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Optimal placement of distributed energy storage systems in distribution networks using artificial bee colony algorithm

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HIGHLIGHTS

- Optimal placement of distributed energy storage systems is presented.
- A uniform and non-uniform energy storage system size approaches are employed.
- Artificial bee colony and particle swarm optimization algorithms are applied.
- Voltage profile is improved, and line losses and line loading are minimized.
- Performance indices are evaluated to analyze the system performance.

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ABSTRACT

The deployment of utility-scale energy storage systems (ESSs) can be a significant avenue for improving the performance of distribution networks. An optimally placed ESS can reduce power losses and line loading, mitigate peak network demand, improve voltage profile, and in some cases contribute to the network fault level diagnosis. This paper proposes a strategy for optimal placement of distributed ESSs in distribution networks to minimize voltage deviation, line loading, and power losses. The optimal placement of distributed ESSs is investigated in a medium voltage IEEE-33 bus distribution system, which is influenced by a high penetration of renewable (solar and wind) distributed generation, for two scenarios: (1) with a uniform ESS size and (2) with non-uniform ESS sizes. System models for the proposed implementations are developed, analyzed, and tested using DIgSILENT PowerFactory. The artificial bee colony optimization approach is employed to optimize the objective function parameters through a Python script automating simulation events in PowerFactory. The optimization results, obtained from the artificial bee colony approach, are also compared with the use of a particle swarm optimization algorithm. The simulation results suggest that the proposed ESS placement approach can successfully achieve the objectives of voltage profile improvement, line loading minimization, and power loss reduction, and thereby significantly improve distribution network performance.

1. Introduction

Present power systems face a period of rapid change driven by various interrelated issues, e.g., demand management [1], greenhouse gas (GHG) reduction targets [2], integration of renewables [3,4], power congestion [5], power quality requirements [6,7], and network expansion [8] and reliability [6,7]. For distribution networks, an energy storage system (ESS) converts electrical energy from a power network, via an external interface, into a form that can be stored and converted back to electrical energy when needed [9]. Depending on the demand or cost benefits, the ESS can store energy to produce and discharge electricity [10]. Consequently, ESSs are increasingly being embedded in distribution networks to offer technical, economic, and environmental advantages. These include mitigation of voltage deviation [11,12], facilitation of renewable energy source (RES) integration [13–15], distributed generation planning [16] and RES energy time-shifting [17], load shifting [18–21], load levelling [22] and peak shaving [23], power quality improvement [5,11,24,25], frequency regulation [5,26], network expansion [27,28] and overall cost reduction [29,30], operating reserves [5,31], GHG reduction [32–34], profit maximization [5,35],

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Nomenclature

Δt	time interval
η_c	ESS charging efficiency
η_d	ESS discharging efficiency
γ_{ESS}	weighting factor for ESS cost
Γ_{LL}	line loading cost rate
γ_{LL}	weighting factor for line loading cost
Γ_{loss}	power loss cost rate
γ_{PL}	weighting factor for power losses cost
Γ_{VD}	voltage deviation cost rate
γ_{VD}	weighting factor for voltage deviation cost
ζ_i	load weighting factor of ith bus
$\mathscr{J}(C_{Fi})$	objective function which is a function of cost
aP, bP, & cP	real power coefficients for phase a, b, & c
aQ, bQ, & cQ	reactive power coefficients for phase a, b, & c
C_{LL}^l	cost for line loading
C_{PL}^l	cost for power losses
C_{VD}^n	cost for voltage deviation
CS	colony size in ABC optimization
$E_{ESS-max}$	maximum ESS energy
$E_{ESS-min}$	minimum ESS energy
E_{ESS}	ESS energy
E_{ESS}^{t+1}	ESS energy at time $t+1$
E_{ESS}^t	ESS energy at time t
I_{ij-max}	current limit of line ij
I_{ij}^t	current magnitude through line ij
It_{max}	maximum number of iterations in ABC optimization
K	total number of active ESSs on the network
L_{trial}	trial limit for improving a food source in ABC optimization
$lb1$	lower boundary of decision variable S_{ESS}^i
$lb2$	lower boundary of decision variable λ_{ESS}^i
M	total number of lines
N	total number of buses
N_D	number of decision variables in ABC optimization
N_{FS}	number of food sources in ABC optimization
$P_{ESS-max}$	maximum ESS power
$P_{ESS-min}$	minimum ESS power
P_{ESS}	ESS power
$P_{i\to k}^d$	real power delivered from i to a neighbouring bus k
P_i^c	real power consumed at bus i
P_i^g	real power generated at bus i
$P_{j\to i}^d$	power delivered to i from a neighbouring bus j
P_{L-base}^l	real power loss for base case (without ESS)
P_{L-ESS}^l	real power loss with optimal ESS placement
P_{LT}	total real power loss
$P_L(i,j)$	real power loss of a line connecting two buses, i and j
$P_{ESS,c}^t$	ESS charging power at time t
$P_{ESS,d}^t$	ESS discharging power at time t
P_{ESS}^t	ESS power at time t
$PLRI_P$	real power loss reduction index with optimal ESS placement
$PLRI_Q$	reactive power loss reduction index with optimal ESS placement
$PLRI_T$	total power loss reduction index with optimal ESS placement
$Q_{i\to k}^d$	reactive power delivered from i to a neighbouring bus k
Q_i^c	reactive power consumed at bus i
Q_i^g	reactive power generated at bus i
$Q_{j\to i}^d$	reactive power delivered to i from a neighbour bus j
Q_{L-base}^l	reactive power loss for base case (without ESS)
Q_{L-ESS}^l	reactive power loss with optimal ESS placement
Q_{LT}	total reactive power loss
$Q_L(i,j)$	reactive power loss of a line connecting two buses, i and j
$R_L(i,j)$	resistance of a line connecting two buses, i and j
$S_{ESS-max}$	maximum ESS size
$S_{ESS-min}$	minimum ESS size
S_{Li}	load at bus i in p.u.
S_{wind}	total capacity (kVA) of wind DG
SL^{l-t}	loading of line l
SL_{base}^l	loading of line l without ESS placement
SL_{ESS}^l	loading of line l after ESS placement
SL_{max}^l	maximum loading of line l
SL_{rated}^l	rated ampacity of line l
SOC_{ESS}^k	state of charge of kth ESS
$ub1$	upper boundary of decision variable S_{ESS}^i
$ub2$	upper boundary of decision variable λ_{ESS}^i
UUC	ultrabattery unit cost
V_{bi}	bus voltage of ith bus in per unit (p.u.)
V_{bi}^t	voltage magnitude at different times t in a day
V_i^+	positive sequence voltage
V_i^-	negative sequence voltage
V_{max}	upper voltage limit
V_{min}	lower voltage limit
V_{rated}	rated voltage of the system in p.u.
V_{ref}	reference bus voltage in p.u.
V_{target}	target voltage of the system
VUF_{max}	maximum VUF
$X_L(i,j)$	reactance of a line connecting two buses, i and j

and network reliability [36].

Unfortunately, misplacement or misuse of ESSs in distribution networks can adversely affect network performance [37], voltage and frequency regulation, power quality, reliability, and load controllability. Appropriate ESS placement can facilitate an optimal ESS operation for voltage and power quality improvement [5,12,24,25], peak demand mitigation [12], relief of distribution congestion [5,25], power flow adjustment [5], power loss reduction [12,25], network reliability [36], overall network cost reduction [36,38], RESs integration [27,39,40], and system effectiveness [36,41]. As the use of large-scale ESSs in distribution networks involves substantial investment, placing ESSs optimally on the basis of performance expectations is challenging and has been addressed in several studies [5,11,12,24,25,27,29,30,36,38,39,41–51].

Asset management of distribution networks is an essential task of network service providers to ensure safe and secure operation of the networks. However, this can be an expensive task that also might result in a high network cost and thereby can significantly affect electricity prices. This cost could include network reinforcement for thermal and voltage stability. Therefore, the motivation of this work is to provide low cost solutions to distribution network operators for a better asset management practice.

A comprehensive review, regarding ESS placement to mitigate the issues of distribution networks, is presented in [9]. An optimal allocation and sizing of ESSs, for an IEEE-30 wind power distribution system, is accomplished in [24], while focusing on power system cost minimization and voltage profile improvement. The authors employ a hybrid multi-objective particle swarm optimization (PSO) incorporating a non-dominated sorting genetic algorithm (NSGA-II), a probabilistic load flow technique, and a five-point estimation method (5PEM).

In [42], a multi-objective ESS allocation is performed for both transmission and distribution networks. A detailed analysis, termed as sensitive analysis, is accomplished on the transmission side using complex-valued neural networks, time domain power flow, and economic dispatch to locate the ESSs. On distribution side, the optimal ESS size is estimated to address load curve smoothing and peak load shaving. Ref. [41] proposes optimal distributed ESS planning (specifying locations and sizes) in soft open points-based distribution