Received: March 6, 2023. Revised: April 3, 2023.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Optimal Integration of Multiple D-SVCs for Voltage Stability Enhancement in Radial Electrical Distribution System Using Adaptive Firefly Algorithm

P. Muthukumar[1] **M. V. Ramesh**[1] **Ponnam Venkata Kishore Babu**[2]* **P. Rohinikumar**[2] **S. V. Satyanarayana**[2]

[1]*Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada-520007, Andhra Pradesh, India*
[2]*RVR & JC College of Engineering, Guntur - 522019, Andhra Pradesh, India*
* Corresponding author's Email: kishore.ponnam@gmail.com

Abstract: Most electrical distribution systems (EDS) are radially structured so that primary and secondary protection control devices can work together well. Because they have a high R/X ratio in their design, they also have a bad voltage profile, high distribution losses, and less stability margins. As a result, integrating reactive power compensation devices like the distribution-static VAr compensator (D-SVC) can solve these issues. Yet, the situation can get worse if D-SVCs are placed and rated incorrectly in radial distribution networks (RDNs). Determining the optimum locations and their ratings simultaneously requires an updated version of the Firefly algorithm (FA) with adaptive parameters, which is introduced in this paper as the adaptive firefly algorithm (AFA). The multi-objective function that has been presented relates to improving loadability, voltage stability, and reducing active power loss. On the IEEE 69-bus, simulations are run for three different VAr compensation levels. In comparison to the base case, the losses are reduced by 34.04% and 33.14% with 50% and 75% VAr compensation, respectively. But for the optimal VAr compensation of 73.14 percent by AFA, the losses are reduced by 35.29 percent, which is higher than both under and over compensation cases. Similarly, the loadability margin is increased to 3.099 p.u. with optimal VAr compensation, but it is observed as only 2.833 p.u. and 2.939 p.u. with 50% and 75% VAr compensation, respectively. On the other hand, the findings produced with APF demonstrate its efficiency for resolving complex optimization issues and outperform those obtained with previous research. Also, the proposed D-SVCs allocation has improved RDN's overall performance, demonstrating how well it adapts to real-time applications.

Keywords: Radial distribution networks, Adaptive parameter, Distribution-static VAr compensator, Firefly algorithm, Multi-objective optimization.

1. Introduction

Industrialization and automation have resulted in a high demand for electricity in almost all power systems around the world. In comparison to the growth rate of active power generation sources in any power system, the growth rate of reactive power compensation sources is very low. And thus, most of the electrical distribution networks (EDNs) draw more reactive power from the main grid, resulting in inadequate voltage magnitudes and voltage instability/blackouts [1]. In addition, the radial structure and high r/x ratio branches of EDNs cause the network performance to worsen significantly [2]. Thus, many researchers have been focused on reactive power compensation in power systems after experiencing blackouts. Flexible AC transmission system (FACTS) devices are highly suggested for reactive power flow control in transmission lines [3]. On the other hand, capacitor banks (CBs), on-load tap-changers (OLTC), booster transformers, voltage regulators, network reconfiguration (NR), etc. have been playing a key role in reactive power compensation at the distribution side [4].

The technical (actual power loss reduction, feeder voltage profile improvement, and overall voltage stability margin enhancement) and financial (operating cost reduction) benefits of integrating FACTS in distribution networks are numerous. Yet, these advantages are only accessible when they are perfectly networked. In this context, studies on power system planning have given a lot of attention to the issue of optimal FACTS device integration in EDN.

In [5], loss sensitivity factors (LSFs) are proposed for determining pre-defined candidate locations for CBs integration, and hybrid artificial bee colony-particle swarm optimization (ABC-PSO) with fuzzy logic is introduced for deducing the optimal locations and ratings. The multi-objective function is formulated for real power loss and annual loss reduction. In [6], the dragonfly algorithm (DFA) and fuzzy expert system are employed for identifying the optimal sites and ratings of CBs in RDNs for real power loss reduction. In [7], minimization of active energy loss and voltage deviation is aimed by optimally controlling the OLTCs along with distribution generation (DGs) using moth search optimization (MSO). In addition to DGs, CBs, and OLTCs, the NR approach is also highly explored for managing network power flows and improving overall performance [8]. In [9], the modified culture algorithm (MCA) is employed for reducing the active power loss in EDNs by using an optimal NR approach. In [10], NR and DGs are proposed for improving the consistency of EDN in terms of loss reduction and voltage stability enhancement under multiple loading conditions. The optimization problem is solved using the enhanced marine predator algorithm (EMPA). In [11], NR with soft open points (SOPs) is proposed using artificial rabbit optimization (ARO) for improving the resilience of multi-lateral EDNs under renewable energy (RE)-based DGs and electric vehicle (EV) uncertainty.

CBs can be either fixed or switched configuration and not able to provide appropriate and dynamic VAr support. Thus, CBs can lead to either under or over compensation, results for either low voltage or high voltages in the EDNs. On the other side, NR method needs remote control switches (RCSs) in each branch and need to cooperatively to control these switches along with tie-lines. Unfortunately, most of the EDNs are not fully automated with RCSs for dynamic NR and this approach for performance improvement of EDNs is limited. Similarly, OLTC transformers designed with fixed tap-settings and are not fine tuneable for dynamic VAr control. In comparison to these methods using CBs, NR, and OLTC, now a days, the adaptation of FACTS devices at the distribution side, namely D-FACTS devices, is getting high attention due to their dynamic and fast response to the uncertainties [12]. Unified power quality controllers (UPQCs), Distribution- static synchronous compensators (D-STATCOMs), distribution-static VAr compensators (D-SVCs), and distributed thyristor-controlled series compensators (D-TCSCs) are the best examples of such D-FACTS devices. In order to accommodate high DG penetration, the need for voltage regulation in uncertain EDNs is optimised by using OLTCs and static VAr compensators (SVCs) using robust optimization (RO) [13]. In [14], a literature survey on optimal allocation of D-FACTS such as distribution-static synchronous compensators (DSTATCOMs), unified power quality controllers (UPQCs), and CBs is presented. In addition, the grasshopper optimization algorithm (GOA) is adapted for the allocation of DSTATCOMs in the 69-bus EDN towards loss reduction, voltage profile improvement, and voltage stability enhancement. In [15], the impact of D-STATCOM on RDNs with different kinds of load models is analyzed, and the optimal location and sizes are determined using improved bald eagle search (IBES) by targeting a multi-objective function of loss, voltage profile, and voltage stability. In [16], the improved flower pollination algorithm (IFPA) and the voltage stability index (VSI) are hybridised for solving the CBs and DSTATCOMs in RDNs and mitigating the negative impact of electric vehicle (EV) loads considering techno-economic benefits. In [17], optimal ratings and locations for UPQC along with NR are solved using the improved whale optimization algorithm (IWOA) for reducing the active power loss and cost of UPQC and switching operations. In [18], basic open-source mixed-integer nonlinear programming (BONMIN) is proposed for optimal integration of D-SVC and D-TCSC along with DGs for improving the efficiency of EDN. In [19], the adaptive differential search algorithm (ADSA) is utilised for solving the SVC location and sizes, along with active power DGs for ensuring minimum distribution losses. In [20], a gradient-based optimizer with a crossover operator (GBOC) is introduced for solving D-SVCs in RDN for techno-economic benefits. Further, different approaches to reactive power compensation in EDNs via conventional approaches and D-FACTS can be reviewed in [21].

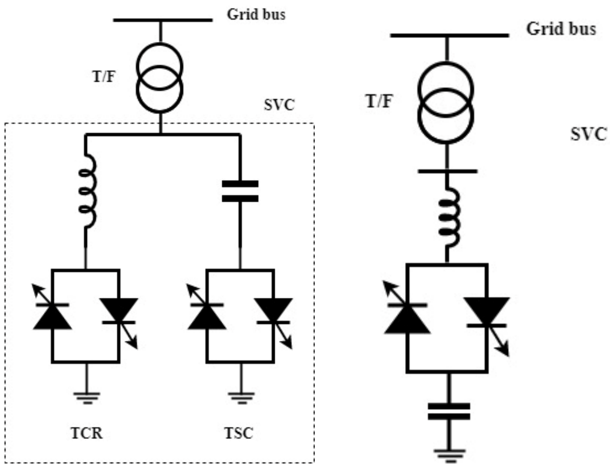
From the above reviewed works, different methodologies, like linear programming (LP), non-linear programming (NLP), and dynamic programming (DP), were employed for solving the optimal allocation of D-FACTS in EDN. Meta-heuristics were highly used due to their multiple advantages. The complexity involved in solving real-time engineering problems with multiple objectives formulated with various simultaneous linear and non-linear constraints, equal and unequal constraints, and continuous and discrete variables can be easily overcome by meta-heuristics. They are free from derivatives and easy to adapt with minimum control variables [22]. However, meta-heuristics suffer from the generation of a random population in the optimization process, which can lead to poor exploration and/or exploitation characteristics and further result in a local minima trap. On the other hand, the no-free-lunch (NFL) theorem states that many algorithms may not suit solving all kinds of optimization problems [23]. Thus, the researchers are still motivated to introduce new algorithms and also make improvements to the existing algorithms. Firefly algorithm (FA) is one such simple and efficient algorithm in recent times inspired by the flashing patterns and behaviour of fireflies [24]. But it has to be strengthened and made simpler because it sometimes gets stuck in local optima and loses its ability to optimise [25]. The performance of basic FA is dependent on mainly two controlling factors i.e., light variation and attraction. In literature [26], various improvements have been suggested for basic FA by modifications to these parameters. On the other side, some researchers are also experimented with hybridizing with other algorithms. In order to overcome these issues, adaptive parameters are introduced for improving the search ability of the basic FA in the adaptive firefly algorithm (AFA) [27].

In light of the above-identified research problem and in comparison to the literature, the following are the major contributions of this paper:

1) A multi-objective approach for optimal allocation of D-SVC is proposed.
2) At the first stage, the preferable locations for installing D-SVC are determined using the voltage stability index (VSI).
3) In the second stage, AFA is used to get the best reactive power output from D-SVC.
4) Adaptive parameters are introduced for the basic Firefly algorithm (FA) for developing the proposed adaptive Firefly algorithm (AFA) for improving its search capabilities in the optimization process.
5) The optimal VAr values of D-SVC are evaluated under different loading conditions on the IEEE 69-bus radial EDN.

The D-SVC is not optimally integrated to figure out how much the RDN can be loaded. The effectiveness of FA in resolving the D-SVC allocation issue in EDN has not yet been investigated. Hence, adding adaptive parameters to FA's exploration and exploitation stages can enhance its convergence characteristics. In light of this, this work presents an intriguing subject for studies on power system management and performance enhancement.

The mathematical modelling of D-SVC is covered in section 2. The suggested multi-objective problem is described in section 3 along with its equal and unequal restrictions. The solution methodology utilising AFA and its mathematical relationships in the optimization process is presented in section 4. The simulation results on the IEEE 69-bus using the suggested AFA and a comparison of effeteness to literary works are covered in section 5. Lastly, section 6 projects the thorough study results and major advancements made by this paper.



(a) (b)

Figure. 1 Schematic diagram of D-SVC, (a) combination of TCR and TSC, (b) fixed CB and TCR

2. Modelling of D-SVC

One of the shunt type FACTS devices is SVC which is designed basically with thyristor switched capacitor (TSC) and thyristor controlled reactor (TCR) for working in either reactive power source (under capacitive mode) or reactive power sink (under inductive mode). The schematic diagram of SVC is given in Fig. 1.

By controlling the firing angles of thyristors, the total susceptance of either TCR or TSC can be regulated. The relation between firing angle and susceptance of the TCR is given by,

$$B_{L(\alpha)} = \frac{1}{\omega L}\left(1 - \frac{2\alpha}{\pi}\right) \text{ and } B_C = \omega C \quad (1)$$

The total susceptance of the D-SVC is equal to the summation of both $B_{L(\alpha)}$ and B_C, given by,

$$B_{SVC} = B_{L(\alpha)} + B_C \tag{2}$$

The reactive power support by D-SVC under reactive power source/ sink scenarios is given by,

$$Q_{SVC} = \mp B_{SVC} V_{grid}^2 \tag{3}$$

where $B_{L(\alpha)}$, B_C and B_{SVC} are the susceptances of TCR, CB and D-SVC, respectively, ω is the angular frequency, L and C are the inductance and capacitances, respectively; α is the firing angle of thyristor, Q_{SVC} is the reactive power compensation by D-SVC; V_{grid} is the voltage magnitude of grid-bus or D-SVC incident bus in the network.

In Eq. (3), positive sign indicates the reactive power consumption state by D-SVC for reducing the grid-bus voltage magnitude and whereas negative sign indicates the reactive power support by D-SVC for increasing the voltage magnitude of grid-bus. Thus by changing the α, the overall susceptance of the D-SVC can be changed and consequently, the reactive power output from D-SVC can be adjusted dynamically as per the operating conditions.

3. Problem formulation

This section introduces the proposed multi-objective optimization problem along with its various equal and unequal constraints.

3.1 Multi-objective function

Reduction of power losses(f_1), improvement of voltage stability index (f_2), and enhancement of loadability (f_3) are aimed in optimizing the location and sizes of D-SVC in this paper. Mathematically,

$$f_1 = \frac{P_{loss(DSVC)}}{P_{loss(base)}} \tag{4}$$

$$f_2 = \frac{VSI_{(base)}}{VSI_{(DSVC)}} \tag{5}$$

$$f_3 = \frac{\lambda_{max(base)}}{\lambda_{max(DSVC)}} \tag{6}$$

$$OF = min(w_1 f_1 + w_2 f_2 + w_3 f_3) \tag{7}$$

where $P_{loss(base)}$ and $P_{loss(DSVC)}$ are the real power losses with and without D-SVC in the network, respectively; $VSI_{(base)}$ and $VSI_{(DSVC)}$ are the voltage stability index (VSI) of the network before and after D-SVC integration in the network, respectively; $\lambda_{max(base)}$ and $\lambda_{max(DSVC)}$ are the maximum loadability margin before and after D-SVC integration in the network, respectively; w_1, w_2 and w_3 are the weighting factors for the objective functions f_1, f_2 and f_3, respectively. .

3.2 Constraints

The bus voltage magnitudes, VAr and location limits for D-SVC and VSI limit are considered.

$$|V|_{min} \le |V|_n \le |V|_{max}, \forall n = 2{:}nbus \tag{8}$$

$$\sum_{k=1}^{ndsvc} Q_{DSVC(k)} \le= \sum_{i=1}^{nbus} Q_{d(i)} \tag{9}$$

$$2 \le L_{DSVC} \le nbus \tag{10}$$

$$VSI > 0, \forall n = 2{:}nbus \tag{11}$$

where $|V|_n$, $|V|_{min}$ and $|V|_{max}$ are the voltage magnitude of bus-*n*, and its minimum and maximum limits, respectively; $Q_{DSVC(k)}$ and $Q_{d(i)}$ are the VAr capacity of D-SVC at bus-k and VAr load at bus-*i*, respectively; L_{DSVC} is the location of D-SVC in the network, $nbus$ and $ndsvc$ are the number of buses and number of D-SVCs in the network, respectively.

4. Solution methodology

The mathematic modelling of firefly algorithm concept and the proposed modifications with dynamic parameter are explained in this section.

4.1 Evaluation of objective functions

The real power distribution losses are evaluated by using the Newton Raphson load flow method (NRLF) [28]. The VSI is evaluated by using the methodology defined in [29]. The maximum loadability is evaluated by using the repeated power flow (RPF) [29]. Mathematically,

$$L = \left\{\sum_{i=1}^{nbus}\left(P_{d(i)} + jQ_{d(i)}\right)\right\}(1 + \lambda_{max}) \tag{8}$$

where $P_{d(i)}$ is the real power demand at bus-*i*, λ_{max} is the maximum load increment factor at which the NR load flow method fails to converge. In other words, the loading condition at which Jacobian matrix becomes singular.

4.2 Strategy for D-SVC locations

The VSI should be more than 0 and less than 1, according to [28]. The buses that are getting close to 0 can be thought of as having more potential for voltage collapse. Hence, enhancing the voltage profile and consequently the VSI at those locations can lead to an improvement in overall stability of the network. All of the locations are ranked in descending order based on their respective VSI values after being determined. As a pre-defined search space for D-SVC integration, the top ten locations are taken into consideration. Next, by employing the suggested optimization approach, the optimal locations are deduced from them together with the ratings.

4.3 Basic firefly algorithm

In nature, fireflies' flashing inspired the firefly algorithm (FA). Fireflies release quick, rhythmic bioluminescent flashes. Flashing lights attract companions, prey, and predators. Hence, the intensity of the light affects other fireflies' approach. The FA's main objective function is brightness, based on the fireflies' f_i and f_j. The particle's lesser brightness helps find and brighten the brightest particles. Distance between particles reduces brightness. Fireflies are ordered by brightness. The particle will locate their ideal partner until the number of generations is limited.

The light intensity (L_i) of the firefly associated with the solution is proportional to the target value of the fitness function and is defined by:

$$\gamma_{i(d)} = \gamma_{i(0)} e^{-\sigma d^2}, d \geq 1 \tag{9}$$

where d is the distance between two fireflies, $L_{i(0)}$ and $\gamma_{i(d)}$ are the firefly's initial (d=0) and distance based light intensity, respectively; σ is the light absorption factor.

The distance (d) is modelled using Euclidian distance formula, as follows:

$$d_{(i,j)} = \|f_i - f_j\| = \sqrt{\sum_{k=1}^{ns} \left(f_{i,k} - f_{j,k}\right)^2} \tag{10}$$

where $f_{i,k}$ and $f_{j,k}$ are the *k*th member of *i*th and *j*th firefly, respectively; ns is the number of search variables of the problem.

The movement between *i*th and *j*th fireflies is modelled by,

$$f_i = f_i + \gamma_{i(0)} e^{-\sigma d^2}\left(f_i - f_j\right) + \delta\left(r - \frac{1}{2}\right) \tag{11}$$

Here, the first and second parts in Eq. (11) are used to define attraction and third is for defining random step movement by a parameter δ and r is a randomly generated uniform number between 0 and 1.

4.4 Adaptive firefly algorithm

An adaptive parameter strategy is used in the AFA to control the step factor and attractiveness. In the basic FA, the parameters δ and γ are constant and thus subjected to local optima trap. In AFA, they are dynamically tuned for improving search characteristics.

$$\gamma(t+1) = \gamma(t) \times e^{\left(-k\frac{t}{t_{max}}\right)} \tag{12}$$

$$\delta(t+1) = \delta(t) - \vartheta e^{\left(-m\frac{t}{t_{max}}\right)} \tag{13}$$

where $\vartheta =$ 0.9, $k\{= 1,2,3,..\}$ and $m\{= 1,2,3,..\}$ are used to defined the rate of decrease and increase the dynamic movements, respectively; 0.5 and 1 are used for $\gamma(0)$ and $\delta(0)$, respectively; t and t_{max} are the number of present and maximum iteration, respectively.

5. Results and discussion

The proposed AFA is implemented for solving the D-SVC locations and ratings in IEEE 69-bus feeder. The load data and branch data are taken from [29]. It has real and reactive power loading levels as 3802.1 kW and 2694.7 kVAr, respectively.

5.1 Simulations with different algorithms

Base case: For the standard test system data [30], NRLF is performed for determining the performance of EDN. It is noted that the total real and reactive power losses of $P_{loss(base)}$ = 225 kW and 102.2 kVAr, respectively. The minimum voltage magnitude is registered at bus-65 as 0.9092 p.u. The least VSI is determined as $VSI_{(base)}$= 0.55 at bus-60. By implementing repeated power flow (RPF) [31], the maximum loadability of the network is determined as $\lambda_{(base)}$ = 2.211 p.u. These results treated as base case for comparison.

Ideal case: Before optimization the locations and ratings of D-SVCs, the global optima values or ideal case values are determined by considering total reactive power loading as zero, which is aimed by VAr compensation with D-SVCs in the network. The total real and reactive power losses reduced to $P_{loss(base)}$ = 143.523 kW and 65.298 kVAr, respectively. The minimum voltage magnitude is registered at bus-65 as 0.9317 p.u. The least VSI is determined as $VSI_{(base)}$ = 0.7012 at bus-60. By implementing RPF, the maximum loadability of the network is determined as $\lambda_{(base)}$= 3.064 p.u. These results treated as ideal case for comparison.

Table 1. Results of different algorithms

Method	D-SVC in ± kVAr (bus #)	P_{loss} (kW)	VSI
CSA	604 (66), 699 (47), 1250 (61)	147.553	0.7178
FPA	172 (52), 1255 (61), 340 (19)	145.985	0.7170
TLBO	510 (50), 1252 (61), 368 (19)	145.778	0.7155
FA	303 (23), 1169 (61), 469 (53)	145.721	0.7166
AFA	281 (21), 1184 (61), 506 (53)	145.605	0.7175

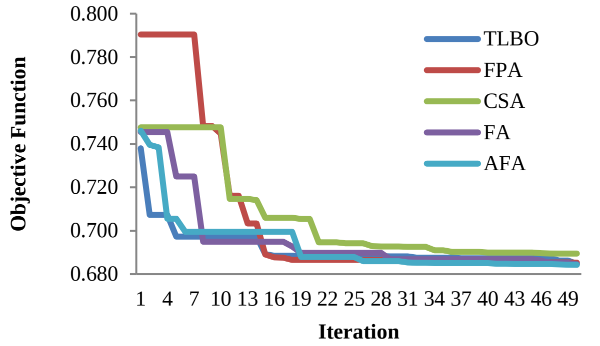


Figure. 2 Convergence characteristics

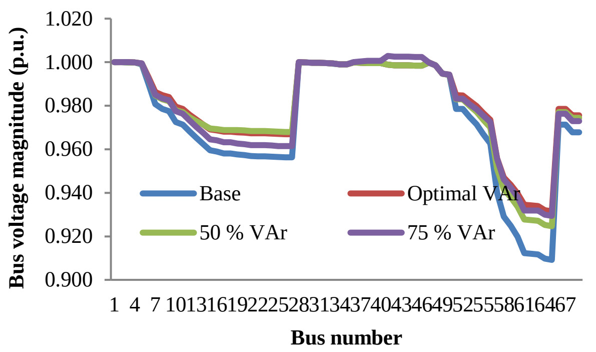


Figure. 3 Comparison of voltage profile

Optimal Case: For improving this operating state, three D-SVCs are proposed to integrate optimally. The search dimension is equal to 6 (i.e., 3 for locations and 3 for ratings). In the proposed multi-objective function, the weighting factors w_1, w_2 and w_3 are taken as 0.6, 0.2 and 0.2, respectively. The best results obtained by AFA are as follows:

The sizes (locations) in ± kVAr are 281 (21), 1184 (61), and 506 (53), respectively. The total real and reactive power losses reduced to $P_{loss(base)}$ = 145.605 kW and 67.844 kVAr, respectively. The minimum voltage magnitude is registered at bus-65 as 0.9315 p.u. The least VSI is determined as $VSI_{(base)}$= 0.7175 at bus-63. By implementing RPF, the maximum loadability of the network is determined as $\lambda_{(DSVC)}$ = 3.099 p.u. These results treated as optimal VAr comparison level of 73.14%.

In addition to APFA, basic FA, cuckoo search algorithm (CSA) [32], flower pollination algorithm (FPA) [33] and teaching learning based optimization (TLBO) [34] also used solve the proposed objective function. With respect to base case values, the best results obtained by each algorithm over 25 independent runs are given in Table 1. The convergence characteristics of these algorithms are given in Fig. 2.

In order to compare the effectiveness of VAr compensation on the performance of EDN, the AFA is used for determining the D-SVCs' locations and ratings. The corresponding results for different VAr compensation levels are given in Table 2. From this analysis, it is evident that the under compensation (less than optimal) or over compensation (more than optimal) of VAr can result for adverse effects on the network performance. The improved voltage profiles for different VAr compensation levels are compared and given in Fig. 3.

5.2 Comparison with literature

5.2.1. Simulations with D-SVCs

In this section, the efficiency of AFA is compared with literature for two different case studies. In case 1, the VAr compensation limit is defined as 50% of total reactive power demand of the network and whereas in case 2, it is taken as 75%, respectively. From [20], the results of gradient-based optimizer (GBO), GBO with crossover operator (GBOC), dwarf mongoose optimization algorithm (DMOA), salp swarm algorithm (SSA), differential evolution (DE), bernstein-levy search DE (BSDE) and honey badger algorithm (HBA) are compared with the proposed AFA.

Under Compensation (50%): In this case, three D-SVCs are optimally integrated for 50% reactive power compensation. This is less than optimal VAr compensation and treated as under compensation. The best sizes of D-SVCs by AFA in ± kVAr (bus #) are as follows: 163 (63), 973 (61) and 212 (18). The total real and reactive power losses reduced to $P_{loss(base)}$ = 148.342 kW and 69.197 kVAr, respectively.

The minimum voltage magnitude is registered at bus-65 as 0.9287 p.u. The least VSI is determined as $VSI_{(base)}$= 0.7029 at bus-60. By implementing RPF, the maximum loadability of the network is determined as $\lambda_{(DSVC)}$= 2.833 p.u. The comparison

Table 2. Network performance for different VAr compensation levels

VAr Comp (%)	**Locations (bus #)**	**Ratings (± kVAr)**	**P_{loss} (kW)**	**Q_{loss} (kVAr**	**V_{min} (p.u.)**	**VSI**
Base	-	-	225	102.2	0.9092 (65)	0.55 (60)
Ideal			143.523	65.298	0.9317 (65)	0.7012 (60)
10	27, 26, 64	13, 13, 1995	192.034	88.448	0.9424 (61)	0.6266 (60)
20	59, 61, 64	13, 981, 1026	175.018	79.694	0.9434 (61)	0.7367 (60)
30	22, 61, 64	9, 1398, 614	170.679	77.598	0.9424 (65)	0.7739 (64)
40	62, 61, 22	697, 1128, 196	158.363	72.832	0.9387 (65)	0.7408 (63)
50	64, 61, 69	292, 1448, 281	155.952	71.774	0.9385 (65)	0.7612 (64)
60	61, 61, 18	579, 902, 540	149.921	69.403	0.9347 (65)	0.7279 (63)
70	61, 26, 11	1336, 138, 548	146.063	67.996	0.9331 (65)	0.7227 (63)
73.14	**21, 61, 53**	**281, 1184, 506**	**145.605**	**67.844**	**09315 (65)**	**0.7175 (61)**
80	53, 17, 61	643, 255, 1123	145.892	67.967	0.9310 (65)	0.7160 (63)
90	61, 15, 29	927, 319, 776	151.868	71.159	0.9257 (65)	0.6902 (60)
100	2, 62, 11	511, 859, 651	152.907	70.805	0.9260 (65)	0.5920 (60)

Table 3. Comparison of AFA with various methods reported in [20] for of 50% VAr compensation

Method	**D-SVC in ±kVAr (bus #)**	**P_{loss} (kW)**	**VSI**
BSDE	31 (61), 259 (62)	196.124	0.5656
SSA	226 (61), 259 (64)	180.630	0.5944
DMOA	393 (62), 236 (63), 309 (64)	158.448	0.5889
HBA	321 (61), 618 (62)	158.221	0.6232
DE	557 (62), 382 (63), 82 (69)	156.658	0.5897
GBO	189 (21), 876 (61)	154.847	0.6813
GBOC [20]	204 (21), 589 (62), 355 (64)	152.690	0.5912
AFA	308 (22), 818 (61), 221 (20)	149.405	0.7085

Table 4. Comparison of AFA with various methods reported in [20] for of 75% VAr compensation

Method	**D-SVC in ±kVAr (bus #)**	**P_{loss} (kW)**	**VSI**
BSDE	560 (22), 233 (62), 413(63)	196.124	0.5656
SSA	226 (61), 259 (64)	180.630	0.5944
DMOA	393 (62), 236 (63), 309 (64)	158.448	0.5889
HBA	321 (61), 618 (62)	158.221	0.6232
DE	557 (62), 382 (63), 82 (69)	156.658	0.5897
GBO	189 (21), 876 (61)	154.847	0.6813
GBOC [20]	204 (21), 589 (62), 355 (64)	152.690	0.5912
AFA	681 (63), 546 (41), 793 (57)	150.442	0.6020

Table 5. Comparison of AFA in solving optimal VAr compensation using CBs

Method	**CB in kVAr (bus #)**	**P_{loss} (kW)**	**VSI**
FIS-ABC-POS [5]	126 (11), 93 (13), 145 (17), 117 (21), 94 (28), 104 (39), 96 (45)	214.28*	-
FES-DA [6]	1230 (61), 190 (64), 100 (59), 100 (65), 360 (21)	150.43*	-
AFA	526 (12), 1035 (61), 43 (69), 208 (64)	146.27	0.7177

* Indicates, results are revised as per the load flow

is given in Table 3 and the results of AFA are observed as superior to all other algorithms by having least objective function value.

Over Compensation (75%): In this case, the reactive power compensation target is set as 75% by integrating three D-SVCs are optimally. This is more than optimal VAr compensation and treated as over compensation. The best sizes of D-SVCs by AFA in ± kVAr (bus #) are as follows: 308 (22), 818 (61) and 221 (20). The total real and reactive power losses reduced to $P_{loss(base)}$ = 148.405 kW and 69.24 kVAr, respectively.

The minimum voltage magnitude is registered at bus-65 as 0.9282 p.u. The least VSI is determined as $VSI_{(base)}$= 0.7074 at bus-63. By implementing RPF, the maximum loadability of the network is determined as $\lambda_{(DSVC)}$= 2.939 p.u. The comparison is given in Table 4 and the results of AFA are observed as superior to all other algorithms by having least objective function value.

Table 6. Comparison CBs and D-SVCs

Method	Total kVAr (%)	P_{loss} (Kw)	VSI
-	-	225	0.55
CBs	1812 (67.24)	146.27	0.7172
D-SVCs	1971 (73.14)	145.605	0.7175

5.2.1. Comparison of CBs and D-SVCs

In this case study, VAr compensation by means of CBs and D-SVCs is compared. In [5, 6], the impact of CBs on the performance of EDNs is analyzed. Thus, the effectiveness of AFA in solving the CBs allocation problem is first analyzed, and then the performance of EDN with CBs and D-SVCs is compared. The simulation results obtained with AFA are given in Table 5.

Table 6 provides a comparison of CBs and D-SVCs. CBs only reach the ideal VAr compensation of 67.24%, but it should be closer to 73.14%. D-SVCs produced a result of 145.605 kW, while the losses decreased to 146.27 kW from the base case of 225 kW. Moreover, the stability index is greater than the base case of 0.55 and equivalent to 0.7175 with D-SVCs. Nonetheless, CBs' stability index is 0.7172, which is once again lower than D-SVCs. In this fashion, D-SVCs are demonstrated to perform better than CBs.

6. Conclusion

In this paper, a novel meta-heuristic approach is presented for solving the optimal locations and ratings of distribution-static VAr compensators (D-SVCs) for reducing active power loss, voltage stability index, and loadability margin in radial electrical distribution networks (EDNs). An adaptive firefly algorithm (AFA) with improved search capabilities is proposed for solving the multi-objective function with different equal and unequal constraints. The computational efficiency of AFA is compared with that of other algorithms and literature. From the comparative study, it is observed that the AFA is performing well by resulting in a global optimum. Simulations are performed on the IEEE 69-bus EDN for different scenarios. For different VAr compensation levels, the network performance is evaluated and compared with the base case, ideal case, and optimal case. The results emphasise the need for optimal VAr compensation for ensuring the network's performance.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, writing-original draft preparation: P Muthukumar; Software, validation, review and editing: M V Ramesh; Formal analysis, investigation, visualization: Ponnam Venkata Kishore Babu; Resources, data curation: S V Satyanarayana; Supervision, project administration: P Rohinikumar.

Notation list

$B_{L(\alpha)}$	Susceptance of TCR
B_C	Susceptance of CB
B_{SVC}	Susceptance of SVC
ω	Angular frequency
L	Inductance
C	Capacitance
α	Thyristor firing angle
$\boldsymbol{Q_{SVC}}$	Reactive power by SVC
$\boldsymbol{V_{grid}}$	Grid bus voltage magnitude
$P_{loss(base)}$	Base case real power loss
$\boldsymbol{P_{loss(DSVC)}}$	Real power loss with D-SVC
$\boldsymbol{VSI_{(base)}}$	Voltage stability index at base case
$\boldsymbol{VSI_{(DSVC)}}$	Voltage stability index at base case
$\boldsymbol{\lambda_{max(base)}}$	Loadability factor at base case
$\boldsymbol{\lambda_{max(DSVC)}}$	Loadability factor with D-SVC
$\lvert V\rvert_n$	Voltage magnitude of bus-*n*
$\lvert V\rvert_{min}$	Minimum voltage magnitude
$\lvert V\rvert_{max}$	Maximum voltage magnitude
$Q_{DSVC(k)}$	Reactive power by D-SVC at bus-*k*
$\boldsymbol{P_{d(i)}}$	Real power load at bus-*i*
$Q_{d(i)}$	Reactive power load at bus-*i*
L_{DSVC}	Location of D-SVC
$nbus$	Number of buses
$ndsvc$	Number of D-SVCs
$\boldsymbol{\lambda_{max}}$	Maximum loadability factor
L_i	Light intensity
d	Distance between two fireflies
$L_{i(0)}$	Firefly's intial light intensity
$\gamma_{i(d)}$	Firefly's distance based light intensity
σ	Light absorption factor
t	Present iteration number
t_{max}	Number of maximum iterations

References

[1] H. H. Alhelou, M. E. H. Golshan, T. C. Njenda, and P Siano, "A survey on power system blackout and cascading events: Research motivations and challenges", *Energies*, Vol. 12, No. 4, 682, 2019.

[2] H. R. Bouchekara, Y. Latreche, K. Naidu, H. Mokhlis, W. M. Dahalan, and M. S. Javaid, "Comprehensive review of radial distribution test systems for power system distribution

education and research", *Resource-Efficient Technologies*, Vol. 3, pp. 1-12, 2019.
[3] Z. Čonka, M. Kolcun, M. K. Jr, J. Dudiak, M. Mikita, and M. Vojtek, "Improvement of power system stability using FACTS device", *Power and Electrical Engineering*, Vol. 33, pp: 12-15, 2016.
[4] D. Stanelyte and V. Radziukynas, "Review of voltage and reactive power control algorithms in electrical distribution networks", *Energies*, Vol. 13, No. 1, 58, 2019.
[5] S. Sharma and S. Ghosh, "FIS and hybrid ABC-PSO based optimal capacitor placement and sizing for radial distribution networks", *Journal of Ambient Intelligence and Humanized Computing*, Vol. 11, pp. 901-916, 2020.
[6] E. A. A. Ammar, G. A. Ghazi, and W. Ko, "Optimal capacitor placement in radial distribution systems using a fuzzy-dragonfly method", *Int. J. Smart Grid Clean Energy*, Vol. 8, No. 2, pp. 116-124, 2019.
[7] P. Singh, S. K. Bishnoi, and N. K. Meena, "Moth search optimization for optimal DERs integration in conjunction to OLTC tap operations in distribution systems", *IEEE Systems Journal*, Vol. 14, No. 1 pp. 880-888, 2019.
[8] O. Badran, S. Mekhilef, H. Mokhlis, and W. Dahalan, "Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies", *Renewable and Sustainable Energy Reviews*, Vol. 73, pp. 854-867, 2017.
[9] H. K. Verma and P. Singh, "Optimal reconfiguration of distribution network using modified culture algorithm", *Journal of The Institution of Engineers (India): Series B*, Vol. 99, pp. 613-622, 2018.
[10] A. M. Shaheen, R. A. E. Sehiemy, S. Kamel, E. E. Elattar, and A. M. Elsayed, "Improving distribution networks' consistency by optimal distribution system reconfiguration and distributed generations", *IEEE Access*, Vol. 9, pp. 67186-67200, 2021.
[11] V. Janamala, K. R. Rani, P. S. Rani, A. N. Venkateswarlu, and S. R. Inkollu, "Optimal Switching Operations of Soft Open Points in Active Distribution Network for Handling Variable Penetration of Photovoltaic and Electric Vehicles Using Artificial Rabbits Optimization", *Process Integr. Optim. Sustain*, pp. 1-9, 2022.
[12] G. Shahgholian, "A Brief Overview of Microgrid Performance Improvements Using Distributed FACTS Devices", *Journal of Renewable Energy and Environment*, Vol. 10, No. 1, pp. 43-58, 2023.
[13] S. Wang, S. Chen, L. Ge, and L. Wu, "Distributed generation hosting capacity evaluation for distribution systems considering the robust optimal operation of OLTC and SVC", *IEEE Transactions on Sustainable Energy*, Vol. 7, No. 3, pp. 1111-1123, 2016.
[14] M. Ebeed, S. Kamel, S. H. A. Aleem, and A. Y. Abdelaziz, "Optimal allocation of compensators", *Electric Distribution Network Planning. Power Systems*, pp. 321-253, 2018.
[15] K. R. Rani, P. S. Rani, N. Chaitanya, and V. Janamala, "Improved bald eagle search for optimal allocation of D-STATCOM in modern electrical distribution networks with emerging loads", *Int. J. Intell. Eng. Syst*, Vol. 15, No. 2, pp. 554-563, 2021, doi: 10.22266/ijies2022.0430.49.
[16] R. Puppala and K. Chandrasekhar, "Optimal Allocation of Capacitor Banks and DSTATCOMs in Radial Distribution System Considering Electric Vehicle Load Growth", *Int. J. Intell. Eng. Syst*, Vol. 15, No. 6, pp. 45-53, 2022, doi: 10.22266/ijies2022.1231.05.
[17] Y. Priyanka and R. Raghu, "Performance Analysis of Distribution System with Optimal Allocation of Unified Power Quality Conditioner Considering Distribution Network Reconfiguration", *Int. J. Intell. Eng. Syst*, Vol. 16, No. 1, pp. 364-374, 2023, doi: 10.22266/ijies2023.0228.32
[18] E. M. Ahmed, S. Rakočević, M. Ćalasan, Z. M. Ali, H. M. Hasanien, R. A. Turky, and S. H. Aleem, "BONMIN solver-based coordination of distributed FACTS compensators and distributed generation units in modern distribution networks", *Ain Shams Engineering Journal*, Vol. 13, No. 4, p. 101664, 2022.
[19] B. Mahdad and K. Srairi, "Adaptive differential search algorithm for optimal location of distributed generation in the presence of SVC for power loss reduction in distribution system", *Engineering Science and Technology, An International Journal*, Vol. 19, No. 3, pp. 1266-1282, 2016.
[20] G. Moustafa, M. Elshahed, A. R. Ginidi, A. M. Shaheen, and H. S. Mansour, "A Gradient-Based Optimizer with a Crossover Operator for Distribution Static VAR Compensator (D-SVC) Sizing and Placement in Electrical Systems", *Mathematics*, Vol. 11, No. 5, p. 1077, 2023.
[21] A. A. Téllez, G. López, I. Isaac, and J. W. González, "Optimal reactive power compensation in electrical distribution systems

with distributed resources. Review", *Heliyon*, Vol. 4, No. 8, p. e00746, 2018.

[22] R. P. Parouha and P. Verma, "State-of-the-art reviews of meta-heuristic algorithms with their novel proposal for unconstrained optimization and applications", *Archives of Computational Methods in Engineering*, pp. 4049-4115, 2021.

[23] S. P. Adam, S. A. Alexandropoulos, P. M. Pardalos, and M. N. Vrahatis, "No free lunch theorem: A review", *Approximation and Optimization: Algorithms, Complexity and Applications*, pp. 57-82, 2019.

[24] X. S. Yang, "Firefly algorithm, stochastic test functions and design optimisation", *International Journal of Bio-Inspired Computation*, Vol. 2, No. 2, pp. 78-84, 2010.

[25] M. Ghasemi, S. K. Mohammadi, M. Zare, S. Mirjalili, M. Gil, and R. Hemmati, "A new firefly algorithm with improved global exploration and convergence with application to engineering optimization", *Decision Analytics Journal*, Vol. 5, p. 100125, 2022.

[26] V. Kumar and D. Kumar, "A systematic review on firefly algorithm: past, present, and future", *Archives of Computational Methods in Engineering*, Vol. 28, pp. 3269-3291, 2021.

[27] Y. Wang and S. Song, "An adaptive firefly algorithm for multilevel image thresholding based on minimum cross-entropy", *The Journal of Supercomputing*, Vol. 78, No. 9, pp. 11580-11600, 2022.

[28] R. D. Zimmerman, C. E. M. Sánchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education", *IEEE Transactions on Power Systems*, Vol. 26, No. 1, pp. 12-19, 2010.

[29] V. Janamala and T. K. Pandraju, "Static voltage stability of reconfigurable radial distribution system considering voltage dependent load models", *Mathematical Modelling of Engineering Problems*, Vol. 7, No. 3, pp. 450-458, 2020.

[30] M. A. Kashem, V. Ganapathy, and G. B. Jasmon, "A geometrical approach for network reconfiguration based loss minimization in distribution systems", *International Journal of Electrical Power & Energy Systems*, Vol. 23, No. 4, pp. 295-304, 2001.

[31] J. P. Ham, J. H. Kim, B. H. Lee, and J. R. Won, "Calculation of Active Power Transfer Capability using Repeated Power Flow Program", *KIEE International Transactions on Power Engineering*. Vol. 12, No. 1, pp. 15-19, 2002.

[32] X. S. Yang, and S. Deb, "Engineering optimisation by cuckoo search", *International Journal of Mathematical Modelling and Numerical Optimisation*, Vol. 1, No. 4, pp. 330-343, 2010.

[33] X. S. Yang, "Flower pollination algorithm for global optimization", In: *Proc. of Unconventional Computation and Natural Computation: 11th International Conference, UCNC 2012*, Orléan, France, 2012.

[34] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems", *Computer-Aided Design*, Vol. 43, No. 3, pp. 303-315, 2011.