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Optimal allocation of distributed energy storage systems to improve performance and power quality of distribution networks

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Abstract

The placement of grid-scale energy storage systems (ESSs) can have a significant impact on the level of performance improvements of distribution networks. This paper proposes a strategy for optimal allocation of distributed ESSs in distribution networks to simultaneously minimize voltage deviation, flickers, power losses, and line loading. The optimal ESS allocation is investigated through the PQ injection (considering a variable power factor on the dispatch of ESSs) and the results are compared in terms of performance and power quality improvements. An IEEE-33 bus distribution system (medium voltage), having a high influence of renewable (wind and solar) distributed generation, is used as the test network. The overall investigation is conducted for two distinct scenarios: (1) applying a uniform ESS size and (2) applying non-uniform ESS sizes. DIgSILENT PowerFactory is used for developing, analyzing, and testing the system models. The fitness-scaled chaotic artificial bee colony optimization algorithm (a hybrid meta-heuristic technique) is applied to optimize parameters of the objective function. A Python script is used to automate simulation events in PowerFactory. The optimization results are verified through the application of the conventional artificial bee colony algorithm. Detailed simulation results imply that the proposed ESS allocation technique can successfully minimize voltage deviation, flicker disturbance, line loading, and power losses, and thereby significantly improve performance and power quality of a distribution network.

Keywords: Energy storage systems, flicker minimization, voltage profile improvement, power loss and line loading minimization, power quality, DIgSILENT PowerFactory, asset management, artificial bee colony algorithm.

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Nomenclature

Indices

g	energy storage system (ESS) number
i, j, k	adjacent buses
l	line number
n	bus number

Parameters

γ^{ESS}	cost weighting factor in relation to ESSs
$\Gamma^{flicker}$	cost rate for flicker disturbance
$\gamma^{flicker}$	cost weighting factor in relation to flicker
Γ^{LL}	cost rate for line loading
γ^{LL}	cost weighting factor in relation to line loading
Γ^{PL}	cost rate for power losses
γ^{PL}	cost weighting factor in relation to power losses
Γ^{VD}	cost rate for voltage deviation
γ^{VD}	cost weighting factor in relation to voltage deviation
ψ_k	network impedance angle (degrees)
ζ_n	load weighting factor of n th bus
$aP, bP, \& cP$	coefficients for real power of phase $a, b, \& c$
$aQ, bQ, \& cQ$	coefficients for reactive power of phase $a, b, \& c$
C^{UU}	cost of an UltraBattery unit
$c_F(\psi_k, v_a)$	flicker coefficient
It^{max}	maximum iteration number of the FSCABC optimization approach
$k_f^{step}(\psi_k)$	step factor of flicker disturbance
$k_v(\psi_k)$	factor for voltage change during switching operation of a wind DG (WDG)
L^{trial}	trial limit to improve a food source in FS-CABC optimization
$lb1$	lower limit of decision variable S_n^{ESSP}
$lb2$	lower limit of decision variable S_n^{ESSQ}
$lb3$	lower limit of decision variable λ_n^{ESS}
M	total number of lines
N	total number of buses

N^D	number of decision variables in FSCABC optimization
N_{10}	number of switching operations in a 10-minute period
N_{120}	number of switching operations in a 120-minute period
P^{T-F}	input real power (MW) of the feeder
$PF^{ESS-max}$	maximum power factor (p.f.) on the dispatch of an ESS
$PF^{ESS-min}$	minimum p.f. on the dispatch of an ESS
Q^{T-F}	input reactive power (MVar) of the feeder
$R^L(i, j)$	resistance of a line linking two adjacent buses, i and j
$S^{ESS-nom}$	nominal apparent power (MVA) of an ESS
S^{PV-max}	rated capacity (kVA) of solar DGs
S^{WDG}	rated apparent power of the wind turbine (VA)
S^{wind}	total capacity (kVA) of a WDG
SL_l^{max}	maximum loading of l th line
SL_l^{rated}	rated ampacity of l th line
$ub1$	upper limit of decision variable S_n^{ESSP}
$ub2$	upper limit of decision variable S_n^{ESSQ}
$ub3$	upper limit of decision variable λ_n^{ESS}
V^{max}	upper limit for bus voltage
V^{min}	lower limit for bus voltage
V^{rated}	rated system voltage (p.u.)
V^{ref}	reference voltage of a bus (p.u.)
V^{target}	target voltage of the distribution network
$X^L(i, j)$	reactance of a line linking two adjacent buses, i and j
Variables	
Δt	time interval
δ_i, δ_j	voltage angle of bus i & j
η^c	charging efficiency of an ESS
η^d	discharging efficiency of an ESS
λ_n^{ESS}	variable that represents ESS position in the network

σ^{ABC} & σ^{FSCABC}	standard deviation of objective functions using ABC & FSCABC approaches, respectively	$P_n^{STS_w}$	factor for short-term flicker disturbance during switching operation of WDGs
C_l^{LL}	cost in relation to line loading	$P_t^{ESS,c}$	charging power of an ESS at time t
C_l^{PL}	cost in relation to power losses	$P_t^{ESS,d}$	discharging power of an ESS at time t
$C_n^{flicker}$	cost in relation to flicker emission	P_t^{ESS}	power of an ESS at time t
C_n^{VD}	cost in relation to voltage deviation	$PF^{ESS-min}$	p.f. on the dispatch of n th ESS
$E^{ESS-max}$	maximum energy of an ESS	$PLRI^P$	index for real power loss reduction through optimal ESS allocation
$E^{ESS-min}$	minimum energy of an ESS	$PLRI^Q$	index for reactive power loss reduction through optimal ESS allocation
E^{ESS}	energy of an ESS	$PLRI^T$	index for total power loss reduction through optimal ESS allocation
E_{t+1}^{ESS}	energy of an ESS at time $t + 1$	PLT^{w-ESS}	total power loss of the system through optimal ESS allocation
E_t^{ESS}	energy of an ESS at time t	PLT^{wo-ESS}	total power loss of the system without ESS allocation
K	total number of active ESSs on the network for a optimization run	Q	reactive power
P	active power	Q^{LT}	total reactive power loss of the system
$P^{ESS-max}$	maximum power of an ESS	$Q^L(i, j)$	reactive power loss of a line linking two adjacent buses, i and j
$P^{ESS-min}$	minimum power of an ESS	$Q_{i \rightarrow k}^{del}$	reactive power delivered from i to adjacent bus k
P^{ESS}	power of an ESS	Q_i	reactive power flowing out of bus i
P^{LT}	total active power loss of the system	Q_i^{con}	consumed reactive power at bus i
$P^L(i, j)$	active power loss of a line linking two adjacent buses, i and j	Q_i^{gen}	generated reactive power at bus i
$P_{i \rightarrow k}^{del}$	active power delivered from i to adjacent bus k	$Q_{j \rightarrow i}^{del}$	reactive power delivered to i from a adjacent bus j
P_i	active power flowing out of bus i	Q_l^{L-base}	reactive power loss without ESS placement (base case)
P_i^{con}	consumed active power at bus i	Q_l^{L-ESS}	reactive power loss through optimal ESS allocation
P_i^{gen}	generated active power at bus i	S^{app}	apparent power
$P_{j \rightarrow i}^{del}$	power delivered to i from a adjacent bus j	$S^{ESS-max}$	maximum size of an ESS
P_l^{L-base}	active power loss without ESS placement (base case)	$S^{ESS-min}$	minimum size of an ESS
P_l^{L-ESS}	active power loss through optimal ESS allocation	S^{ESS}	size of an ESS in MWh
P_n^{FCont}	flicker disturbance for continuous operation of WDGs	S^{PV-op}	operational capacity (kVA) of solar DGs
P_n^{FSw}	flicker disturbance for switching operation of WDGs	S_n^{ESSP}	injected real power (MW) by the ESS to the n th bus
P_n^{LTCont}	long-term flicker disturbance factor for continuous operation of WDGs	S_n^{ESSQ}	injected reactive power (MVar) by the ESS to the n th bus
P_n^{LTSw}	factor for long-term flicker disturbance during switching operation of WDGs	S_n^{ESS}	total ESS size (MVA) in n th bus
P_n^{STCont}	short-term flicker disturbance factor for continuous operation of WDGs	S_n^{grid}	short circuit apparent power of the grid (VA)

S_n^L	load at n th bus (p.u.)	$\% LL_l^{base}$	percent line loading of l th line without ESS allocation
SL_{l-t}	loading of l th line	$\% LL_l^{ESS}$	percent line loading of l th line after ESS allocation
SL_l^{base}	loading of l th line without ESS allocation	$\% LLT^{w-ESS}$	total percent line loading of the system after ESS allocation
SL_l^{ESS}	loading of l th line after ESS allocation	$\% LLT^{wo-ESS}$	total percent line loading of the system without ESS allocation
SOC_g^{ESS}	state of charge of g th ESS	$\% d^{Sw}$	% relative change in bus voltage owing to switching operation of WDGs
v_a	average annual wind speed (m/s)		
V_{n-t}^B	voltage value at time t in a day		
V_n^B	bus voltage of n th bus (p.u.)		
X^{TLoss}	total line loss of the system		

1. Introduction

Today's power systems undergo a period of change caused by various correlated issues such as integration of renewable resources [1–4], management of the increasing demand [5–8], power quality requirements [9], power congestion [10], greenhouse gas (GHG) reduction [11, 12], network expansion [13], and power system reliability [14, 15]. Energy storage systems (ESSs) are growingly being integrated in distribution networks to provide various advantages related to economic, technical, and environmental issues [16, 17]. These include facilitation of renewable energy source (RES) integration [18–20], load shifting [21–24], load levelling [25] and peak shaving [26], planning of distributed generation [27], RES energy time-shifting [28], minimization of voltage deviation [29], frequency regulation [10, 30], power quality improvement [10, 31, 32], overall cost reduction [33, 34] and profit maximization [10, 35], network expansion [36, 37], GHG reduction [38–40], operating reserves [10, 41], and network reliability [42]. However, the benefits from the allocation of ESSs cannot be achieved if they are misplaced or misused in distribution networks [43].

Distribution network service providers consider asset management as a crucial task to ensure safe and reliable operation of networks. However, the fulfilment of this target can increase the overall network cost. This cost could comprise network reinforcement for voltage and thermal stability which can significantly affect electricity prices. Voltage profile improvement and flicker disturbance minimization are also crucial for maintaining the network power quality. Therefore, the motivation of this study is to provide distribution system operators with a low cost solution for better asset management practice as well as maintaining power quality. As the implementation of utility-scale ESSs involves considerable capital investment, their optimal placement in distribution networks to achieve expected performance improvements is challenging. From this viewpoint, optimal allocation of ESSs is addressed in several studies [10, 17, 29, 32–34, 36, 44–53].

A comprehensive review on ESS allocation, sizing, operation, and power quality for mitigating various issues of distribution networks is presented in [16]. In [17], an optimal placement of ESSs is undertaken in an IEEE-33 bus distribution network using the artificial bee colony (ABC) algorithm. The targets of the study is to simultaneously minimize the voltage deviation, line losses, and line loading including ESS investment cost. In [17], ESS

sizing is accomplished through the injection of P to the network i.e. by applying a unity power factor (p.f.) approach on the dispatch of ESSs. Furthermore, the particle swarm optimization (PSO) algorithm is employed to justify the optimal results attained from the ABC approach.

A multi-objective ESS placement is accomplished in [44] for both distribution and transmission networks. On the distribution side, the optimal size of ESSs is evaluated for addressing peak load shaving and load curve smoothing. A sensitivity analysis is performed on the transmission side through economic dispatch, time domain power flow, and using complex-valued neural networks to place the ESSs. In [45], an optimal distributed ESS planning is proposed for soft open points-based distribution network scenarios. In that study, the reactive power capability of distributed generators (DGs) is embedded through network reconfiguration and a mixed-integer second order cone programming (MISOCP) model is employed to solve the problem. An optimal ESS allocation problem embedded with network reconfiguration (in an RES-integrated distribution network) is formulated in [33] to minimize overall system costs. The study employs a mixed-integer linear programming (MILP) approach to address the problem.

A network-aware technique, for the control and planning of ESSs in a distribution network (RES-integrated) is proposed in [47] to minimize operational and investment costs. Reference [48] explores the impact of ESS configuration and location on voltage profiles and power losses as well as utilization of ESSs in a feeder of low voltage (LV) distribution networks. Reference [36] proposes an optimal placement of distributed community-based ESSs to gain some distribution network benefits. The benefits are achieved from peaking photovoltaic (PV) generation, energy loss reduction, energy arbitrage, Var support, emission reduction, and network upgrade deferral.

A MILP strategy is proposed in [10] to maximize the overall profit of using distributed ESSs in distribution systems. The study provides a frequency regulation service through controlling active and reactive powers and achieves energy price arbitrage, network congestion management, and energy reserve. In [49], the voltage fluctuation problems of PV-integrated LV networks are minimized through ESS allocation by employing a genetic algorithm (GA)-based approach combined with simulated annealing. On the other hand, a GA-based optimization strategy (bi-level) is applied in [50] for mitigating the same problem. Again in [32], the allocation of distributed ESSs is performed for minimizing both network losses and the energy cost in relation to congestion management and external grid, and providing voltage supports. The study employs an alternating direction strategy to multipliers for obtaining the solution of the problem.

Optimal ESS sizing and allocation are performed and validated through a mathematical modeling and optimal power flow (OPF) approach in [51]. In [52], a game-theory-based multi-agent strategy is proposed for optimal ESS placement to minimize the risk of energy transaction processes for energy agents. In [53], optimal ESS placement in a LV distribution network is performed to prevent over- and under-voltages and minimize overall network costs (regarding ESS and network losses), by employing clustering and sensitivity analysis and a multi-period OPF approach.

In [29], a cost-based optimization technique by MATLAB is employed for optimal distributed ESS placement and operation to improve generation and load hosting capability. Consequently, peak demand and power loss are minimized through the achievement of good voltage regulation. In [34], optimal ESS allocation is accomplished through GA (integrated with linear-programming) and a sequential MCS to maximize distribution network benefits by minimizing the costs of ESS installation, system upgrade, maintenance, interruption, and energy losses. In [46], GA hybridized with a linear programming solver, MATLAB optimization toolbox, and a sequential MCS are used for optimal ESS allocation and sizing. In that research, the distribution system benefits are maximized while managing loads, and minimizing of net present value (NPV) and overall costs.

The importance of power quality for smart grid perspective is discussed in [54]. An ESS also has the capability to improve power quality [55]. Wind DGs emit flicker to the network [56, 57] significantly, which is an important issue for power quality management [58]. In [59], an ESS (supercapacitor) is used to alleviate the voltage flicker due to integration of wind generators. It should be noted here that the above-mentioned literature did not focus on simultaneously minimizing power losses, line loading, voltage deviation, and flicker disturbance of a network. However, optimal solutions combining these parameters together are necessary to improve network performance and power quality and can be obtained through optimal distributed ESS allocation. This paper has adopted this requirement, where the ESSs inject both the P and Q to the network with variable p.f. on the dispatch of an ESS.

In the aforementioned literature, various modeling and optimization approaches (single and hybrid) are used for the optimal allocation of ESSs [10, 17, 29, 32–34, 36, 44–53]. This paper applies a hybrid meta-heuristic optimization approach, the fitness-scaled chaotic artificial bee colony (FSCABC) algorithm, for optimal ESS allocation. A hybrid meta-heuristic approach that combines two or more algorithms (e.g., FSCABC algorithm) provides additional benefits for optimization search compared to single-algorithm methods such as GA, ABC, and PSO by improving their accuracy and convergence capabilities [16]. For instance, the ABC algorithm is hybridized with PSO in [60] to eliminate problems of poor local and global search capabilities of ABC and PSO, respectively. Being robust and simple, the ABC algorithm has triple search capability (done by three types of bees) for solving multi-dimensional and complex combinatorial optimization problems [61–63]. The hybrid FSCABC approach eliminates the trapping problem of ABC algorithm in local optima and improves its performance [64–66].

In this paper, a comprehensive investigation is conducted for optimal allocation of ESSs in an IEEE-33 bus distribution network. DIgSILENT PowerFactory is utilized for developing system models and analysis of the proposed system. The FSCABC optimization approach is used for optimization and python programming language is employed for controlling the system models as well as facilitating optimization. The key contributions of this paper are outlined as follows:

- The optimal allocation of ESSs is investigated focusing on performance and power quality improvements as well as cost minimization. For performance improvement, minimization of line loading as well as active and reactive power losses are targeted,

while flicker minimization and voltage profile improvement are addressed for power quality improvement. The studies related to ESS placement such as [10, 29, 32–34, 36, 44–53] have not simultaneously considered these parameters. Reference [17] considers some of these parameters; however, a unity p.f. approach (P injection approach) on the ESS dispatch is applied while this paper considers variable p.f. conditions. More specifically, in this study, the ESSs inject both the P and Q to the network with variable p.f. on the dispatch of an ESS.

- The performance and power quality indices are estimated to monitor the performance and power quality improvements through the proposed ESS allocation. In addition, new indices for flicker minimization are introduced regarding continuous, switching, and overall network flickers.
- Overall investigation for ESS allocation is carried out through PQ injections in two distinct phases: (1) applying a uniform ESS size, and (2) applying non-uniform ESS sizes. Moreover, results obtained from FSCABC optimization approach are verified using an ABC algorithm.

The remainder of this paper is structured as follows:

The modeling of the ESS is presented in Section 2. The problem is formulated in Section 3, and the optimization and proposed approaches are discussed in Section 4. The test distribution network, assignment of factors, and performance indices are presented in Section 5. The results are analyzed, discussed, and presented in Section 6. The comparison of FSCABC optimization approach with ABC algorithm is also presented in Section 6. Finally, concluding remarks and future research directions are presented in Section 7.

2. Modeling of the ESS

The utility-scale ESSs are selected based on their technical characteristics, various performance factors, and applications [16, 67–70]. From the viewpoint of ESS cost, the UltraBattery (also called advanced lead-acid battery) is chosen in this study similar to [17]. Although the UltraBattery is considered as the ESS technology, the ESS model (developed by [17]) is generic and can be utilized for other ESS technologies.

The ESS model is subject to prerequisites of (1) to (7) in time t (indexed 1, ..., NT) [17, 71]:

$$0.2 \leq SOC_g^{ESS} \leq 0.9 \quad (1)$$

$$P_t^{ESS,c} = \max \left\{ P^{ESS-min}, \frac{(E_t^{ESS} - S^{ESS-max})}{\eta^c \cdot \Delta t} \right\} \quad (2)$$

$$P_t^{ESS,d} = \min \left\{ P^{ESS-max}, \frac{(E_t^{ESS} - S^{ESS-min}) \eta^d}{\Delta t} \right\} \quad (3)$$

Charging mode:

$$E_{t+1}^{ESS} = \min \left\{ \left(E_t^{ESS} - \Delta t P_t^{ESS,c} \eta^c \right), S^{ESS-max} \right\} \quad (4)$$

$$P_t^{ESS,c} \leq P_t^{ESS} \leq P_t^{ESS,d} \quad (5)$$

Discharging mode:

$$E_{t+1}^{ESS} = \max \left\{ \left(E_t^{ESS} - \Delta t \frac{P_t^{ESS,d}}{\eta^d} \right), S^{ESS-min} \right\} \quad (6)$$

$$P_t^{ESS,c} \leq P_t^{ESS} \leq P_t^{ESS,d} \quad (7)$$

where,

- The ESS should control P in both ways and a priority for P and Q is required to fulfil $S^{app} = \sqrt{P^2 + Q^2}$. The SOC_g^{ESS} is subject to (1) [72] and $SOC_g^{ESS} = 1$ and $SOC_g^{ESS} = 0$ indicate that the ESS is fully charged and discharged, respectively.
- Equation (2) and Equation (3) represent the maximum charging and minimum discharging rates, respectively.
- Equation (4) and Equation (5) limit the minimum energy stored to the ESS and charging power of the ESS, respectively. Equation (6) and Equation (7) restrict the maximum energy released from the ESS and power discharged by the ESS, respectively.

3. Formulation of the problem

3.1. Objective function

The objective function of the proposed placement problem is presented in (8) and formulated by means of (9) to (21) [17, 58, 73]. This is mainly a cost function representing the costs associated with network power quality (voltage deviation and network flickers), performance (power losses and line loading), and ESS units. This function comprises important cost factors in the category of power quality cost ($C_{PQuality}$), performance cost ($C_{Performance}$), and ESS cost (C_{ESS}), where all the factors are weighted equally with $\gamma^{VD} = \gamma^{flicker} = \gamma^{PL} = \gamma^{LL} = \gamma^{ESS} = 1$.

$$\begin{aligned} \mathcal{J}(C_{Fi}^{OBJ}) = \text{minimize} \left\{ \underbrace{\sum_n (\gamma^{VD} \cdot C_n^{VD} + \gamma^{flicker} \cdot C_n^{flicker})}_{C_{PQuality}} + \underbrace{\sum_l (\gamma^{PL} \cdot C_l^{PL} + \gamma^{LL} \cdot C_l^{LL})}_{C_{Performance}} \right. \\ \left. + \underbrace{(\gamma^{ESS} \cdot C_{UT}^{ESS})}_{C_{ESS}} \right\} \end{aligned} \quad (8)$$

where,

$$C_n^{VD} = \left(\sum_{n=1}^N |V^{target} - V_n^B(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})| \right) \cdot \Gamma^{VD} \quad (9)$$

$$C_n^{flicker} = \left(\sum_{n=1}^N P_n^{FCont} + P_n^{FSw} \right) \cdot \Gamma^{flicker} \quad (10)$$

$$P_n^{FCont} = P_n^{STCont} = P_n^{LTCont} = c_F(\psi_k, v_a) \cdot \frac{S^{WDG}}{S_n^{grid}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})} \quad (11)$$

$$P_n^{FSw} = P_n^{STSsw} + P_n^{LTSw} \quad (12)$$

$$P_n^{STSsw} = 18 \cdot N_{10}^{0.31} \cdot k_f^{step}(\psi_k) \cdot \frac{S^{WDG}}{S_n^{grid}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})} \quad (13)$$

$$P_n^{LTSw} = 8 \cdot N_{120}^{0.31} \cdot k_f^{step}(\psi_k) \cdot \frac{S^{WDG}}{S_n^{grid}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})} \quad (14)$$

$$C_l^{PL} = X^{TLoss} \cdot \Gamma^{PL} \quad (15)$$

$$X^{TLoss} = \left(\sqrt{\{P^{LT}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})\}^2 + \{Q^{LT}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})\}^2} \right) \quad (16)$$

$$P^{LT}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS}) = \sum_{l=1}^M P^L(i, j) = \sum_{l=1}^M \left(R^L(i, j) \cdot \frac{P_i^2 + Q_i^2}{|\{V_n^B(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})\}^2|} \right) \quad (17)$$

$$Q^{LT}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS}) = \sum_{l=1}^M Q^L(i, j) = \sum_{l=1}^M \left(X^L(i, j) \cdot \frac{P_i^2 + Q_i^2}{|\{V_n^B(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS})\}^2|} \right) \quad (18)$$

$$C_l^{LL} = \left(\sum_{l=1}^M \% LL_l^{ESS}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS}) \right) \cdot \Gamma^{LL} \quad (19)$$

$$\% LL_l^{ESS}(S_n^{ESSP}, S_n^{ESSQ}, \lambda_n^{ESS}) = \left(\frac{SL_l^{ESS}}{SL_l^{rated}} \right) \times 100 \quad (20)$$

The total ESS unit cost is estimated by (21):.

$$C_{UT}^{ESS} = \sum_{n=1}^K S_n^{ESS} \cdot C^{UU} \quad (21)$$

In the above-mentioned equations, $\Gamma^{VD} = 0.142$ \$ p.u. [17, 29], $\Gamma^{flicker} = 0.142$ \$ p.u. (considered same as the voltage deviation rate), $\Gamma^{PL} = 0.503$ \$ p.u. [17, 74], $\Gamma^{LL} = 50.3471$ c/kWh [17, 74], $V^{target} = 1$ p.u.. Furthermore, the $C^{UU} = 460$ \$/kWh taking into account the UltraBattery application regarding commercial and industrial energy management [17, 75].

3.2. Constraints of the objective function

The objective function of (8) is subject to (22) to (32) along with the ESS model equations as defined in (1) to (7) [17]:

$$P_i^{gen} + \sum_{j \in J+} (P_{j \rightarrow i}^{del}) = P_i^{con} + \sum_{k \in J-} (P_{i \rightarrow k}^{del}) \quad (22)$$

$$Q_i^{gen} + \sum_{j \in J+} (Q_{j \rightarrow i}^{del}) = Q_i^{con} + \sum_{k \in J-} (Q_{i \rightarrow k}^{del}) \quad (23)$$

$$V^{min} < |V_{n-t}^B| < V^{max} \quad (24)$$

$$PF^{ESS-min} \leq PF_n^{ESS} \leq PF^{ESS-max} \quad (25)$$

$$SL_{l-t} < SL_l^{max} \quad (26)$$

$$\lambda_n^{ESS} = \begin{cases} 0, & \text{if the ESS is active} \\ 1, & \text{otherwise} \end{cases} \quad (27)$$

$$S_n^{ESSP} = \begin{cases} Assign, & \text{if } \lambda_n^{ESS} = 0 \\ 0, & \text{if } \lambda_n^{ESS} = 1 \end{cases} \quad (28)$$

$$S_n^{ESSQ} = \begin{cases} Assign, & \text{if } \lambda_n^{ESS} = 0 \\ 0, & \text{if } \lambda_n^{ESS} = 1 \end{cases} \quad (29)$$

$$P^{ESS-min} < P^{ESS} < P^{ESS-max} \quad (30)$$

$$P_t^{ESS,c} \leq P_t^{ESS} \leq P_t^{ESS,d} \quad (31)$$

$$E^{ESS-min} < E^{ESS} < E^{ESS-max} \quad (32)$$

where,

- The active and reactive power balances of i th bus are ensured by (22) and (23), respectively [17], where indices i , j , and k represent adjacent buses.
- Equation (24) signifies the voltage constraint of each bus [17].
- Equation (25) guarantees the application of a p.f. limit (with in the range 0.95 to 1 [76]) on the dispatch of ESSs.
- Equation (26) safeguards the line such that the line loading does not go beyond the maximum limit ($SL_l^{max}=80\%$) to ensure the thermal stability of cables [17].
- The ESS allocation constraints are denoted by (27) to (29).
- Equations (30) to (32) ensure that the ESS power or energy will not surpass their designated limits during charging and discharging actions. Furthermore, the ESS operation within the specified SOC limits is ensured by (1) to (7) [17].

4. FSCABC optimization and proposed approaches

4.1. FSCABC optimization approach

In this paper, the grid-connected ESS allocation problem is optimized by the application of FSCABC algorithm whose overall steps are depicted in Fig. 1. The main limitation of the ABC optimization approach is the possibility of being trapped in local optima while global optimization is sought [64–66]. The problem can be resolved by combining two well-known techniques- (1) the fitness scaling technique and (2) the chaotic technique [65, 66].

Figure 1: Flowchart of the FSCABC optimization approach.

A power-rank scaling technique is proposed for fitness scaling, which combines both power

and rank strategies as given below:

$$fit_i^{scale} = \frac{r_{b-i}^m}{\sum_{i=1}^{SN} r_{b-i}^m} \quad (33)$$

where, r_{b-i} = the rank of i th individual bee, SN = the number of food source, and m = the exponential value for power computation.

The chaotic search is delineated by the logistic function of (34).

$$x_{chao-i}^{n+1} = \mu x_{chao-i}^n (1 - x_{chao-i}^n), \quad i = 1, 2, \dots, SN \quad (34)$$

where, n = the iteration number, x_{chao-i}^n = the i th chaotic variable, and μ^{BIF} = the bifurcation parameter of the system with $\mu^{BIF} \in [0, 4]$. The chaotic behaviour is revealed with $\mu^{BIF} = 4$, $x_{chao-i}^0 \in (0, 1)$, and $x_{chao-i}^0 \notin (0.25, 0.5, 0.75)$.

In the initialization phase, the colony size (C_oS) of solutions x_{ij} ($i = 1, 2, \dots, SN$; $j = 1, 2, \dots, D$) (D = problem dimension) is ascertained with the number of employed bees (N_E) and the number of onlooker bees (N_O), while fulfilling $C_oS = N_E + N_O$. The population is initialized with $j = 0$ as given in (35).

$$x_{i0} = lb + \psi_{ij}^{RAND} (ub - lb), \quad i = 1, 2, \dots, SN \quad (35)$$

where, ub = the upper bound, lb = the lower bound, and ψ_{ij}^{RAND} = a random number in the range $[0, 1]$. By utilizing (36), each employed bee travels from one old position x_{ij} to new candidate position v_{ij} :

$$v_{ij} = x_{ij} + \Phi_{ij}^{RAND} (x_{ij} - x_{kj}) \quad (36)$$

In (36), $k \in 1, 2, \dots, SN$ and $j \in 1, 2, \dots, D$ are randomly selected and k has to be dissimilar from i , where, Φ_{ij}^{RAND} = a random uniform number in the range $[-1, 1]$. If the new location value v_{ij} is better than x_{ij} , then x_{ij} is replaced with updated v_{ij} , otherwise x_{ij} is preserved unchanged. The fitness values of the food sources of employed bees (fit^{FS}) and the food source probability (p_i^{FS}) are computed as per (37) and (38), respectively, where, $f(x_i)^{OBJ}$ indicates the values of a objective function to be optimized.

$$fit_i^{FS} = \begin{cases} \frac{1}{1+f(x_i)^{OBJ}}, & f(x_i)^{OBJ} \geq 0 \\ 1 + |f(x_i)^{OBJ}|, & f(x_i)^{OBJ} < 0 \end{cases} \quad (37)$$

$$p_i^{FS} = \frac{fit_i^{FS}}{\sum_{j=1}^{SN} fit_j^{FS}} \quad (38)$$

Depending on the value of p_i^{FS} , the onlooker bee determines a food source by utilizing a roulette wheel selection approach and then, this new location is found by (39), where, ω_i^{EmB} = weight coefficient in relation to employed bee information.

$$v_{ij} = x_{ij} + \omega_i^{EmB} \Phi_{ij}^{RAND} (x_{ij} - x_{kj}) \quad (39)$$

As the parameter Φ_{ij}^{RAND} is the key factor for convergence in ABC [65], the chaotic sequence of this parameter is described by (40) and used into (36) & (39).

$$\Phi_{ij}^{chaos} = 2 \times [4\Phi_{ij}^{RAND} (1 - \Phi_{ij}^{RAND})] - 1 \quad (40)$$

In scout bee phase, the discarded solutions are improved and replaced by a new solution x_{ij}^{chaos} as defined in (41).

$$x_{ij}^{chaos} = MIN(x_{ij}) + \varphi_{ij} [MAX(x_{ij}) - MIN(x_{ij})] \quad (41)$$

where, $MAX(x_{ij}) = MAX\{x_{1j}, x_{2j}, \dots, x_{Nj}\}$ and $MIN(x_{ij}) = MIN\{x_{1j}, x_{2j}, \dots, x_{Nj}\}$, and φ_{ij}^{RAND} = a random number in the range [-1, 1]. Similar to parameter Φ_{ij}^{RAND} , the chaotic sequence of φ_{ij}^{RAND} is defined by (42) and utilized within (41).

$$\varphi_{ij}^{chaos} = 4\varphi_{ij}^{RAND} (1 - \varphi_{ij}^{RAND}) \quad (42)$$

Table 1: Summary of FSCABC optimization variables and parameters

Type	Parameters/variables	Description/settings
Input parameters	$V^{rated}, R^L(i, j), X^L(i, j), P, Q, P^{T-F}, Q^{T-F}, S^{wind}, S^{PV-max}, S^{PV-op}$, and $S^{ESS-nom}$	Required for the network model.
Output parameters	$C_n^{VD}, C_l^{LL}, C_l^{PL}$, and C_{UT}^{ESS}	Required for the objective function.
Decision variables	S_n^{ESSP}	This variable determines the amount of P to be injected by the ESSs in the network.
	S_n^{ESSQ}	This variable determines the amount of Q to be injected by the ESSs in the network.
	λ_n^{ESS}	This variable determines the position of ESSs in the network.
FSCABC parameters	$\mu^{BIF}, \psi_{ij}^{RAND}, \Phi_{ij}^{RAND}, \varphi_{ij}^{RAND}$, and $x_{chaos-i}^0$	Settings: $\mu^{BIF} \in [0, 4]$, $\psi_{ij}^{RAND} \in [0, 1]$, $\Phi_{ij}^{RAND} \in [-1, 1]$, $\varphi_{ij}^{RAND} \in [-1, 1]$, $x_{chaos-i}^0 \in (0, 1)$, and $x_{chaos-i}^0 \notin \{0.25, 0.5, 0.75\}$.
	D, C_oS, SN, L^{trial} , and It^{max}	Settings: $D = 3 = N^D$, $C_oS = 100$, $SN = C_oS/2$ = population size, $L^{trial} = 60$, and $It^{max} = 1000$.
FSCABC bounds	For S_n^{ESSP} : $lb1$ and $ub1$	Settings: $lb1 = 0.1$ MW and $ub1 = 2.5$ MW for investigation phase-I; $lb1 = 0.1$ MW and $ub1 = 3$ MW for investigation phase-II.
	For S_n^{ESSQ} : $lb2$ and $ub2$	Settings: $lb2 = 0.1$ MVar and $ub2 = 1.5$ MVar for both investigation phase-I and investigation phase-II.
	For λ_n^{ESS} : $lb3$ and $ub3$	Settings: $lb3 = 0$ and $ub3 = 1$.

Figure 2: Flowchart of the proposed optimal ESS allocation approach.

4.2. Proposed approach

The methodology for the proposed ESS allocation is depicted in Fig. 2. After inserting the essential data to all components of a distribution system, the FSCABC parameters are initialized. Optimization variables and parameters are summarized in Table 1. Some important steps in the distribution network model, such as feeder load scaling, instigating a voltage dependency of loads, applying the time-variant characteristics (as given in [17]) to the loads, wind, and solar DGs, are accomplished. The flicker disturbance is instigated by the wind DGs which is distributed throughout the network. Afterwards, the optimal placement problem is formulated to minimize the sum of C_n^{VD} , $C_n^{flicker}$, C_l^{PL} , C_l^{LL} , and C_{UT}^{ESS} in two distinct phases- (1) investigation phase-I: applying a uniform ESS size and (2) investigation phase-II: applying non-uniform ESS sizes.

The ESSs are located throughout the network using the decision variable λ_n^{ESS} , where $\lambda_n^{ESS} = 0$ represents an ESS of n th bus is active and $\lambda_n^{ESS} = 1$ signifies the ESS is inactive. The ESS size (MVA) in a bus is determined through decision variables S_n^{ESSP} (MW) and S_n^{ESSQ} (MVar). The S_n^{ESSP} , S_n^{ESSQ} , and λ_n^{ESS} are generated randomly within the nominated ranges (in the ranges $P = 0.1$ MW to 2.5 MW, $Q = 0.1$ MVar to 1.5 MVar for investigation phase-I and $P = 0.1$ MW to 3 MW, $Q = 0.1$ MVar to 1.5 MVar for investigation phase-II) and injected to the network targeting the distributed placement of maximum number of ESSs with smaller sizes. The ESS size determination is subject to $lb1$, $lb2$, $lb3$, $ub1$, $ub2$, $ub3$, ESS string size, inverter specifications, AC and DC bus size, and transformer size. Furthermore, for sizing, a variable p.f. (not less than 0.95) is employed on the dispatch of an ESS. Finally, the optimal values of S_n^{ESSP} , S_n^{ESSQ} , and λ_n^{ESS} are obtained by the FSCABC optimization approach while fulfilling the necessary constraints.

5. Testing and assignment of factors and indices for performance improvement

This section explores the distribution network where the approach is tested, assignment of essential factors regarding flicker assignment, load scaling of the feeder, and creating voltage dependency. This section also describes the required indices to assess the improvements of system performance and power quality.

Figure 3: Single-line diagram of the proposed distribution network model.

5.1. Test distribution network

The IEEE-33 bus radial distribution system is used for testing of the proposed approach. The single line diagram of the distribution system is depicted in Fig. 3. The proposed

Table 2: Information of the proposed distribution network model [17]

Model specification	Model data
Base MVA	10 MVA
Substation voltage	12.66 kV
PV1 and PV3 are allocated on bus5 and bus21, respectively	size = 400 kVA
PV2 is installed on bus8	size = 500 kVA
WDG1, WDG2, WDG3, WDG4, WDG5, and WDG6 are placed on bus12, bus18, bus24, bus31, bus28, and bus33, respectively	size = 1 MVA
S^{PV-op}	85% of S^{PV-max}
P^{T-F} (for feeder load scaling)	3.715 MW
Q^{T-F} (for feeder load scaling)	2.3 MVar

system is modeled using DIgSILENT PowerFactory. The lines and buses are symbolized by the letter 'L' and the numbers 1 to 33, respectively, where L33 to L37 indicate tie lines and bus 1 represents the feeder. In this model, three solar DGs and six wind DGs are installed to create a scenario of high RES penetration. The wind DGs (WDGs), solar DGs (PVs), and loads are modeled using built-in templates within PowerFactory and the system data is taken from [17]. The overall model information is provided in Table 2.

5.2. Assignment of factors

Assignment of flicker disturbance: The flicker coefficients of WDGs are assigned considering $v_a=10$ m/s as presented in Table 3 [56]. The flicker disturbance is generated for various ψ_k values such as 30° , 50° , 70° , and 85° . It is assumed that during switching operations, a turbine starts-up at cut-in wind speed with $N_{10} = 3$ and $N_{120} = 30$. The flicker disturbance generated from a WDG is distributed throughout the network which affects the S_n^{grid} of a bus n .

Assignment of feeder load scaling and voltage dependency: The feeder loads are scaled using the instructions described in [17], while the loads of the system follow the IEEE-RTS model. The total active and reactive powers are estimated by applying a scale (Ψ^{scale}) and the voltage dependency of loads as denoted in (43) and (44), respectively [17]. The scaling of wind and solar DG outputs is performed using the characteristics provided in [17].

$$P = \Psi^{scale} \cdot P_0 \left[aP \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{aP}} + bP \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{bP}} + (1 - aP - bP) \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{cP}} \right] \quad (43)$$

$$Q = \Psi^{scale} \cdot Q_0 \left[aQ \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{aQ}} + bQ \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{bQ}} + (1 - aQ - bQ) \cdot \left(\frac{V_n^B}{V_{ref}} \right)^{e_{cQ}} \right] \quad (44)$$

Table 3: Applied flicker coefficient values to wind DGs

ψ_k	$c_F(\psi_k, v_a)$	$k_f^{step}(\psi_k)$	$k_v(\psi_k)$
30°	7.9	0.35	0.7
50°	6.6	0.34	0.7
70°	5.7	0.38	0.8
85°	7.3	0.43	0.9
Maximum switching operations			
$N_{10} = 3, N_{120} = 30$			

where, $(1 - aP - bP) = cP$, $(1 - aQ - bQ) = cQ$, $aP = aQ = 0.4$, $bP = bQ = 0.3$, $cP = cQ = 0.3$, $e_{aP} = e_{aQ} = 0$, $e_{bP} = e_{bQ} = 1$, and $e_{cP} = e_{cQ} = 2$ [17].

5.3. Performance improvement indices of the system

Indices for voltage deviation and profile improvement: The voltage deviation of n th bus is calculated using V^{max} and V^{min} (assuming deviation limit $= \pm 5\%$). The percent voltage deviation index (%VDI) is described by (45) [17].

$$\% VDI = \sum_{n=1}^N \left(\frac{|V^{rated} - V_n^B|}{V^{rated}} \right) \times 100 \quad (45)$$

The overall voltage profile (VP) and the index for voltage profile improvement (VPPI) of the system are described by (46) and (47), respectively [17], where VP_n is the voltage profile of n th bus and $\sum_{n=1}^N \zeta_n = 1$.

$$VP = \sum_{n=1}^N VP_n = \sum_{n=1}^N V_n^B S_n^L \zeta_n \quad (46)$$

$$VPPI = \frac{VP^{w-ESS}}{VP^{wo-ESS}} \quad (47)$$

Indices for flicker minimization: Flicker minimization indices (FMI^{Cont} , $FMI^{STS w}$, and $FMI^{LTS w}$), for both continuous and switching operations, are defined according to IEC standard 61400-21 ((11), (13), and (14)) as presented in (48), (49), and (50).

$$FMI^{Cont} = \frac{\sum_{n=1}^N P_n^{FCont-ESS}}{\sum_{n=1}^N P_n^{FCont-base}} \quad (48)$$

$$FMI^{STS w} = \frac{\sum_{n=1}^N P_n^{STS w-ESS}}{\sum_{n=1}^N P_n^{STS w-base}} \quad (49)$$

$$FMI^{LTSw} = \frac{\sum_{n=1}^N P_n^{LTSw-ESS}}{\sum_{n=1}^N P_n^{LTSw-base}} \quad (50)$$

Total flicker minimization index is defined as:

$$FMI^T = \frac{\sum_{n=1}^N (P_n^{FCont-ESS} + P_n^{STSw-ESS} + P_n^{LTSw-ESS})}{\sum_{n=1}^N (P_n^{FCont-base} + P_n^{STSw-base} + P_n^{LTSw-base})} \quad (51)$$

The improvement index for relative voltage change ($RVCII$) at 20 °C is defined as:

$$RVCII = \frac{\sum_{n=1}^N d_n^{Sw-ESS}}{\sum_{n=1}^N d_n^{Sw-base}} \quad (52)$$

where,

$$\%d^{Sw} = 100 \cdot k_v(\psi_k) \cdot \frac{S^{WDG}}{S_{grid}} \quad (53)$$

Indices for power loss reduction: The indices for the reduction of line losses such as real, reactive, and total line losses ($PLRI^P$, $PLRI^Q$, and $PLRI^T$) are defined by (54), (55), and (56), respectively [17].

$$PLRI^P = \frac{\sum_{l=1}^M P_l^{L-ESS}}{\sum_{l=1}^M P_l^{L-base}} \quad (54)$$

$$PLRI^Q = \frac{\sum_{l=1}^M Q_l^{L-ESS}}{\sum_{l=1}^M Q_l^{L-base}} \quad (55)$$

$$PLRI^T = \frac{\sum_{l=1}^M \sqrt{(P_l^{L-ESS})^2 + (Q_l^{L-ESS})^2}}{\sum_{l=1}^M \sqrt{(P_l^{L-base})^2 + (Q_l^{L-base})^2}} \quad (56)$$

Line loading index: The line loading index (LLI) of (57) is computed using the percent line loading of l th line for base case ((58)) and after ESS placement ((20)) [17].

$$LLI = \frac{\% LLT^{w-ESS}}{\% LLT^{wo-ESS}} = \frac{\sum_{l=1}^M \% LL_l^{ESS}}{\sum_{l=1}^M \% LL_l^{base}} \quad (57)$$

$$\% LL_l^{base} = \left(\frac{SL_l^{base}}{SL_l^{rated}} \right) \times 100 \quad (58)$$

Power quality improvement index: The power quality index (PQI), after minimizing the voltage deviation and flicker disturbance through the ESS placement, can be defined as (59). The index for power quality improvement ($PQII$) can be defined as (60).

$$PQI = \frac{VDI^{w-ESS} + \sum_{n=1}^N (P_n^{FCont-ESS} + P_n^{STSw-ESS} + P_n^{LTSw-ESS})}{VDI^{wo-ESS} + \sum_{n=1}^N (P_n^{FCont-base} + P_n^{STSw-base} + P_n^{LTSw-base})} \quad (59)$$

$$PQII = \frac{1}{PQI} \quad (60)$$

6. Results and Discussion

This section explores the impact of the proposed ESS placement in the distribution network regarding system power quality, system performance, and cost minimization. The performance analysis is conducted for three different case studies: (i) Case 1- base case (without ESSs), (ii) Case 2- placement of ESSs applying a uniform size, and (iii) Case 3- placement of ESSs applying non-uniform sizes. The ESS sizing is accomplished through PQ injection by the ESSs with a variable p.f. (not less than 0.95). The system results are presented in Table 4 and Table 5. This section also compares the optimization results achieved from FSCABC approach with ABC algorithm. In this study, ESS power rating (MVA) is taken into account as constant over one hour [17].

Table 4: ESS size and locations for various case studies

Case studies	P (MW), Q (MVar), and locations of ESSs	Total ESS Size (MWh)
Case 1—Without ESS allocation (base case)	-	-
Case 2—Distributed ESS allocation for a uniform ESS size	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs P = 1.269 Q= 0.417	12.022
Case 3—Distributed ESS allocation for non-uniform ESS sizes	ESS7-P=1.491 Q=0.231; ESS8-P=1.234 Q=0.231; ESS10-P=0.703 Q=0.231; ESS13-P=0.851 Q=0.231; ESS15-P=1.094 Q=0.231; ESS22-P=0.703 Q=0.231; ESS24-P=1.736 Q=0.231; ESS25-P=3 Q=0.231; ESS27-P=0.703 Q=0.231; ESS29-P=0.838 Q=0.231; ESS30-P=3 Q=0.231; ESS31-P=0.703 Q=0.231; ESS32-P=1.258 Q=0.231	17.572

Table 5: System results after a quantitative analysis for various cases of Table 4

Case Details	%VDI	$\sum_{n=1}^N P^{FCont}$	$\sum_{n=1}^N P^{STS w}$	$\sum_{n=1}^N P^{LTS w}$	$\sum_{n=1}^N \%d^{Sw}$	P^{LT} (MW)	Q^{LT} (MVar)	%LLT
Case 1	82.707	5.454	4.808	4.363	29.357	0.107	0.083	269.024
Case 2	53.129	5.024	4.432	4.022	27.449	0.080	0.064	226.546
Case 3	51.205	4.891	4.300	3.902	26.743	0.060	0.042	201.322

6.1. Case study 1- base case without ESS placement

Various parameter results obtained from the base case analysis (without ESS allocation) are presented in Table 5. The values of parameter %VDI, $\sum_{n=1}^N P^{FCont}$, $\sum_{n=1}^N P^{STS w}$, $\sum_{n=1}^N P^{LTS w}$, P^{LT} , Q^{LT} , and %LLT are targeted to be optimized. In Case 2 and Case 3 of Table 5, a parameter value lower than the corresponding base value represents the performance improvement and vice-versa.

6.2. Case study 2- placement of ESSs through uniform sizing approach

Results of optimal ESS allocation by applying uniform S_n^{ESSP} and S_n^{ESSQ} are presented in Table 4. The S_n^{ESSP} , S_n^{ESSQ} , and λ_n^{ESS} can be recognized in Table 4 by the ESS P (MW), ESS Q (MVar), and ESS number, respectively. For instance, P = 1.269 and Q= 0.417 of ESS7 indicate that an ESS of 1.269 MW and 0.417 MVar (total size = 1.336 MVA) is connected to bus7. Nine ESSs having a uniform size (1.336 MVA) are allocated on bus numbers 7, 9, 14, 24, 25, 29, 30, 31, and 32. Table 4 suggests that all parameters such as %VDI, $\sum_{n=1}^N P^{FCont}$, $\sum_{n=1}^N P^{STSw}$, $\sum_{n=1}^N P^{LTSw}$, $\sum_{n=1}^N \%d^{Sw}$, P^{LT} , Q^{LT} , and %LLT are reduced compared to Case 1. The results of Case 2 parameters are obtained with a total ESS size of 12.022 MWh.

6.3. Case study 3- placement of ESSs through non-uniform sizing approach

The impact of optimal ESS placement, using the non-uniform ESS sizing approach, is analyzed and obtained results are presented in Table 5 (Case 3). During Case study 3, the S_n^{ESSP} is allotted non-uniformly to all ESSs, while the S_n^{ESSQ} is assigned uniformly to all ESSs. The S_n^{ESSP} , S_n^{ESSQ} , and λ_n^{ESS} can be recognized in Table 4 by the ESS P (MW), ESS Q (MVar), and ESS number, respectively. For instance, ESS7-P = 1.491 Q= 0.231 indicates that an ESS of 1.491 MW and 0.231 MVar (total size = 1.509 MVA) is allocated to bus7. Thirteen ESSs having non-uniform sizes are allocated on bus number 7, 8, 10, 13, 15, 22, 24, 25, 27, 29, 30, 31, and 32. Table 5 shows that all Case 3 parameters, e.g., %VDI, $\sum_{n=1}^N P^{FCont}$, $\sum_{n=1}^N P^{STSw}$, $\sum_{n=1}^N P^{LTSw}$, $\sum_{n=1}^N \%d^{Sw}$, P^{LT} , Q^{LT} , and %LLT are further minimized compared to Case 2. However, a total ESS size of 17.572 MWh is required for Case 3, which indicates an augmentation in distribution system investment cost over Case 2 (12.022 MWh).

6.4. Overall result analysis and comparison

Comparison in relation to voltage profiles: Figure 4(a) and Fig. 4(b) depict the voltage profiles of various cases in terms of bus voltage and VP_n , respectively. The feeder voltage profiles (in terms of feeder distance) for Case 1, Case 2, and Case 3 are displayed in Fig. 5, Fig. 6, and Fig. 7, respectively. According to these illustrations, both Case 2 and Case 3 provide improved voltage profiles compared to Case 1. However, Case 3 has improvements in voltage deviation compared to Case 2 such as at buses 5 to 13, 20 to 22, and 25 to 29. For instance, the voltage at bus 12 for Case 3 is 0.974 p.u., while this is 0.980 p.u. for Case 2. In contrast, Case 2 provides improved voltage at buses 16 to 18 and 31 to 33 compared to Case 3. Figure 6 and Fig. 7 indicate that the feeder voltage profiles have been significantly improved for Case 2 and Case 3 compared to Case 1 (Fig. 5). The improvement in feeder section L02-L22-L23-L24-L37-L29-L30-L31-L32 is significant for both cases compared to Case 1. The parameter %VDI also indicates the comparison of voltage deviations for various cases as given in Table 5. Overall, Case 3 (%VDI = 51.205) provides a slightly better voltage profile than Case 2 (%VDI = 53.129).

Comparison of flicker minimization characteristics: The characteristics for continuous and switching flickers (at various buses) of various cases are presented in Fig. 8(a) and

Figure 4: Voltage profiles of buses for various cases—(a) in terms of bus voltage and (b) in terms of VP_n .

Fig. 8(b), respectively. Both continuous and switching flicker characteristics have similar patterns, where higher flicker disturbances are observed at bus 18 and bus 33 compared to others. In contrast, the lowest flicker disturbance is noticed at bus 1. The values of flicker parameters such as $\sum_{n=1}^N P^{FCont}$, $\sum_{n=1}^N P^{STS w}$, and $\sum_{n=1}^N P^{LTS w}$ are reduced for Case 2 and Case 3, while Case 3 minimizes these disturbances better than Case 2 (as per Table 5). Relative voltage change (%) during switching of WDGs (for various cases) is depicted in Fig. 9. As referred to Table 5, the $\sum_{n=1}^N \% d^{Sw}$ for Case 1 is 29.357, while this reduced to 27.449 and 26.743 for Case 2 and Case 3, respectively.

Figure 10(a) and Fig. 10(b) compare the short circuit power (S_n^k) and impedance angle (Ω_n^k) for various cases, respectively. The S_n^k and Ω_n^k at various buses are slightly affected through PQ injection by the ESSs. For instance, the value of S_n^k at bus 1 is 9094.344 MVA, 9099.133 MVA, and 9099.618 MVA for Case 1, Case 2, and Case 3, respectively. A change of about 500 kVA is observed in S_n^k for Case 3 compared to Case 2. On the other hand, the value of Ω_n^k on the same bus (bus 1) is 84.231° , 84.176° , and 84.148° for Case 1, Case 2, and Case 3, respectively. Figure 11(a) compares flicker disturbances for various cases, while Fig.

Figure 5: Voltage profile of the network feeder for Case 1.

Figure 6: Voltage profile of the network feeder for Case 2.

Figure 9: Relative voltage change (%) during switching of WDGs for various cases.

11(b) exhibits the total flicker characteristics which is calculated based on total flicker of various buses. Figure 11 suggests that Case 3 minimizes the total flicker disturbance better than Case 2, while demanding a larger ESS installation (17.572 MWh) compared to Case 2.

Comparison of line losses and loading: The comparative performance of various cases in terms of real, reactive, and total line losses is presented in Fig. 12. As referred to in Fig. 12(a), Case 2 exhibits a higher active power loss at lines L3-L5, L8-L9, L16-L20, and L30, while a higher active power loss value is noticed at lines L13-L15, L22-L24, and L26-L29 for Case 3. The line L2 has the highest active power loss of 0.0186 MW and 0.0193 MW for Case 2 and Case 3, respectively. According to Fig. 12(b), L30 exhibits the highest reactive power loss of 0.0163 MVar for Case 2. Overall, Case 3 minimizes the active, reactive, and total power losses (0.060 MW, 0.042 MVar, and 0.075 MVA) compared to Case 2 (0.080 MW, 0.064 MVar, and 0.106 MVA) as per Table 5. Percent line loadings, with respect to individual line numbers, is represented in Fig. 13. For all cases, the loading of individual lines is below the maximum loading limit (80%). Significantly, a maximum loading of 41.513% is observed at L1 for all cases, while L2 has a loading of 27.824%, 23.357%, and 23.784% for Case 1, Case 2, and Case 3, respectively. The loading of all other lines varies closely for Case 2 and Case 3. As referred to in Fig. 13 and Table 5, the overall line loading for Case 2 and Case 3 are reduced to 226.546% and 201.322%, respectively, compared to Case 1 (269.024%). These characteristics of line loading suggest that the system feeder has adequate surplus capacity to recover unexpected situations during outage through load sharing.

Statistical analysis of FSCABC approach with ABC algorithm: The same ABC approach given in [17] is utilized to justify the results obtained from the FSCABC algorithm. The same settings (D , C_oS , SN , L^{trial} , and It^{max}) are used for both FSCABC and ABC approaches

Figure 10: (a) The short circuit power of buses for various cases and (b) impedance angle of buses for various cases.

Figure 11: (a) Network flicker comparison for various cases and (b) total flicker for various cases.

(a)

(b)

(c)

Figure 12: Comparison of losses— (a) comparison of active power loss, (b) comparison of reactive power loss, and (c) comparison of total line loss.

Figure 13: Percent line loading for various cases.

as displayed in Table 1. For both approaches, the optimization is executed 30 times and thereby the best, worst, and mean solutions of the objective function are obtained. Table 6 compares the optimization results obtained from both approaches along with the evaluation of standard deviations (σ^{FSCABC} and σ^{ABC}). The smaller standard deviation signifies lower deviation among solutions obtained from 30 optimization runs. For investigation phase-I, the values of standard deviations in Table 6 are $\sigma^{FSCABC} = 25032.807$ and $\sigma^{ABC} = 31082.370$, while these values are $\sigma^{FSCABC} = 31169.112$ and $\sigma^{ABC} = 82427.240$ for investigation phase-II. In other words, the FSCABC approach provides further benefits for the optimization search (obtain solutions with smaller deviation) compared to the ABC algorithm. It is clear from the statistical analysis presented in Table 6 that the FSCABC technique is successful in obtaining expected optimal solutions for both investigation phases.

The computer that is used for the simulation study possesses the following configuration: Windows 10 (64-bit), Intel(R) Xeon 3.5 GHz processor, and 16 GB RAM. For two investigation phases, the convergence characteristics of both the FSCABC and ABC optimization algorithms are illustrated in Fig. 14, while the computation time is listed in Table 7. Table 7 demonstrates that the FSCABC-based technique converges after 206 and 294 iterations for investigation phase-I and investigation phase-II, respectively. In contrast, the ABC approach converges after 279 and 413 iterations during investigation phase-I and investigation phase-II, respectively. In particular, the FSCABC-based optimization approach converges faster than the ABC algorithm. In real time, FSCABC and ABC algorithms take about 378 s and 620 s, respectively, for placing the ESSs during investigation phase-I. For investigation phase-II, the FSCABC and ABC algorithms require around 562 s and 818 s, respectively, for allocating the ESSs on the distribution network.

Overall performance and power quality analysis: Table 8 compares the performance in-

Table 6: Optimization results of FSCABC and ABC algorithms for 30 runs

Optimization statistics	ESS real & reactive powers and locations	%VDI	Total flicker	P_{Tot} (MW)	Q_{Tot} (MVar)	%LLT	Total ESS size (MWh)	Objective function value (\$)
Distributed ESS placement for uniform ESS sizing (investigation phase-I)								
FSCABC best	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.269$ $Q=0.417$	53.129	13.478	0.0797	0.0644	226.546	12.022	5530150.257
FSCABC worst	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.322$ $Q=0.333$	53.702	13.49	0.0817	0.0668	230.198	12.27	5644231.09 0
FSCABC mean	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.296$ $Q=0.387$	53.196	13.477	0.0804	0.0654	227.937	12.173	5599610.575
σ^{FSCABC}								25032.807
ABC best	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.288$ $Q=0.390$	53.28	13.481	0.0803	0.0652	227.664	12.112	5571550.52 0
ABC worst	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.337$ $Q=0.301$	54.009	13.497	0.0824	0.0676	231.675	12.334	5673671.376
ABC mean	ESS7, ESS9, ESS14, ESS24, ESS25, ESS29, ESS30, ESS31, ESS32; for all ESSs $P=1.315$ $Q=0.338$	53.734	13.491	0.0815	0.0665	229.855	12.22 0	5621230.997
σ^{ABC}								31082.370

Table 6 continues

Optimization statistics	ESS real & reactive powers and locations	%VDI	Total flicker	P_{Tot} (MW)	Q_{Tot} (MVar)	%LLT	Total ESS size (MWh)	Objective function value (\$)
Distributed ESS placement for non-uniform ESS sizing (investigation phase-II)								
FSCABC best	ESS7-P=1.491 Q=0.231; ESS8-P=1.234 Q=0.231; ESS10-P=0.703 Q=0.231; ESS13-P=0.851 Q=0.231; ESS15-P=1.094 Q=0.231; ESS22-P=0.703 Q=0.231; ESS24-P=1.736 Q=0.231; ESS25-P=3 Q=0.231; ESS27-P=0.703 Q=0.231; ESS29-P=0.838 Q=0.231; ESS30-P=3 Q=0.231; ESS31-P=0.703 Q=0.231; ESS32-P=1.258 Q=0.231	51.205	13.093	0.0596	0.042	201.322	17.572	8083142.248
FSCABC worst	ESS7-P=1.504 Q=0.222; ESS8-P=1.413 Q=0.222; ESS10-P=0.713 Q=0.222; ESS13-P=0.884 Q=0.222; ESS15-P=1.208 Q=0.222; ESS22-P=0.752 Q=0.222; ESS24-P=1.714 Q=0.222; ESS25-P=3 Q=0.222; ESS27-P=0.707 Q=0.222; ESS29-P=1.070 Q=0.222; ESS30-P=3 Q=0.222; ESS31-P=0.692 Q=0.222; ESS32-P=1.038 Q=0.222	51.684	13.07	0.0595	0.0416	203.168	17.929	8247362.172
FSCABC mean	ESS7-P=1.531 Q=0.218; ESS8-P=1.210 Q=0.218; ESS10-P=0.703 Q=0.218; ESS13-P=0.790 Q=0.218; ESS15-P=1.249 Q=0.218; ESS22-P=0.737 Q=0.218; ESS24-P=1.782 Q=0.218; ESS25-P=3 Q=0.218; ESS27-P=0.692 Q=0.218; ESS29-P=0.758 Q=0.218; ESS30-P=3 Q=0.218; ESS31-P=0.706 Q=0.218; ESS32-P=1.208 Q=0.218	51.606	13.098	0.0595	0.042	202.061	17.596	8247362.172
σ^{FSCABC}	ESS32-P=1.208 Q=0.218							31169.112
ABC best	ESS7-P=1.500 Q=0.227; ESS8-P=1.233 Q=0.227; ESS10-P=0.701 Q=0.227; ESS13-P=0.794 Q=0.227; ESS15-P=1.184 Q=0.227; ESS22-P=0.712 Q=0.227; ESS24-P=1.756 Q=0.227; ESS25-P=3 Q=0.227; ESS27-P=0.713 Q=0.227; ESS29-P=0.814 Q=0.227; ESS30-P=3 Q=0.227; ESS31-P=0.699 Q=0.227; ESS32-P=1.249 Q=0.227	51.606	13.093	0.0595	0.0419	201.484	17.604	8097862.212
ABC worst	ESS7-P=1.626 Q=0.222; ESS8-P=1.378 Q=0.222; ESS10-P=0.739 Q=0.222; ESS13-P=0.866 Q=0.222; ESS15-P=1.406 Q=0.222; ESS22-P=0.740 Q=0.222; ESS24-P=2.240 Q=0.222; ESS25-P=2.996 Q=0.222; ESS27-P=0.707 Q=0.222; ESS29-P=1.144 Q=0.222; ESS30-P=3 Q=0.222; ESS31-P=0.722 Q=0.222; ESS32-P=0.908 Q=0.222	53.049	13.013	0.0589	0.0414	204.549	18.696	8600182.013
ABC mean	ESS7-P=1.552 Q=0.222; ESS8-P=1.24 Q=0.222; ESS10-P=0.688 Q=0.222; ESS13-P=0.744 Q=0.222; ESS15-P=1.187 Q=0.222; ESS22-P=0.706 Q=0.222; ESS24-P=2.440 Q=0.222; ESS25-P=3 Q=0.222; ESS27-P=0.707 Q=0.222; ESS29-P=0.752 Q=0.222; ESS30-P=3 Q=0.222; ESS31-P=0.699 Q=0.222; ESS32-P=1.232 Q=0.222	53.812	13.052	0.0592	0.0419	204.065	18.178	8361902.158
σ^{ABC}	ESS32-P=1.232 Q=0.222							82427.240

Discussion: Although both FSCABC and ABC approaches provide nearer solutions (i.e. very close to each other) in relation to objective function costs (\$) including %VDI, total flicker, P_{Tot} , Q_{Tot} , %LLT, and ESS size, the σ^{FSCABC} value is smaller than the σ^{ABC} value for both investigation phases. The $\sigma^{FSCABC} < \sigma^{ABC}$ indicates lower deviations amongst objective function results (\$) obtained by the FSCABC approach, which signifies higher accuracy of the FSCABC approach compared to ABC algorithm.

Figure 14: Convergence graph of FSCABC and ABC algorithms.

Table 7: Convergence and computation time of FSCABC and ABC approaches

Investigation type	FSCABC convergence	FSCABC computation time (s)	ABC convergence	ABC computation time (s)
I	After 206 iterations	378	After 279 iterations	620
II	After 294 iterations	562	After 413 iterations	818

indices of the system which are estimated according to Section 5.3. Generally, $VPII > 1$ indicates that the system has good voltage profile. On the contrary, the higher values of $PLRI^P$, $PLRI^Q$, $PLRI^T$, and LLI imply higher real, reactive, total power losses, and line loading, respectively. Similarly, higher values of FMI^{Cont} , FMI^{STSw} , FMI^{LTSw} , FMI^T , and $RVCII$ denote higher flickers in the system. The $VPII = 1.248$ for Case 3 indicates that this case has good voltage profile which is better than Case 2 ($VPII = 1.200$). All other performance indices are lower during Case 3 compared to Case 2, which suggests that Case 3 provides better performance than Case 2. The results of the above indices are presented in Table 8, which suggests that Case 2 and Case 3 have improved the power quality of the system. Case 3 has better power quality than Case 2 (Higher $PQII$ signifies higher power quality of the system).

Table 8: Performance and power quality indices for various cases

Case Details	$VPII$	FMI^{Cont}	FMI^{STSw}	FMI^{LTSw}	FMI^T	$RVCII$	$PLRI^P$	$PLRI^Q$	$PLRI^T$	LLI	PQI	$PQII$
Case 1	-	-	-	-	-	-	-	-	-	-	-	-
Case 2	1.200	0.921	0.922	0.922	0.922	0.935	0.742	0.773	0.757	0.842	0.907	1.103
Case 3	1.248	0.897	0.894	0.894	0.895	0.911	0.556	0.504	0.536	0.748	0.881	1.135

Figure 15: Comparison of various cases in relation to performance and cost.

The comparison of various cases, in relation to overall performance and total ESS unit cost, is depicted in Fig. 15. This figure suggests that the ESS placement using non-uniform ESS sizes (Case 3) improves the system performance better than a uniform sizing approach (Case 2), by minimizing voltage deviation, flicker, power losses, and line loading. However, this approach (Case 3) involves a higher investment cost of the distribution system compared to Case 2. It should be noted here that this research did not cover any cost analysis or financial impacts, which could be another constraint in the objective function and investigated in future works.

7. Conclusions

This paper has presented an effective strategy for optimal allocation of distributed ESSs in distribution networks employing the FSCABC optimization method. The key problems associated with voltage deviation, flicker, power losses, and line loading are minimized. The results attained from the FSCABC technique are verified through the application of the ABC algorithm. Performance improvements of the system are evaluated through related performance indices. The main conclusions are:

- The improvement in system performance is achieved through both approaches—optimal allocation of distributed ESSs through uniform and non-uniform sizing approaches.
- Improvement of the voltage profile and minimization of flicker disturbances are achieved through the PQ injection of ESSs, and thereby power quality of the distribution network is improved.

- The proposed optimal ESS allocation strategy can be employed for asset management applications of distribution networks.

As with most meta-heuristic approaches, the FSCABC algorithm has some limitations in determining the most optimal solution compared to traditional linear approaches. However, due to the computational burdens involved in using traditional linear optimization search methods, the FSCABC approach has been applied in this study. Regarding future research, more power quality parameters such as over voltage, under voltage, and interruptions (short term and long term) can be incorporated for overall power quality analysis. Furthermore, sensitivity analyses on the ESS placement, development of optimal operation strategy of distributed ESSs that considers RES uncertainties and the impact on ESS lifetime, detailed analysis regarding cost or financial impacts of the obtained ESS sizes, and intelligent control methods via the on-line communication among the placed ESSs can be targeted.

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