Distribution Network Optimization through Siting and Sizing of BESS

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***Abstract*—Modern distribution network with trends of growing penetration of renewable energy systems involve uncertainty and variability. This results in the use of battery energy storage technologies to mitigate the uncertainty and variability associated along the renewable energy resources and enhance network performance. This paper presents the optimal siting and sizing of battery energy storage systems (BESS) in an electrical network. The objective is to reduce total network power losses and provide voltage support to the network. Multiple optimization techniques are applied to reduce the time taken to obtain the proper site and size of battery energy storage systems. The optimal siting and sizing are necessary to avoid huge investments in power systems. Optimization Techniques such as particle swarm optimization (PSO), reducing variable trend search (RVTS) and differential evolution (DE) are discussed briefly. In the first stage, we apply the proposed optimization techniques for obtaining the optimal sizing and siting of BESS. Then in second stage, we connect BESS according to the solution obtained from the first stage and load flow analysis is done using MATLAB. The IEEE 33 bus radial distribution system is implemented and results of siting and sizing along with reduced losses and voltage support across each bus using various optimization techniques are compared.**

***Index Terms*—Battery Energy Storage System (BESS), Siting, Sizing, Artificial Intelligence (AI), Particle Swarm Optimization (PSO), Differential Evolution (DE), Reducing Variable Trend Search (RVTS).**

I. Introduction

Varying demand profiles and increased integration of renewable energy systems into the power system, guide towards the incorporation of BESS as a fast-acting measure to maintain the variability in the demand and generation [1]. The BESS with the ability to handle renewable energy fluctuations, to incorporate peak shaving so as to reduce higher investment cost in new equipment, postpone up-gradation of network, capability to handle voltage and frequency variations and potential for improvement of power quality makes it a significant part in power system to enhance reliability and stability of grid [2].

The BESS is associated with huge capital investment, installing them at each bus is not viable, also inappropriate location effects the losses. Inappropriate sizing at an optimal location would lead to voltage and power flow violations [3]. Hence, optimal siting and sizing of BESS are crucial.

In literature, optimal siting and sizing are performed by using different analytical, mathematical optimization and AI methods for meeting various objectives. In [4], heuristic method based on voltage sensitivity is suggested for finding an ideal number, size and location of ESSs by making different clusters so as to reduce the under-voltage and over-voltage in the distribution network, then overall cost is considered for determining the best optimal solution. Irrespective of number of clusters formed, ESSs are positioned at critical buses. In [5], network reconfiguration is proposed. The exact convex model of optimal power flow and Benders decomposition are utilized for determining the optimal size and site of BESS, for minimizing the voltage deviations, line congestion, cost of supplying loads and investment costs of ESSs. This is achieved by dividing the problem as Master problem and a number of subproblems. In [6], the optimal placement of BESS to reduce reverse power flow by using voltage profile analysis for different scenarios of PV installation cases is discussed. In [7], the optimal allocation of BESS with integration of solar generation is considered. In this network impedance matrix is utilized, for improving voltage profile. In this, the solar source is modeled as a current source and BESS current is modeled as a function of solar current. The time taken for optimal allocation is also justified. In [8], backward forward sweep optimal power flow is proposed for solving the problem, in this non-linear AC power flow equations are transformed into linear power flow by linear programming problem. Then an economic assessment is provided for distributed and centralized energy storage in low voltage grids. In [9], mixed-integer linear programming is utilized for obtaining an optimal size of ESS and Monte Carlo simulation is used for interpreting random uncertainties to determine ESS investment cost, microgrid operating cost and its reliability.

In [10], Genetic Algorithm (GA) based bi-level optimization method is proposed for minimizing voltage fluctuations raised by the inclusion of PV. In [11], at first stage GA optimization, is used to find the allocation parameters and in the second stage, the AC power flow is evaluated for the combined voltage deviation and total power losses. In [12], for obtaining more profits in Discos the siting and sizing of ESS and DG are determined simultaneously. The active and reactive power are included during planning. Modified PSO is used for solving the problem. In [13], a two-layer

978-1-7281-4103-9/19/$31.00 ©2019 IEEE

problem is presented, in the first stage power and energy capacities of BESS calculated using Mesh Adaptive Direct Search, these calculated values are used in the second stage for finding the operation costs of microgrid with improved PSO. In [14], siting and sizing are modeled as a multi-objective model and weighted minimum module ideal point based on PSO are proposed to find the optimal solution. In [15], three algorithms improved firefly, original firefly and gravitational search are applied and compared, to obtain the site and size of BESS. The optimization techniques are used to mitigate voltage fluctuations caused with the integration of photovoltaic based distribution generation.

In [10] — [15], a number of optimization techniques are proposed for optimal location and sizing of BESS.

This paper emphasizes on applying three different optimization techniques PSO, RVTS and DE for optimal siting and sizing of BESS. The total power losses and voltage deviations are minimized, by formulating this suitably as a multi-objective problem of optimization.

The paper is organized in the following sections, section 2, discusses PSO, RVTS and DE in brief. In section 3, the problem formulation and methodology are discussed. Results for optimal siting and sizing of BESS for IEEE 33 bus system are presented in Section 4. In section 5, the results are discussed and conclusions are derived.

II. Optimization Techniques Proposed For Siting and Sizing

A. Particle Swarm Optimization (PSO)

The siting and sizing of BESS in the network to reduce losses without variation in the voltage are considered to be a nonlinear complex problem. PSO is used to address multiple optimization problems such as reactive power flow and voltage control, economic dispatch, state estimation, fuel cost minimization and power loss minimization [16].

PSO is a population-based stochastic optimisation approach, motivated from flocking of birds or fish schooling that are looking for food. Each particle of PSO applies the concept of social interaction such that they get to benefit from the personal experience and findings of the other particles in the population [17]. Every particle is a potential solution, which is flying throughout multidimensional space based on its own flying experience and that of neighbouring particle experience such that each particle can fly only in feasible areas, by saving in memory their personal best position and best position attained by any particle in the population as global best [18]. The movement of particles from one position to other is controlled by its velocity.

$$\begin{aligned} v_{i+1} = \omega * v_i + c_1 * rand() * (p_{id} - x_{id}) \\ + c_2 * rand() * (p_{gd} - x_{id}) \end{aligned} \tag{1}$$

$$x_{id+1} = x_{id} + v_{i+1} \tag{2}$$

where
$v_i \longrightarrow velocity$
$\omega \longrightarrow inertia\ constant$
$c_1, c_2 \longrightarrow acceleration\ constants$
$p_{id} \longrightarrow personal\ best\ position$
$p_{gd} \longrightarrow global\ best\ position$
$x_{id} \longrightarrow current\ particle\ position$
$rand() \longrightarrow random\ function\ this\ generates\ a\ random\ value\ between$ [0 1].

The inertia constant influences the particle movements in the same direction and with the same velocity in order to obtain convergence. Also, values considered for inertia constant determine the search process of particles. The value of inertia constant could be constant or dynamically changing. A higher value of inertia leads to global search and lesser value leads to local search, so at the start of PSO, inertia value is considered to be 1 reducing it to 0.4 during the process [19]. But in this paper, we use a constant value for inertia. The acceleration constants (c_1 and c_2) depict speed of flying particles towards the optimal location. c_1 and c_2 are considered to be 2 for obtaining optimal solutions [20].

B. Reducing Variable Trend Search (RVTS)

RVTS is a multi-dimension search optimization technique which depends on a number of control variables. It attains an optimal solution by reducing the search space while assigning a certain value to the control variables or by varying limits of control variable.

RVTS mimics the modified decision-making methodology of the Delphi process. Delphi is a structured communication technique, where it requires panel of experts for decision making [21]. In [22] for RVTS, a group of experts is shortlisted related to the field, based on a criterion, these experts are sorted and top experts are selected to discover an optimal solution after consultation. Based on the opinions of these experts, the search proceeds in the direction of a common idea. An analysis is performed on views provided by experts for finding an optimal solution. Based on consent and difference of views we derive to two possible results for different control variables. Firstly, the control variable on which all the expert views coincide, that variable is assigned the common value given by experts and is discarded from the further process. Secondly, the control variable on which consensus does not arrive. Then the limits of the control variable are varied based on the values provided by experts. The values of the control variable can also maximize instead of minimizing, but should not exceed the limits considered initially.

One iteration of RVTS is complete and the complexity of the problem is reduced because some of the control variables are assigned a certain value and eliminated from the further process, where other remaining variables limits are minimized. This process is repeated again until all the variables are eliminated with a certain value allotted to them so that views of all experts consent to an optimal solution.

C. Differential Evolution (DE)

DE finds a number of applications in power system like reactive power optimization, losses minimization and voltage regulation [23]. DE is a population-based direct search method similar as GA with an ability to handle non-linear and non-differential functions [24].

DE utilizes the three GA operators viz: selection, crossover and mutation with some variations. After random generation of 'N' number of vectors, in mutation, the difference of two population vectors is multiplied with a mutation weight factor (F) and then added to a third population vector to generate a new mutated vector according to equation 3 [24]. This mutated vector is now mixed with initial vectors to form a new vector called a trial vector using equation 4, this process is crossover. For selection, any method which utilizes the greedy selection criterion is used.

$$s_{i,G+1} = x_{r1,G} + F * (x_{r2,G} - x_{r3,G}) \tag{3}$$

Where
$F \longrightarrow mutation\ weight\ factor$
$F > 0\ and\ F \in [0\ 2]$.
$r_1, r_2, r_3 \longrightarrow are\ random\ indexes\ of\ vectors$
$r_1, r_2, r_3 \in \{1, 2, .., N\}$.

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & if(randb(j) \leq CR)\ or\ j = rnbr(i) \\ x_{ji,G} & if(randb(j) > CR)\ or\ j \neq rnbr(i) \end{cases} \tag{4}$$

Where
$j = 1, 2, .., D$.
$CR \longrightarrow is\ the\ crossover\ constant \in [0\ 1]$.
$randb(j) \longrightarrow random\ number\ generator\ in\ j^{th}\ iteration$
$randb(j) \in [0\ 1]$
$rnbr(i) \longrightarrow is\ the\ randomly\ chosen\ index \in 1, 2, ..., D$.

Different comparison's mentioned in [25] with respect to amount of time, diversification, premature convergence by each method and advantage of using analogy of human intelligence in [22] lead to selection of above techniques. Some changes are introduced in the DE technique so that the ideal placement of BESS is not on the same bus. Mutation weight factor (F) in equation (3) is taken as 0.5 and the crossover constant (CR) in equation (4) is considered as 0.55.

III. Problem Formulation and Methodology

The aim of the problem is to optimize the site and size of BESS in the power network, such that total losses in the network are minimized with optimum voltage control. The proposed problem is solved in two stages, in first stage the optimal allocation of the BESS is acquired by using multiple optimization techniques mentioned above. In second stage, we run the distribution load flow until the constraints are satisfied for obtained locations and size. BESS connected to grid are associated with power electronic converters. These power electronic converters are usually of high efficiencies. So generation and absorption of reactive power will not effect the energy-reservoir level : this assumption is followed [26].

Voltage and total power losses, these two variables are considered to determine the objective in order to handle the distribution network. The objective function is formulated as shown equation (5). The first part of the equation considers the voltage variation at all nodes in the network and defines impact of BESS on voltage deviation. The second part considers the impact of BESS on total power losses.

$$obj(F) = w_1 \sum_{i}^{n} (V_i - V_{ref})^2 + w_2 P_{Tloss} \tag{5}$$

where
$V_i \longrightarrow voltage\ magnitude\ across\ bus\ i$
$V_{ref} \longrightarrow voltage\ magnitude\ across\ reference\ bus$
$n \longrightarrow total\ number\ of\ bus\ in\ system$
$P_{Tloss} \longrightarrow total\ power\ loss$
$w_1\ and\ w_2\ are\ the\ objective\ function\ weights\ such\ that\ sum\ of\ w_1 + w_2 = 1$.

The values of w_1 and w_2 are considered to be 1 and 0.003, such that both voltage deviation and power loss have same weightage to normalize the objective function.

A. Constraints

The following are two optimization constraints which are to be satisfied along with objective function:

1) Voltage constraint
The voltage across all the buses must lie within the maximum and minimum limits.

$$V_{min} \leq V_i \leq V_{max} \tag{6}$$

Where V_i is the voltage across the corresponding bus, V_{min} is considered to be the minimum voltage across the bus as 0.89 and V_{max} is considered to be the maximum voltage across the bus as 1.0

2) Total power loss constraint
The total power loss in the network after installing BESS should be less than before installing BESS.

$$P_{Tloss} \leq 100\% P_{actual} \tag{7}$$

Where
$P_{Tloss} \longrightarrow total\ power\ loss\ with\ BESS$
$P_{actual} \longrightarrow total\ power\ loss\ without\ BESS$

In MATLAB programming respectively, the optimization methods PSO, RVTS, DE with the above-mentioned limitations, the backward/forward sweep load flow for radial distribution system is applied and solved.

IV. Case Study

The IEEE 33 bus radial distribution system, implemented in MATLAB environment, is shown above in Fig. 1. This system is considered to illustrate the proposed optimization techniques. It consists of 33 buses and 32 lines with current carrying capability of 400A for lines between node-1 to node-9 and other lines with capability of 200 A. The base voltage is taken as 11KV. The total active and reactive power load of 33 bus system is 3,715 KW and 2,300 KVAr, respectively. Corresponding to the total load on the system, the bounds of BESS is considered to be in between 60MW to 70MW. Without including BESS the total losses in the network are

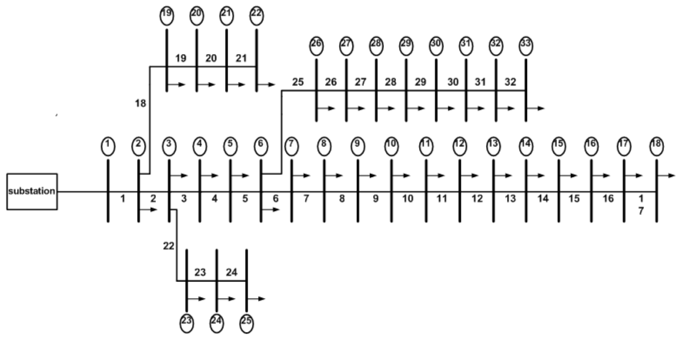

Fig. 1. IEEE 33 bus radial distribution system

281.5691 MW and the voltage magnitude range is between 0.88 to 1.0 for all the buses.

On applying PSO, RVTS, DE algorithms for obtaining the ideal location and size of BESS, the results for the aforementioned study case is provided in table I. From table I, the total losses are reduced significantly and voltage support is also provided with placement of BESS. The DE algorithm provides the optimal solution with objective function value 0.9056 and success rate of 100% in comparison with other two optimization techniques.

TABLE I
OPTIMAL SITING AND SIZING RESULTS FOR PSO, RVTS AND DE

Method	Bus No (BESS Capacity)	Average total losses	Voltage range	Average Objective Function value
PSO	17(68MW) 32(67MW) 14(70MW)	246.25	0.89-1.0	0.9192
RVTS	18(70MW) 9(66MW) 31(62MW)	254.9844	0.89-1.0	0.9580
DE	16(70MW) 17(70MW) 18(70MW)	243.6149	0.89-1.0	0.9056

Each optimization technique is executed 10 times. Comparison of time taken by the optimization techniques is shown in table II. From table II, it can be observed that the DE algorithm takes minimum time to determine optimal location and size.

TABLE II
TIME COMPARISON OF PSO, RVTS, DE. FOR OPTIMAL LOCATION AND SIZING

Method	Average time	Minimum Time
PSO	13.4622282	12.889543
RVTS	173.3954766	56.162711
DE	4.1832028	3.994318

Initially, the optimal siting and sizing of BESS was obtained through different optimization techniques. As DE algorithm gave optimal solution for sizing of BESS, the other optimization techniques were again executed to find the optimal siting only with obtained results. The optimization techniques were applied only for obtaining the optimal location. Nodes 16, 17, 18 were obtained as optimal locations by all optimization techniques with an objective function value of 0.9056. After including BESS at the optimal nodes, the total network power losses reduced to 243.6149 MW and voltage magnitude at all nodes was in the range of 0.89 pu and 1.0 pu, for PSO, RVTS and DE respectively. The comparison of the average time and the minimum time taken for siting of BESS for 10 executions is presented in Table III.

TABLE III
TIME COMPARISON OF PSO, RVTS, DE. FOR OPTIMAL LOCATION

Method	Average time	Minimum Time
PSO	13.8431308	12.856147
RVTS	6.6577493	6.124815
DE	5.0251901	4.694045

V. Conclusion

A performance analysis of PSO, RVTS and DE in siting and sizing of BESS application for reduction of total power losses along with voltage support to the network is assessed. Then considering the optimal size obtained from DE was applied as an input to find optimal BESS location through different optimization techniques. For this two-stage method is applied, with optimization techniques being applied in the first stage to achieve the location and size of BESS. The second stage, assesses the objective function, through backward/forward sweep distribution load flow based on stage one. The optimization techniques and backward/forward sweep distribution load flow are performed in MATLAB.

The IEEE 33 bus system is utilized for case study. The algorithms have been compared based on the objective function value and the amount of time taken for providing the optimal solution. From, case study, DE takes minimum amount of time and provides a optimal solution compared to the other two optimization techniques.

References

[1] R. H. Byrne, T. A. Nguyen, D. A. Copp, B. R. Chalamala, and I. Gyuk, "Energy management and optimization methods for grid energy storage systems," *IEEE Access*, vol. 6, pp. 13 231–13 260, 2018.

[2] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," *Sandia National Laboratories*, vol. 20, no. 10, p. 5, 2010.

[3] S. B. Karanki and D. Xu, "Optimal capacity and placement of battery energy storage systems for integrating renewable energy sources in distribution system," in *2016 National Power Systems Conference (NPSC)*. IEEE, 2016, pp. 1–6.

[4] A. Giannitrapani, S. Paoletti, A. Vicino, and D. Zarrilli, "Optimal allocation of energy storage systems for voltage control in lv distribution networks," *IEEE Transactions on Smart Grid*, vol. 8, no. 6, pp. 2859–2870, 2017.

[5] M. Nick, R. Cherkaoui, and M. Paolone, "Optimal planning of distributed energy storage systems in active distribution networks embedding grid reconfiguration," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 1577–1590, 2018.

[6] H. Kihara, A. Yokoyama, K. M. Liyanage, and H. Sakuma, "Optimal placement and control of bess for a distribution system integrated with pv systems," *Journal of International Council on Electrical Engineering*, vol. 1, no. 3, pp. 298–303, 2011.

[7] H. Nazaripouya, Y. Wang, P. Chu, H. R. Pota, and R. Gadh, "Optimal sizing and placement of battery energy storage in distribution system based on solar size for voltage regulation," in *2015 IEEE Power & Energy Society General Meeting*. IEEE, 2015, pp. 1–5.

[8] P. Fortenbacher, M. Zellner, and G. Andersson, "Optimal sizing and placement of distributed storage in low voltage networks," in *2016 Power Systems Computation Conference (PSCC)*. IEEE, 2016, pp. 1–7.

[9] S. Bahramirad, W. Reder, and A. Khodaei, "Reliability-constrained optimal sizing of energy storage system in a microgrid," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2056–2062, 2012.

[10] O. Babacan, W. Torre, and J. Kleissl, "Siting and sizing of distributed energy storage to mitigate voltage impact by solar pv in distribution systems," *Solar Energy*, vol. 146, pp. 199–208, 2017.

[11] S. Salee and P. Wirasanti, "Optimal siting and sizing of battery energy storage systems for grid-supporting in electrical distribution network," in *2018 International ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI-NCON)*. IEEE, 2018, pp. 100–105.

[12] H. Saboori and R. Hemmati, "Maximizing disco profit in active distribution networks by optimal planning of energy storage systems and distributed generators," *Renewable and Sustainable Energy Reviews*, vol. 71, pp. 365–372, 2017.

[13] H. Xiao, W. Pei, Y. Yang, and L. Kong, "Sizing of battery energy storage for micro-grid considering optimal operation management," in *2014 International Conference on Power System Technology*. IEEE, 2014, pp. 3162–3169.

[14] Z. Qing, Y. Nanhua, Z. Xiaoping, Y. You, and D. Liu, "Optimal siting & sizing of battery energy storage system in active distribution network," in *IEEE PES ISGT Europe 2013*. IEEE, 2013, pp. 1–5.

[15] L. A. Wong, H. Shareef, A. Mohamed, and A. A. Ibrahim, "Optimal placement and sizing of energy storage system in distribution network with photovoltaic based distributed generation using improved firefly algorithms," *World Academy of Science, Engineering and Technology, International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering*, vol. 11, no. 7, pp. 864–872, 2017.

[16] Y. Del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J.-C. Hernandez, and R. G. Harley, "Particle swarm optimization: basic concepts, variants and applications in power systems," *IEEE Transactions on evolutionary computation*, vol. 12, no. 2, pp. 171–195, 2008.

[17] J. Kennedy and R. Eberhart, "Particle swarm optimization (pso)," in *Proc. IEEE International Conference on Neural Networks, Perth, Australia*, 1995, pp. 1942–1948.

[18] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*, vol. 3. IEEE, 1999, pp. 1945–1950.

[19] M. Abido, "Multiobjective particle swarm optimization for environmental/economic dispatch problem," *Electric Power Systems Research*, vol. 79, no. 7, pp. 1105–1113, 2009.

[20] R. C. Eberhart and Y. Shi, "Comparing inertia weights and constriction factors in particle swarm optimization," in *Proceedings of the 2000 congress on evolutionary computation. CEC00 (Cat. No. 00TH8512)*, vol. 1. IEEE, 2000, pp. 84–88.

[21] H. A. Linstone, M. Turoff *et al.*, *The delphi method*. Addison-Wesley Reading, MA, 1975.

[22] A. Q. Badar, B. Umre, and A. Junghare, "Reducing variable trend search algorithm for optimizing non linear multidimensional space search," in *2014 International Conference on Advances in Engineering & Technology Research (ICAETR-2014)*. IEEE, 2014, pp. 1–4.

[23] A. A. El Ela, M. Abido, and S. Spea, "Differential evolution algorithm for optimal reactive power dispatch," *Electric Power Systems Research*, vol. 81, no. 2, pp. 458–464, 2011.

[24] R. Storn and K. Price, "Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces," *Journal of global optimization*, vol. 11, no. 4, pp. 341–359, 1997.

[25] V. Kachitvichyanukul, "Comparison of three evolutionary algorithms: Ga, pso, and de," *Industrial Engineering and Management Systems*, vol. 11, no. 3, pp. 215–223, 2012.

[26] M. Nick, M. Hohmann, R. Cherkaoui, and M. Paolone, "Optimal location and sizing of distributed storage systems in active distribution networks," in *2013 IEEE Grenoble Conference*. IEEE, 2013, pp. 1–6.