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ORIGINAL PAPER

A novel hybrid algorithm based on optimal size and location of photovoltaic with battery energy storage systems for voltage stability enhancement

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Abstract
This paper proposes utilizing a recent metaheuristic technique, artificial rabbits' optimization (ARO), enhanced with the quasi-opposition-based learning (QOBL) technique to improve global search capabilities. Furthermore, the novel line stability index (NLSI) is used to show weak buses in radial distribution systems (RDSs), aiding in the optimal placement and sizing of renewable energy sources (RES) such as photovoltaic (PV) systems. This enhanced algorithm, named the hybrid quasi-oppositional ARO (Hybrid QOARO) algorithm, addresses both single-objective and multi-objective functions. The single-objective approach focuses on reducing active power loss in the RDS, while the multi-objective function seeks to minimize active power loss with total voltage deviation (VD) and maximize the voltage stability index (VSI). This multi-objective approach helps determine the appropriate sizing of PV and battery energy storage systems (BESS) over 96 h (four seasons), considering the variability of photovoltaic power generation. To evaluate the effectiveness of the proposed approach compared to different optimization strategies, the IEEE 33-bus RDS is used. The highest reduction in energy losses and VD, at 92.48% and 99.78%, respectively, is achieved by applying PV + BESS at optimal power factor (PF) compared to PV only, PV + BESS at unity PF, and PV + BESS at 0.95 lagging PF.

Keywords Optimization · DG allocation · Voltage stability index · Photovoltaic · Battery energy storage · Voltage stability enhancement

1 Introduction

1.1 Motivation

Voltage instability poses a significant challenge in conventional power systems due to transmission line failures, increased load demands, and congestion in radial distribution systems (RDSs). To enhance system reliability during stressed conditions, various methods are employed, including the use of distributed generators (DGs), FACTS devices, and load shedding. DGs can be categorized into non-renewable sources such as micro-turbines, small gas turbines, and combustion turbines, as well as renewable sources like wind, solar, biomass, hydro, and geothermal energy. Additionally, energy storage systems (ESSs) play a crucial role, encompassing battery energy storage system (BESS), flywheel energy storage (FES), energy capacitors (EC), and superconducting magnetic energy storage (SMES) systems [1].

To minimize CO_2 emissions, the electrical systems industry is swiftly integrating renewable energy sources (RES), such as photovoltaic (PV) technology. The incorporation of RESs into RDSs offers numerous benefits, including improved power efficiency, reduced power loss, better voltage profiles, and enhanced system stability. However, integrating RESs into existing electricity networks presents challenges. PV technology is gaining popularity due to its increased efficiency, lower cost, and favourable sun irradiation levels [2]. However, PV systems, being stochastic energy sources, can lead to grid instability. BESS is utilized to address this issue.

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1.2 Literature review

Most researchers have focused on developing methods for deciding the appropriate sizes and locations for DGs in RDSs using two distinct strategies over the past decade. The first strategy relies on analytical optimization techniques (OTs), while the second employs metaheuristic OTs. By utilizing both single- and multi-objective OTs, the problem of DG allocation has been effectively addressed.

Within this subject, metaheuristic algorithms and analytical techniques [3–5] are often used. As an illustration, consider single-objective optimization problems (OPs) with the goal of minimizing power losses (PL). Four different types of DG are optimally sized using the honey badger algorithm (HBA) [6], solar-based DGs are optimally located, sized, and numbered using Harris Hawk's optimization (HHO) [7], distribution network (DN) PL is reduced using the whale optimization algorithm (WOA) [8], PL is reduced using the Manta Ray foraging optimization algorithm (MRFO) on three different systems (IEEE 33, 69, and 85 test systems) [9], OPs in electrical power systems are addressed using the improved wild horse optimization algorithm (IWHO) [10], and a technique for positioning and scaling solar PV-DGs inside RDS depending on the location's solar PV capacity factor is investigated using particle swarm optimization (PSO) [11].

For multi-objective OPs such as minimizing active and reactive PL, enhancing voltage profiles, and improving voltage stability. Methodologies such as multi-objective thermal exchange optimization (MOTEO) and the multi-objective Lichtenberg algorithm (MOLA) are used for the optimal allocation of shunt capacitors (SCs) and different types of DGs while considering multiple voltage-load models [12]. For the best possible distribution of distributed energy storage units in DS, the artificial bee colony (ABC) method is utilized [13]. The moth-flame optimization (MFO) method is used to optimize the placement of solar and wind RES and DN reconfiguration with an emphasis on dependability [14]. Furthermore, the artificial hummingbird algorithm (AHA) is engineered to accomplish several goals, such as maximizing voltage stability margin (VSM), decreasing voltage variation, lowering PL, and generating annual economic savings [15].

PSO is used to determine where DGs should be placed in the DN to improve the voltage profile and compensate for reactive and active PL [16]. To handle the multi-objective OPs of integrating DG into DS, the multi-objective bonobo optimizer (MOBO) is utilized [17]. System reliability is increased by carefully placing and sizing ESSs inside DN using the teaching-learning-based optimization (TLBO) technique [18]. Finally, an enhanced technique known as the "golden jackal optimization" (IGJO) is suggested to optimize many CBs and multi-type DGs in DNs that tackle both single and multi-objective [19].

Two main approaches that researchers are using to either develop new algorithms or improve current ones are hybrid techniques and enhanced metaheuristic optimization algorithms. Hybrid-enhanced grey wolf optimizer coupled with PSO (EGWO-PSO)[20], hybrid analytical tree growth algorithm (ATGA) [21], a combination of coupled power loss sensitivity (CPLS) and improved GWO[22], binary PSO with shuffling frog leap algorithm (SFLA) [23], PSO-coral reef optimization (PSO-CRO) [24], combining voltage stability index (VSI) and loss sensitivity factor (LSF) with cuckoo search algorithm (CSA) [25], genetic-moth swarm algorithm (GMSA) [26], and combining cuckoo search (CS) with the grasshopper optimization algorithm (GOA) [27] are some examples of the algorithms that are included in the hybrid approach.

Quasi-oppositional chaotic symbiotic organisms search (QOCSOS) [28] is an example of how the optimization of metaheuristic algorithms has been enhanced by the use of methods such as chaos theory and quasi-oppositional-based learning (QOBL).

However, previous studies have overlooked several important aspects, including the availability of primary energy resources and variations in load over time. These factors must be taken into account when dealing with RES. As a result, regardless of the level of RES penetration or the magnitude of load demands, issues related to voltage levels and PL can arise. The best placement and size of renewable DG units, especially PV and WT, are decided upon using the AHA framework [15]. Using unknown WT, PV, and plug-in electric vehicle (PEV) units, this method presents the gradient bald eagle search (GBES) algorithm for solving the nonlinear optimum power flow issue [29]. The size and placement of RES and BESS in distribution systems are optimized in [30] using a modified version of the bald eagle search optimization algorithm (LBES). Furthermore, the equilibrium optimization (EO) method was used in [31] to obtain the best possible integration of PV systems with BESS. For merging PV and DSTATCOM units with optimum planning, the multi-agent lion optimizer (MALO) is presented in [32]. To determine the ideal location and size of PVs and BESS in a DS, a multi-objective optimization strategy utilizing genetic algorithms (GA) is used [33]. Lastly, the problem of efficiently allocating generating technologies while considering the unpredictable variations in solar irradiation and fluctuating power system demands is addressed in [34].

1.3 Contribution

To improve DG unit allocation in RDSs, the hybrid quasi-oppositional artificial rabbits' optimization (Hybrid QOARO) metaheuristic is presented in this study. Hybrid

QOARO improves ARO [35] performance by integrating QOBL to improve algorithms and using the novel line stability index (NLSI) to limit the search area. Its objective function (OF) serves as a single-objective approach, aiming to reduce PL in RDSs. Additionally, the multi-objective Hybrid QOARO aims to minimize PL, total voltage deviation (VD), and increase VSI. Evaluation and comparison using the IEEE 33-node RDS highlight the effectiveness of these methods, addressing DG size and placement by comparing their results with QOARO, the original ARO, and other published OTs. This paper aims to address some of the limitations of previous research by examining the impact of different power factor (PF) values on DG operation with multiple DGs. It also studies the effect of integrating PV-only and PV + BESS systems at various power factors on energy losses (EL) reduction alongside voltage stability improvement, all while considering the uncertainty of PV generation with BESS over four seasons (96 h). The study's contributions are summarized as:

- Modelling PV power uncertainty was developed to optimize BESS scheduling throughout the four seasons (96 h).
- A comparison of modern algorithms such as the pelican optimization algorithm (POA) [36], Kepler optimization algorithm (KOA) [37], and ARO, revealing that ARO is the most optimal, and it was utilized in this paper.
- Introduction of a novel method called Hybrid QOARO, addressing the optimal location and sizing of DGs for single and multi-OFs, and, comparing its results with QOARO, the original ARO, and other published OTs using the IEEE 33-node RDS.
- Integration of PV-only and PV + BESS units at unity PF, 0.95 lagging PF, and optimal PF into the RDS throughout four seasons, resulting in reduced total EL and improved voltage profile.

1.4 Paper organization

The remaining text follows this order: Problem formulation in Sect. 2, Modelling of PV Power Generation in Sect. 3, Modelling of BESS in Sects. 4, and Modelling of PV with BESS sizing in Sect. 5. Section 6 discusses optimal location and sizing techniques, while Sect. 7 focuses on the Application of Hybrid QOARO algorithm in DG allocation. Section 8 covers multi-objective Hybrid QOARO. Section 9 contains Results and Discussion, and the Conclusions and Future Research are finally presented in Sect. 10.

2 Problem formulation

The primary challenge lies in determining the optimum position and capacity of DGs in an RDS.

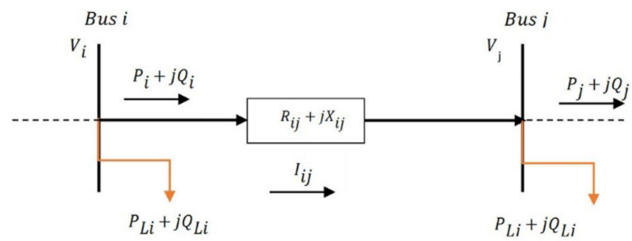

Fig. 1 One line diagram of RDS

2.1 Power flow analysis

In this paper, the backward/forward sweep algorithm [38] has been used to compute power flow within the RDS.

Considering a simple RDS is apparent in Fig. 1, where the buses i and j are the busses at the sending and receiving ends, respectively, V_i, V_j are the voltage at sending and receiving bus, respectively; P_{Li} and Q_{Li} are the power of the active and reactive loads at the bus i, respectively; P_{Lj} and Q_{Lj} are the power of the active and reactive loads at the bus j, respectively. R_{ij} and X_{ij} are the resistance and reactance between bus i, j.

To calculate the load flow solution, two matrices are used: BIBC and BCBV [39]. The branch-current matrix (B) is calculated from the load current matrix (I) using the bus-injection to branch-current matrix (BIBC) method [9].

$$[B] = [\text{BIBC}][I] \tag{1}$$

Using the branch-current to bus-voltage matrix (BCBV), Kirchhoff's voltage law is used to determine the voltage drop at each bus with respect to the reference bus:

$$[\Delta V] = [\text{BCBV}][B] \tag{2}$$

2.2 Objective function (OF)

The optimum DG allocation problem is formulated as a single-objective and multi-objective OPs in this research.

2.2.1 Single OF

The mathematical expression of single OF is described as follows:

$$f_1 = \min(P_{\text{loss}}) \tag{3}$$

where, f_1 minimize the real PL (P_{loss}).