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Optimal Location and Sizing of Hybrid Photovoltaic Public Charging Stations in Reconfigurable Feeders Using Levy Flight Honey Badger Algorithm

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Abstract: Rapid electric vehicle (EV) adoption has increased the need for public charging infrastructure. Public charging station (PCS) placement and size must be determined to enable efficient and sustainable charging services. This work proposes a novel method for optimal design and allocation of hybrid photovoltaic systems (HPVs) and PCSs in reconfigurable feeders. A novel LFHBA combines the strengths of the levy flight (LF) exploration technique and the honey badger algorithm (HBA) to solve the multi-objective function focused on distribution loss reduction, improve voltage profiles, and improve reliability index. To test the suggested technique, modified IEEE 69-bus distribution feeders are simulated with varied EV load penetrations. LFHBA is compared to basic HBA, butterfly optimization algorithm (BOA), pelican optimization algorithm (POA), pathfinder algorithm (PFA) in computing performance. The comparison analysis shows that LFHBA has lower target values and greater convergence. Reconfigurable feeder topology permits distribution network design changes, improving system dependability and minimizing power losses. In comparison to base case, EV penetration causes to raise the losses by 26.65%, by optimal allocation of PCSs alone causes to reduce the losses by 38.82%, optimal allocation of PVs and ONR causes reduce losses by 92.19%, whereas, simultaneous allocation of PCSs, and HPVs results to reduce losses by 96.47%. This study emphasizes the need of optimizing PCS placement and capacity with HPVs for efficient and sustainable charging services. As shown by its greater performance over other optimization methods, the LFHBA algorithm helps achieve these goals. Reconfigurable feeders and renewable energy sources improve system dependability and power losses, increasing EV charging infrastructure.

Keywords: Electric vehicles, Honey badger algorithm, Levy flight, Photovoltaic systems, Network reconfiguration, Public charging stations.

1. Introduction

With the rapid increase in the adoption of electric vehicles (EV) for handling global warming and CO_2 emissions, the development of an efficient and reliable public charging infrastructure has become a priority [1]. To handle the effect of the stochastic behaviour of the EV load penetration in electrical distribution feeders, there is a need for optimised combined operational and planning studies. The optimal placement and sizing of power quality devices like soft open points (SOPs) [2] and distribution static compensator (DSTATCOM) [3] are inevitable for ensuring improved performance of distribution networks under EV load penetration. Many researchers have attempted to improve the performance of distribution feeders using optimal network reconfiguration (ONR) [4-6], optimal allocation of distribution generation (OADG) [7-12] and optimal allocation of charging stations (OACS) [13-17]. Other studies have focused on simultaneous approaches using (i) ONR and OADG [18-20], (ii)

ONR and OACS [21-23], and (iii) OADG and OACS [24-26] respectively.

In [4], simultaneous OADG and OACS problem is solved by focusing loss reduction and voltage stability enhancement. In [5], the honey badger algorithm (HBA) reconfigures networks and integrates renewable DGs for EV load penetration. Their research optimised electric vehicle penetration. Time varying acceleration coefficient (TVAC)-binary particle swarm optimization (BPSO) was created for the ONR problem in [6]. This research shows the algorithm's performance and the potential to improve the distribution network operation. An artificial electric field algorithm-pattern search (AEFA-PS) is used for many-criteria ONR, including power quality and energy not supplied [7]. Various parameters were used to optimise the network reconfiguration.

The OADG problem is addressed in [8]. Heuristics reduce annual energy losses and the voltage deviation index. The integration of RES into distribution networks is important. The radial power distribution system with distributed generation allocation was optimised in [9]. An efficient honey badger algorithm (HBA) is used. Their work improves the power distribution efficiency. The distribution network RES allocation is optimised by the single- and multi-objective modified aquila optimiser (AO) in [10]. The artificial hummingbird algorithm (AHA) optimises RES allocation under uncertainty in [11]. A hybrid optimisation-based approach for single- and multi-objective optimal distribution network with OADG problem was solved in [12]. It specialise in multi-optimisation approaches for optimal solutions. Adaptability supports various aims and network arrangements.

Electric vehicle (EV) charging stations were optimised in [13]. They employed a cost model and advanced genetic algorithm (GA). This work reduces costs, aiding charging infrastructure planning. EV charging infrastructure planning, including integrated transportation and power distribution networks, was examined in [14]. While not proposing a new algorithm, their paper explains the difficulties and methods of this complex field. In [15], artificial intelligence (AI) analyzes grid-connected EV charging the techno-economic and environmental consequences of grid-connected EV charging stations. The whale optimisation algorithm (WOA) determines the location and size of EVs in [16]. An improved optimisation strategy makes their solution to this essential problem more efficient and effective. In [17], intra-city public charging-station planning was optimised. Their optimisation algorithm is not explained explicitly, but their work developed a city-charging infrastructure, which is essential for EV adoption in cities.

In [18], the study addressed simultaneous ONR and OADG problem, and optimal shunt capacitors. Their key contribution was to address numerous factors simultaneously. The metaheuristic method for simultaneous network reconfiguration and distributed generation allocation was enhanced in [19]. This work improved the optimisation. System performance is improved by network reconfiguration and DG allocation in the objective function. Artificial ecosystem-based optimization (AEO) was used to reconfigure distribution networks with DG and capacitors in [20]. This novel optimisation approach was applied in the case study. An investment study for optimal EVCSs planning on a reconfigured imbalanced radial distribution system was conducted in [21]. Their investment-focused contributions use an unclear optimisation strategy. A comparison of grid reactive voltage regulation and network reconfiguration for EV penetration was described in [22]. Its main contribution was to compare various solutions to optimise the impact of the EVs on distribution network. In [23], the stochastic optimal sizing of plug-in EV parking lots in reconfigurable power distribution networks was analysed. They used stochastic optimisation to size the charging infrastructure under uncertainty. Student psychology optimization algorithm (SPOA) and AdaBoost algorithm, (SPOA^{2}B) optimises DGs and EVCSs allocation [24]. The unique allocation method is the main contribution of this study. In [25], the optimal allocation of plug-in EVCSs and DGs in distribution networks was presented. A dynamic planning technique for EV charging stations considers dispersed generation and electronic units into account in [26]. They proposed a revolutionary charging-station distribution strategy.

From this literature, it is evident that the ONR, OADGs and OACSs can ensure efficient operation in distribution networks. Also, various optimization techniques and meta-heuristic approaches were employed. However, it can be finding that the combined approach of ONR, OADG and OACS is not focused and has been the major motivation for this research. This paper presents a comprehensive study on the optimal location and sizing of hybrid photovoltaic public charging stations in reconfigurable feeders. The proposed methodology combines the levy flight (LF) exploration strategy and the honey badger optimization (HBA) algorithm to determine the optimal location and sizing of PCSs and HPVs. The LF introduces stochasticity and long-range jumps, while the HBA enhances the exploration and exploitation capabilities. The reconfigurable feeder topology allows for changes in the distribution network configuration to improve system performance. In comparison to the literature, this work claims the following contributions.

- The work introduces the LFHBA, a hybrid algorithm that optimizes the design and allocation of HPVs and PCSs in reconfigurable feeders by integrating levy flight exploration and honey badger algorithm (HBA).
- LFHBA utilizes multi-objective optimization to reduce distribution losses, improve voltage profiles, and improve reliability, enabling efficient and sustainable deployment of PCSs and HPVs for EV adoption.
- LFHBA outperforms other optimization approaches including HBA, BOA, POA, and PFA in optimizing PCS location and capacity, with lower goal values and greater convergence.
- Reconfigurable feeders and renewable energy sources like HPVs minimize power losses and increase system reliability. Our analysis reveals that optimizing PCS and HPV distribution may considerably minimize losses, making it vital for efficient and sustainable EV charging infrastructure.

The remaining paper sections follow this structure: Section 2 details the hybrid photovoltaic public charging station model and its components. In section 3, the study's problem, variables, restrictions, and goals are stated. The LFHBA (low-frequency harmonic bat algorithm) is used to solve the multi-objective function in section 4, explaining its method and efficacy. Section 5 discusses and compares case studies, highlighting their results and consequences. Section 6 concludes with a summary of major findings, study contributions, and future research directions.

2. Modelling of theoretical concepts

This section presents the mathematical model for the hybrid photovoltaic public charging station and the associated modelling for the load flow study.

2.1 Composite load modeling

Present distribution feeders are experiencing and associating with multiple types of consumers at every location such as residential, industrial, commercial, and electric vehicles etc. Thus, there is a need for developing composite load model in response to voltage profile sensitivities. In the present work, at every node, 50% of residential, 30% of commercial and 20% of industrial loads are considered. In addition, EV load penetration is included. The modified net-effective loading of a bus-i is given by:

$$P_{di(n)} = P_{di(0)}\left\{0.5V_i^{0.92} + 0.3V_i^{1.51} + 0.2V_i^{0.18} + \lambda_{ev}V_i^{2.59}\right\}, \forall i = 2{:}\,nbus \quad (1)$$

$$Q_{di(n)} = Q_{di(0)}\left\{0.5V_i^{4.04} + 0.3V_i^{3.4} + 0.2V_i^{6} + \lambda_{ev}P_{di(0)}tan(acos\theta_{ev})V_i^{4.06}\right\}, \forall i = 2{:}\,nbu \quad (2)$$

2.2 Public charging station

The public charging station (PCS) is designed to facilitate multiple level-1 and level-2 charging ports and thus, the real power rating of PCS is given by:

$$P_{d(ev)} = ncp_{l1} \times P_{r(l1)} + ncp_{l2} \times P_{r(l2)} \quad (3)$$

In order to accommodate total EV load penetration in the feeder, the required PCS can be estimated by:

$$npcs = \frac{1}{P_{pcs}}\left\{\sum_{i=1}^{nbus}\left[P_{di(0)}\lambda_{ev}V_i^{2.59}\right]\right\} \quad (4)$$

By having PCS at a specific bus-i, the net-effective loadings expressed in Eqs. (1) and (2) are modified as:

$$P_{di(n)} = P_{di(0)}\left\{0.5V_i^{0.92} + 0.3V_i^{1.51} + 0.2V_i^{0.18}\right\} + P_{d(ev)}V_i^{2.59}, \forall i = 1{:}\,npc \quad (5)$$

$$Q_{di(n)} = Q_{di(0)}\left\{0.5V_i^{4.04} + 0.3V_i^{3.4} + 0.2V_i^{6}\right\} + P_{d(ev)}tan(acos\theta_{ev})V_i^{4.06}, \forall i = 1{:}\,npc \quad (6)$$

For other buses, the net-effective loadings are determined by:

$$P_{di(n)} = P_{di(0)}\left\{0.5V_i^{0.92} + 0.3V_i^{1.51} + 0.2V_i^{0.18}\right\}, \forall i = 2{:}\,nbus, i \neq npcs \quad (7)$$

$$Q_{di(n)} = Q_{di(0)}\left\{0.5V_i^{4.04} + 0.3V_i^{3.4} + 0.2V_i^{6}\right\} + P_{d(ev)}tan(acos\theta_{ev})V_i^{4.06}, \forall i = 2{:}\,nbus, i \neq npcs \quad (8)$$

2.3 Hybrid photovoltaic system

Photovoltaic systems (PVs) inject real power at a bus, but feeders must optimize reactive power compensation. Hybrid photovoltaic systems (HPVs) are connected to reactive power compensators such as capacitor banks (CBs). Thus, HPV integration yields net-effective bus loading:

$$P_{di(n)} = P_{di(n)} - P_{hpv,i}, \forall i = 1: nhpv \tag{9}$$

$$Q_{di(n)} = Q_{di(n)} - Q_{hpv,i}, \forall i = 1: nhpv \tag{10}$$

3. Problem formulation

The multi-objective optimization problem (OF) is developed to handle simultaneously loss (f_1), voltage profile (f_2) and reliability (f_3).

$$OF = f_1 + f_2 + f_3 \tag{11}$$

$$f_1 = P_{loss} = \sum_{b=1}^{nbr} I_b^2 r_b \tag{12}$$

$$f_2 = AVD = \frac{1}{nbus}\sqrt{\sum_{i=1}^{nbus}|1 - V_i|^2} \tag{13}$$

$$f_3 = SAIFI = \left(\sum_k f_{r(k)} N_{b(k)}\right)/nbus \tag{14}$$

The overall objective function is subjected to the following constraints:

$$I_b \leq I_{b,max} \tag{15}$$

$$V_{i,min} \leq V_i \leq V_{i,max} \tag{16}$$

$$(nbr + ntl) = nbus - 1 \;\&\; |\bar{A}| \neq 0 \tag{17}$$

$$\sum_{i=1}^{nhpv} P_{hpv,i} \leq \sum_{i=1}^{nbus} P_{di(n)} \tag{18}$$

$$\sum_{i=1}^{nhpv} Q_{hpv,i} \leq \sum_{i=1}^{nbus} Q_{di(n)} \tag{19}$$

4. Solution methodology

In this section, the theoretical concept of HBA and its improved variant using levy flights is explained mathematically. Further, its application to solve optimization problem is discussed.

4.1 Honey badger algorithm

Hashim et al. [27] introduced the honey badger algorithm (HBA), a meta-heuristic optimization that includes exploration and exploitation. The HBA phases are mathematically defined.

The initial population using Eq. (20) generates *n* honey badgers for HBA.

$$x_i = lb_i + r_1 \times (ub_i - lb_i) \tag{20}$$

where $i = 1, \ldots, n$ and $j = 1, \ldots, d$, l_{bi} and ub_i are the lower and upper boundaries for the search variables, r_1 is uniformly randomized number, x_i is the location of *i*th honey badger, *n* and *d* are the size of population and their dimensions, respectively.

Digging and honey are the next stages of HBA, which are comparable to the exploration and exploitation phases in conventional meta-heuristic algorithms.

Honey badger location is updated during the digging phase (exploration) utilizing smell strength and changes in flying direction, as provided by:

$$x_i^{t+1} = x_i^{b,t} + d_f r_2 \sigma d_i |cos(2\pi r_3)[1 - cos(2\pi r_4)]| + + f_d \gamma I_i \times x_i^{b,t} \tag{21}$$

where x_{ij}^{t+1} is the next position of HB, r_2, r_3 and r_4 are the random numbers, d_i is the distance of *i*th HB with best prey at time-*t*, $x_i^{b,t}$ is the best prey, $\gamma \geq 1$ to define the ability of honey badger to explore the food and is set to 6, σ is a dynamic decreasing factor to tune exploration to exploitation, I_i and d_f are the smell intensity and changes in flying direction, respectively. Mathematically,

$$I_i = r_5 \times \frac{s_c}{4\pi d_p^2} \tag{22}$$

$$d_f = \begin{cases} +1 & if\ r_6 \leq 0 \\ -1 & other\ wise \end{cases} \tag{23}$$

$$\sigma = \tau \times e^{(t/T)}, \tau > 1 \tag{24}$$

where$s_c = \left(x_i^t - x_i^{t+1}\right)^2$ is the prey strength of concentration and $d_i = \left(x_i^{b,t} - x_i^k\right)$ is the distance between best prey and present HB, respectively, r_5 and r_6 are the random numbers, t and T are the number to represent present and maximum iteration, respectively; τ is a constant equal to 2.

During the honey phase (exploitation), honey badgers use follower behaviour to go to a beehive by following a guide honey badger. This situation can be expressed mathematically as:

$$x_i^{t+1} = x_i^{b,t} + I_i r_7 \sigma d_f \tag{25}$$

Based on spatial search information of d_f, Eq. (25) helps to surrounds nearly to best prey $x_i^{b,t}$. At this stage, the direction of search is influenced by dynamic behaviour σ and d_f.

4.2 Levy flight

Levy flight is a type of chaotic system in which

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the probability function controls the size of the leap. In our line of work, we use the Levy flight as in [28, 29].

$$x_i^{t+1} = x_i^{b,t} + Levy(d) + x_r^t + r_8(y - x) \quad (26)$$

The suggested method to change solution x_i uses the LF or HBA operators. Utilizing the probability p_i associated with each x_i allows for this. The following equations state that the LF will be used if the probability of p_i is larger than 0.5.

5. Results and discussion

To assess the efficacy of the proposed methodology, a series of case studies are conducted utilizing the IEEE 69-bus distribution network as the testing ground. Through these case studies, the results obtained from the LFHBA are compared against alternative optimization techniques, thereby showcasing the superior performance of the LFHBA.

Furthermore, the impact of various factors on the optimal solutions is investigated. This includes analyzing the influence of load variations and solar generation profiles on the outcomes. By examining these variables, a more comprehensive understanding of the proposed methodology's robustness and adaptability is achieved.

In accordance with the composite load modelling approach outlined in section 2.1, the performance of the network is evaluated, serving as case 1. The resulting net effective load is determined to be 3629.56 kW, accompanied by a reactive power of 2210.57 kVAr. Additionally, the losses incurred are calculated as 163.48 kW and 75.73 kVAr, respectively. Furthermore, the average voltage deviation (AVD) is recorded as 0.004, while the system average interruption frequency index (SAIFI) is registered as 1.8174.

5.1 Optimal allocation of PCSs

The network performance is re-evaluated for 50% EC load penetration in the network. The net effective load becomes 5307.66 kW and 2576.24 kVAr, respectively. Further, the losses are raised to 331.316 kW and 153.07 kVAr, respectively. In addition, AVD and SAIFI are registered as 0.0057 and 1.8174, respectively. The increased values of losses and AVD indicate decrement in network performance. However, there is no change in network configuration, SAIFI remains same. This status is treated as case 2.

In designing of a PCS, 30 level-1 charging ports of 11 kV and 20 level-2 charging ports of 22 kV are considered and thus, the total power rating becomes 770 kW with a lagging power factor of 0.95. Further, the availability of PCS is treated as 3/4th of the day and overlapping scenario with other PCSs is treated as 15%. By all these aspects, the required PCS are determined as 3. In order to ensure easy reachability for all buses, the search space for optimal locations for three PCSs is divided respectively as buses 2 to 35, buses 36 to 50 and buses 51 to 69. The beast locations obtained by LFHBA are buses 3, 36 and 53, respectively.

Thus, the net effective load becomes 4399.43 kW and 2463.58 kVAr, respectively. Further, the losses are raised to 202.7 kW and 96.4 kVAr, respectively. In addition, AVD and SAIFI are registered as 0.0045 and 1.8174, respectively. This status is treated as case 3.

5.2 Optimal configuration, PVs and PCSs

In this case, the network is assumed to have three PCSs at their respective optimal locations as determined in section 5.1, and further, three PVs are proposed to integrate simultaneously changing the network configuration optimally. By implementing LFHBA, the best locations of PVs are determined as buses 9, 26, and 61, correspondingly, their best sizes are 923.98 kW, 514.95 kW and 1151.03 kW, respectively. In addition, the best switches to open are 14, 56, 61, 69 and 70, respectively. Thus, the net effective load becomes 1809.48 kW and 2463.58 kVAr, respectively. Further, the losses are raised to 25.886 kW and 25.474 kVAr, respectively. In addition, AVD and SAIFI are registered as 0.0009 and 1.3783, respectively. This status is treated as case 4.

5.3 Optimal configuration, HPVs and PCSs

This case is extension to section 5.2 by integrating hybrid PVs also simultaneously. By implementing LFHBA, the best locations of PVs are determined as buses 61, 64, and 8, correspondingly, their best sizes are 1326.48 kW, 160 kW and 858.59 kW, respectively. The best CB sizes are 592.01 kVAr, 335.96 kVAr and 456.75 kVAr, respectively. In addition, the best switches to open are 12, 26, 55, 69 and 70, respectively. Thus, the net effective load becomes 2054.34 kW and 1078.85 kVAr, respectively. Further, the losses are raised to 11.683 kW and 11.639 kVAr, respectively. In addition, AVD and SAIFI are registered as 0.00075 and 1.3072, respectively. This status is treated as case 5.

The results of all cases are listed in Table 1 for comparative analysis. Among all, case 5 has improved the network performance significantly.

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Table 1. Comparison of all case studies

Case	P_{load} (kW)	Q_{load} (kVAr)	P_{loss} (kW)	Q_{loss} (kVAr)	AVD	SAIFI
1	3629.56	2210.57	163.48	75.73	0.004	1.8174
2	5307.66	2576.24	331.316	153.07	0.0057	1.8174
3	4399.43	2463.58	202.7	96.4	0.0045	1.8174
4	1809.48	2463.58	25.886	25.474	0.0009	1.3783
5	2054.34	1078.85	11.683	11.639	0.00075	1.3072

Table 2. Comparison of LFHBA with literature works

Ref	Case 1: ONR		Case 2: PVs		Case 3: ONR + PVs		
	Open Switches	P_{loss} (kW)	Size/ Loc	P_{loss} (kW)	Open Switches	Size/Loc	P_{loss} (kW)
Base	-	225	-	225	-	-	225
CTLHSO [41]	14, 56, 61, 69, 70	98.57	526.8/ 11 379.6/ 18 1719/ 61	69.388	14, 56, 61, 69, 70	537.6/ 11 1441.5/ 61 490/ 64	35.145
ESCA [42]	14, 55, 61, 69, 70	98.6	760.4/ 12 760.4/ 62 760.4/ 61	74.4	12, 19, 57, 63, 69	436/ 11 1300/ 61 461.6/ 65	36.95
BOA	69, 70, 14, 57, 61	98.59	602.2/ 11 380.4/ 18 2000/ 61	72.44	69, 61, 70, 58, 12	1749.6/ 61 156.6/ 62 409/ 65	40.49
POA	14, 55, 61, 69, 70	98.62	408.5/ 65 1198.6/ 61 225.8/ 27	77.85	69, 63, 70, 55, 13	1127.2/ 61 275/ 62 415.9/ 65	39.25
PFA	69, 18, 13, 56, 61	99.35	101.8/ 65 369/ 64 1302.4/ 63	86.77	69, 61, 17, 58, 13	1066.6/ 61 352.5/ 60 425.7/ 62	40.3
HBA	14, 58, 61, 69, 70	98.58	1410/ 61 417/ 17 604/ 11	72.626	14, 58, 70, 69, 63	147.2/ 61 538/ 11 673/ 17	37.11
LFHBA	69, 70, 14, 56, 61	98.56	526.8/ 11 380.4/ 18 1719/ 61	69.44	14, 55, 61, 69, 70	406.2/ 12 1400.4/ 61 474.6/ 64	35.355

6. Comparative study

In this section, the computational efficiency of LFHBA is compared with basic HBA, butterfly optimization algorithm (BOA) [30], pelican optimization algorithm (POA) [31], pathfinder algorithm (PFA) [32]. Simulations are performed on IEEE 69-bus (i.e., without EV penetration and composite load models). The case study is repeated by each algorithm for 50 independent times to quantify their convergence features statistically. The comparative results are given in Table 2. Three Case studies are compared here.

In case 1, by performing only ONR, the network performance is evaluated. As seen in Table 2, the results of LFHBA are highly competitive with comprehensive teaching learning harmony search optimization algorithm (CTLHSO) [41] and enhanced sine–cosine algorithm (ESCA) [42]. Further, optimal switches given by LFHBA are 69, 70, 14, 56, and 61, consequently, the losses are reduced to 98.56 kW from 225 kW. In comparison to BOA, POA, PFA and HBA, the results of LFHBA are well superior with low objective function.

In case 2, only three PVs are optimally integrated. The best locations and sizes are 526.8 kW (11), 380.4 kW (18) and 1719 kW (61), respectively. The losses are reduced to 69.44 kW.

In case 3, simultaneous allocation of PVs and ONR problem is solved. The best locations and sizes are 406.2 kW (12), 1400.4 kW (61) and 474.6 kW (64), respectively. Further, optimal switches given by LFHBA are 14, 55, 61, 69, and 70, consequently, the losses are reduced to 35.355 kW from 225 kW.

In case 2 and case 3, the results of LFHBA are slightly higher than CTLHSO [3], but, better than ESCA [4] as well as to other compared algorithms.

Although the selected algorithms competitively optimised the proposed problem, according to the no free lunch (NFL) theorem, there is no single

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algorithm for solving all types of real-time optimisation problems. Thus, researchers are still motivated to develop new algorithms such as the puzzle optimisation algorithm (POA) [33], stochastic komodo algorithm (SKA) [34], extended stochastic coati optimiser (ESCO) [35], guided Pelican algorithm (GPA) [36], swarm magnetic optimiser (SMO) [37], walk-spread algorithm (WSA) [38], four directed search algorithms (FDSA) [39], and artificial rabbit optimisation (ARO) [40] are such recent works. In this regard, there is a need for further comparative studies using state-of-the-art metaheuristics. This study can be further extended to a comparative study.

7. Conclusion

The proposed LFHBA effectively located and sized hybrid photovoltaic public charging stations in reconfigurable feeders. The charging infrastructure has become more sustainable with renewable energy sources, decarbonising the transportation and energy sectors. Loss reduction tendencies arise when comparing the basic case to the EV penetration scenarios. The losses increased by 26.65% with EVs. Optimising power conditioning systems (PCSs) alone reduces losses by 38.82%. Optimal network reconfiguration (ONR) with smart PV allocation can reduce losses by 92.19%. Integrating renewable energy and improving the network architecture have a significant impact. The best result was a 96.47% loss reduction by allocating PCSs and HPVs together. This demonstrates how energy storage and optimal power allocation work together. Comprehensive methods that consider numerous aspects and technologies are crucial, as these data show. By optimising the PCS, PV, ONR, and HPV allocation, losses may be reduced, creating a more efficient and sustainable power distribution system.

Notations

$P_{di(0)}$	Real power loads of bus-*i* for nominal voltage profile
$Q_{di(0)}$	Reactive power loads of bus-*i* for nominal voltage profile
$P_{di(n)}$	Net effective real power loadings of bus-*i* with composite loads
$Q_{di(n)}$	Net effective reactive power loadings of bus-*i* with composite loads
V_i	voltage magnitude of bus-*i*
λ_{ev}	EV load penetration
θ_{ev}	Power factor AC/DC converter of EV charging station
$P_{d(ev)}$	total real power demand of a PCS
ncp_{l1}	Number of level-1 charging ports in a PCS
ncp_{l2}	Number of level-2 charging ports in a PCS
$P_{r(l1)}$	Rated power of level-1 charging port
$P_{r(l2)}$	Rated power of level-2 charging port
$nbus$	Number of buses in the feeder
$npcs$	Number of PCSs in the feeder
$P_{hpv,i}$	Real power injections at bus-*i* due to HPV
$Q_{hpv,i}$	Reactive power injections at bus-*i* due to HPV
$nhpv$	Number of HPVs in the feeder
P_{loss}	Real power loss
AVD	Average voltage deviation
$SAIFI$	System average interruption frequency index
I_b	Branch current
r_b	Resistance of branch
$f_{r(b)}$	Failure rate of a branch
$N_{b(k)}$	Number of buses disconnected due to failure a branch-*k*
nbr	Number of branches
ntl	Number of tie-lines
$\lvert\bar{A}\rvert$	Determinant of bus-incident matrix

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, software and original draft preparation are done by Srinivasarao Thumati; supervision, review, and formal analysis are done by Vadivel V and Venu Gopala Rao M.

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