 1000 kVAr respectively. By having these VAr injections in the system, it is observed that the system has real power loss of 132.3156 kW (34.71% reduction as compared with base case) and reactive power loss of 88.4727 kVAr respectively. The minimum voltage at bus-18 is raised to 0.9397 p.u. from 0.9131 p.u. And the voltage stability index is raised to 0.7787 from 0.694. Also, the total operating cost includes CB installation cost is only 22794.26 $. This is around 33.05% net savings as compared to uncompensation system performance. By observing the results of other approaches, it can be said that the proposed IFPA is outperformed by resulting minimum losses and maximum net savings as compared with other works. Also, the system voltage profile and stability are improved than uncompesnation case.

5.1.2. Case-2: allocation of DSTATCOM

The similar procedure of CBs is implemented for DSTATCOM allocation also. By implementing the proposed IFPA, the best location for DSTATCOM is bus-30 and the size is 1278.7 kVAr, respectively. By having this VAr injection in the system, it is observed that the system has real power loss of 142.879 kW (i.e., 29.51% reduction as compared with base case) and reactive power loss of 95.957 kVAr respectively. The minimum voltage at bus-18 is raised to 0.9262 p.u. from 0.9131 p.u. And the voltage stability index is raised to 0.736 from 0.694. The annual savings are around 24644.29$. By observing the results of other approaches as given in Table 2 for VSI [16], IA and GA [15], DE [14] and

Table 3. Network performance under EV load growth (without CBs/DSTATACOMs)

Annual EV load growth (%)	P_{load} (kW)	Q_{load} (kVAr)	P_{loss} (kW)	Q_{loss} (kVAr)	$V_{min,18}$ (p.u.)	VSI
0	3715.00	2300.00	202.677	135.141	0.9131	0.6575
10	4041.30	2367.18	231.876	154.541	0.9068	0.6417
20	4367.60	2445.30	264.272	176.065	0.9002	0.6256
30	4693.90	2534.36	300.033	199.825	0.8935	0.6094
40	5020.21	2634.35	339.348	225.948	0.8866	0.5929
50	5346.51	2745.29	382.424	254.573	0.8794	0.5735

Table 4. Network performance under EV load growth with CBs

ρ_{ev} (%)	Locations			Sizes			P_{loss} (kW)	Q_{loss} (kVAr)	$V_{min,18}$ (p.u.)	VSI
0	24	30	12	450	1050	450	132.371	88.404	0.9366	0.7495
10	24	30	10	600	1050	450	156.680	104.577	0.9302	0.7276
20	24	30	13	600	1050	450	183.074	122.167	0.9280	0.7191
30	7	14	30	600	300	1050	213.752	142.768	0.9249	0.7077
40	30	24	13	1200	600	450	243.547	162.474	0.9164	0.6801
50	10	24	30	600	600	1200	277.802	185.132	0.9092	0.6571

Table 5. Network performance under EV load growth with DSTATCOMs

ρ_{ev} (%)	Locations			Sizes			P_{loss} (kW)	Q_{loss} (kVAr)	$V_{min,18}$ (p.u.)	VSI
0	30	15	24	1048	364	533	132.521	88.651	0.9403	0.7616
10	13	30	3	377	1028	930	157.634	105.423	0.9323	0.7341
20	12	32	30	512	230	872	186.949	124.437	0.9254	0.7109
30	24	13	30	636	432	1111	211.960	141.430	0.9216	0.6977
40	13	24	30	459	637	1147	243.405	162.349	0.9163	0.6798
50	30	9	24	1104	670	681	278.201	185.395	0.9068	0.6501

BA [12], it can be said that the proposed IFPA is outperformed by resulting minimum losses and maximum net savings as compared with other works. Also, the system voltage profile and stability are improved significantly when compared with uncompensation case.

5.2 Scenario – 2: with EV load growth

In this Scenario-2, the optimal allocation of CBs/DSTATCOMs problem is solved only using IFPA for different annual EV load growths expressed in terms of total percentage of load increment to the base case load. The performance of EDN under different EV load growth scenarios is given in Table 3 without compensation. The operating power factor of the charging infrastructure of EVs is taken as 0.98, correspondingly EV real and reactive power loads are estimated. From the results, it is clear that the EDN performance is degraded with increased losses, reduced voltage profile and decreased VSI, as EV loading increases. Thus, in this section, it is aimed to optimize the EDN performance by allocating either three CBs or three DSTATCOMs optimally using IFPA. The simulations are performed in two scenarios. In scenario 1, 3 CBs and in scenario 2, 3 DSTATCOMs are integrated.

5.2.1. Case 1: allocation of CBs

For this Case-1, the performance of the system w.r.t. annual load growth after VAr compensation using IFPA is given in the Table 4. For each EV load growth, the optimized CB locations and sizes in kVAr are given in the same table. The optimized kVAr compensation levels and correspondingly the obtained system performance in terms of P_{loss} reductions w.r.t. different annual EV load growth scenarios are determined.

At this movement, it can be said that the percentage of net savings are almost equal to the percentage of P_{loss} reduction. In addition, the lowest voltage in the system before compensation and improved lowest voltage after CBs integration optimally are given for different EV load growth scenarios. Similarly, the improved voltage stability indices at each EV load growth with CBs are also given.

5.2.2. Case 2: allocation of DSTATCOM

For this Case-1, the performance of the system w.r.t. annual load growth after VAr compensation using IFPA is given in the Table 5. For each EV load growth, the optimized DSTATCOMs locations and sizes in kVAr are given in the same table. The optimized kVAr compensation levels and correspondingly the obtained system performance in terms of P_{loss} reduction w.r.t. annual EV load growth are determined.

At this movement, it can be said that the percentage of net savings are almost equal to the percentage of P_{loss} reduction. In addition, the lowest voltage in the system before compensation and improved lowest voltage after DSTATCOMs integration optimally are given for different EV load growth scenarios. Similarly, the improved voltage stability indices with DSTATCOMs for each EV load growth scenarios are also given in Table 5.

6. Conclusion

The optimal allocation of capacitor banks (CBs) and distribution-static synchronous compensator (DSTATCOM) problems are solved using a new and efficient nature-inspired meta-heuristic method flower pollination algorithm (FPA). An improved flower pollination algorithm uses a new double-direction learning technique to boost local search (IFPA). CB/DSTATCOM actual power loss and installation cost are minimized using a multi-objective function. The search space for numerous CBs/DSTATCOMs is first minimized using VSI, and then the ideal locations and sizes are identified using IFPA. The proposed optimization problem needs to solve for discrete (locations) and continuous (sizes) variables. The search space can be reduced for locations by using voltage stability index (VSI) based pre-defined locations. Thus, the algorithm can deduce the optimal locations effectively. In addition, the modifications to the basic FPA by a new double-direction learning strategy to advance local searching capacity, a novel dynamic switching probability method to balance global and local searching, and a new greedy technique to increase population diversity. These strategies can increase searching precision and make solution more accurate. To handle the DSTATCOM allocation problem in IEEE 33-bus radial distribution systems, a hybrid VSI-FPA solution is proposed (RDS). The proposed approach's effectiveness is compared to other heuristic approaches in the literature. The IFPA outperforms existing algorithms in terms of minimal losses, decreased installation costs, and enhanced voltage profile and voltage stability regardless of EV load growth.

Conflicts of Interest

Authors declare that no conflicts of interest.

Author Contributions

Ramesh Puppala: Conceptualization, software, investigation, writing—original draft preparation, Chandra Sekhar K: validation, formal analysis, and supervision.

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