11th International Conference on Electrical, Electronics and Computer Engineering (IcETRAN), Nis, 3-6 June 2024

# Review on the Optimal Placement and Sizing of Battery Energy Storage Systems

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***Abstract*— The increasing penetration of renewable energy sources (RES), such as photovoltaics (PV) and wind turbines, has brought many challenges to the grid due to their intermittency and variability. Battery energy storage systems (BESS) are considered as one of the most effective solutions to mitigate adverse impacts of RES integration and ensure stability and reliability. BESS offer several advantages over other energy storage systems, such as fast response, controllability, geographical independence and flexibility. This paper reviews techniques for optimal placement, sizing and operation of BESS. The optimization objectives and techniques have been classified into three categories. The advantages and disadvantages of different methods are emphasized. Additionally, this paper compares different battery technologies and discusses BESS applications.**

***Keywords*— *Renewable sources, battery energy storage systems, objective functions, optimization methods***

## I. INTRODUCTION

Conventional power systems have significantly changed in the last few decades due to the technological advancements, global electricity demand growth, electricity market liberalization and initiatives to reduce carbon-dioxide emissions. Electricity generation in the past predominantly relied on non-renewable sources such as fossil fuels. Fossil fuels combustion releases large amounts of greenhouse gases (GHG) that affect global warming and climate change. Shifting towards cleaner and more sustainable sources has become main strategy in fight against climate change. Renewable energy sources (RES) like solar, wind, hydroelectric and biomass stand as the main alternatives to fossil fuels and most effective way to reduce emission of harmful gases. Renewable sources integration enables power generation near the consumers. This local power generation in the proximity of load centers is known as distributed generation (DG) [1]. Distributed generation from RES offers many economical and technical improvements within the grid, such as: power loss reduction, voltage profile improvements, stability and reliability enhancement [2]. The output power of renewable sources is highly variable due to their intermittent nature, influenced by factors such as weather conditions and time of day. This variability creates constant mismatch between demand and supply, and can lead to potential issues with grid stability and reliability. To address these issues, energy storage systems (EES) are employed. In order to balance demand and supply, EES can store excess energy during the periods of high production and release energy during times of low production. To this day, a large number of different storage technologies have been developed, such as: supercapacitors, superconducting magnets, flywheels, pumped hydroelectric storage, compressed air energy storage (CAES) and battery energy storage systems (BESS). With flexibility in terms of capacity and location, rapid response and scalability, battery systems stand out among all aforementioned technologies. These advantages make BESS suitable for various power system applications such as power quality improvements, peak shaving, voltage regulation, frequency regulation and energy arbitrage [3]. The implementation of oversized BESS can lead to unnecessary costs, while undersized BESS may not provide desired improvements. To avoid unnecessary costs and ensure technical improvements to the network, optimal sizing and placement of BESS are of key importance.

This paper provides an overview of various battery technologies employed in distribution system (DS) and discusses the practical applications of BESS. With a primary emphasis on optimizing BESS integration, it surveys various methods used to optimize location and size of BESS. The aim of this paper is to give readers a better understanding of the current state, challenges, and opportunities associated with BESS implementation by providing a detailed overview of different battery technologies, their applications in grid and methods for optimal location and size determination.

## II. TYPES AND APPLICATIONS OF BATTERY TECHNOLOGIES

BESS represent technical solutions for numerous issues in distribution systems. Their flexibility and fast response makes them a suitable tool for improving network stability, reliability and profitability. Different BESS technologies and their applications are discussed in the following subsection.

### A. Comparison of Battery Technologies

A various types of batteries have been developed. Each type of battery differs in efficiency, cycle life, operating temperature, depth of discharge (DOD), response time, self-discharge rate, power and energy density. Comparison of different batteries technologies is presented in Table I. Based on its features, each type of battery has a suitable application. In recent times, lithium-ion batteries have become dominant technology in grid-scale BESS deployments [4]. Different grid-scale application has different requirements in terms of response time, efficiency, stability and reliability of BESS. The selection of appropriate battery technology depends on type of application, costs, energy density and environmental impacts.

ISBN 978-86-6200-001-9 ©2024 AM & ETRAN

https://doi.org/10.69994/11Ic24009

TABLE I. COMPARISON OF CHARACTERISTICS OF DIFFERENT BATTERY TECHNOLOGIES [5-9]

| **Battery technology** | ***Efficiency (%)*** | ***Cycle life*** | ***Power density (Wh/kg)*** | ***Energy density (W/kg)*** | ***Self-discharge rate (daily)*** | ***Strength*** | ***Weakness*** |
|---|---|---|---|---|---|---|---|
| Lead-acid (LA) | 70-90 | 1200-1800 | 25–50 | 180-200 | <0,3% | Simple and cheap | Very heavy, low energy density |
| Nickel-Cadmium (NiCd) | 75-85 | <3500 | 50-75 | 150-300 | 0.2-0.6% | Low maintenance requirements, long cycle life | Environmental hazardous, memory effect |
| Lithium-Ion (Li-Ion) | 85-90 | 1000-20,000 | 75-200 | 150-2000 | 0.1-0.3 | High efficiency and energy density | Safety concerns, performance degradation over time, limited operating temperature |
| Sodium–Sulfur Battery (NaS) | 75-95 | 2500-4500 | 150-240 | 150-230 | 0.05 | High efficiency and cycle life, fast response (<5ms), environmentally friendly technology | Safety issues at higher temperature, sodium polysulfide is a very corrosive material |
| Sodium-Nickel Chloride (ZEBRA) | *95* | *>2000* | 100-120 | 150-200 | 5 | Low maintenance requirements, long cycle life and safety | Expensive technology, lower corrosion compared with NaS |
| Vanadium-Redox (VRB) | 75-85 | 1200-1400 | 10-50 | 166 | Very low | Long life cycle and stability, Adaptable for various RES | Complexity and small energy density |
| Zinc-Bromine (ZBB) | 75-85 | 2000-20000 | 30-85 | 100 | Almost zero | Low self-discharge rate, long lifetime, deep discharge capability (100% DOD) | Operating costs due to the control of electrolytic flows and pumps, dendrite formation, corrosivity |
| Polysulfide-Bromine (PSB) | 75-85 | <2000 | 30-85 | / | Almost zero | Fast response time | Complexity and difficult maintenance, environmental hazardous |

### B. *BESS Applications*

Some applications of BESS in distribution systems include: improvement of power quality, voltage regulation, peak load shaving, frequency regulation and energy arbitrage.

Degradation in power quality affects consumers, highly automated industries and sensitive loads, specifically. BESS can effectively compensate various fluctuations in network such as: voltage sags and swells, flickers, frequency deviations, harmonics, etc. This is achieved by adequate control of the charging and discharging modes of the batteries.

Voltage variations in the network have a major impact on the stability of the network. Voltage regulation is achieved by controlling the flow of reactive power in the network. BESS can maintain voltage levels within specified limits by injecting or absorbing reactive power. Control strategies for voltage regulation using BESS are presented in [10] and [11].

Peak load shaving refers to the process of flattening the daily load curve by shifting some loads from peak period to off-peak period. Control algorithms for peak load shaving using BESS are presented in [12] and [13].

To maintain frequency within specified limits it is necessary to immediately balance production and demand. The fast response of BESS (<20ms) makes them suitable for frequency stabilization. Control strategies for frequency regulation with BESS are developed in [14] and [15].

Energy arbitrage is a strategy of buying or producing electricity when prices are low, and selling it when prices are high. BESS can optimize economic value of electricity through energy arbitrage. In order to achieve maximum profits through energy arbitrage, various strategies for BESS management were considered in [16] and [17].

## III. OPTIMAL PLANNING OF BESS

Optimal planning of BESS involves determining variables such as location, size or optimal management schemes of BESS in order to achieve a specific goal expressed by an objective function. Generally, an objective function is a mathematical expression to be minimized or maximized:

$$OF = \min f(x), \tag{1}$$

where f is objective function to be optimized and x is the vector of variables. The goal is to find the values of those variables that minimize (or maximize) the objective function while simultaneously satisfying various equality and inequality constraints. The objective function can have one or combine several optimization goals that can be based on technical, economic or environmental criteria. Economic optimization is most often carried out with the aim of minimizing overall costs in the network and/or maximizing profits from electricity trading. The technical objectives of the optimization include: minimization of the total power losses, voltage profile improvement, minimization of frequency deviations and improvement of system reliability. Environmental optimization criteria refer to the minimization of harmful gas emissions and the promotion of sustainability. Many mathematical expressions have been developed to evaluate the costs, power losses, voltage and frequency deviations and ecological benefits. Some of them used in the optimization of size and location of BESS and DG are summarized in Table II.

In the following section, an overview of methods for optimal sizing and placement of BEES is provided.

## IV. CLASSIFICATION OF OPTIMIZATION METHODS

Methods for optimal planning of BESS can be classified into three groups: conventional, metaheuristic, and artificial intelligence-based methods.

TABLE II. OBJECTIVE FUNCTIONS FOR DIFFERENT CRITERIA OF OPTIMIZATION

| ***Criteria of optimization*** | ***Objective of optimization*** | ***Mathematical expression*** | ***Reference*** |
|---|---|---|---|
| Economic | Minimization of total cost | $\min C_t = C_{Cpt} + C_{Mnt}$<br>$C_{Cpt}$ and $C_{Mtn}$ are the annual capital cost and the annual maintenance cost. | [18] |
| | Maximization of the net present value (NPV) | $\text{NPV}=\sum_{t}^{M}\frac{R^t\text{-}C^t_{O\&M}\text{-}C_{Rep}}{(1+i_d)^t}\text{-}C_{cap}$<br>$R^t$ is the system revenue in year t due to the use of the RES; $i_d$ is the discount rate; $C^t_{O\&M}$ is the annual operation and maintenance cost; $C_{Rep}$ is the replacement cost; $C_{cap}$ is the capital cost. | [19] |
| | Minimization of levelized cost of electricity (LCOE) | $LCOE=\frac{TLCC}{E}=\frac{TLCC_{PV}+TLCC_{BESS}+TLCC_{disgen}+TLCC_{ROR}}{\sum_{t=1}^{8760}P_{load}(t)\times\triangle t}$<br>E is the annual energy demand of the system (kWh); $TLCC_{PV}$, $TLCC_{BESS}$, $\text{TLCC}_{\text{disgen}}$, $TLCC_{HE}$ are the total cost of PV, BESS, diesel generator and run-of-the-river hydropower system, respectively. | [20] |
| | Minimization of total cost of PV/BESS system | $\text{TC}=\text{Profit}_{PV}\text{-}\text{TI}_{PV/BESS}$<br>$\text{Profit}_{PV}$ is the profit coming from energy generated by the PV system $\text{TI}_{PV/BESS}$ is the total investment of the PV/BESS | [21] |
| Technical | Minimization of total losses of active power | $\text{OF}=\min\left(\sum_{i=1}^{N_{br}}\lvert I_i\rvert^2R_i\right)$<br>$I_i$ is the current of the *i*-th branch, $R_i$ is the resistance of the *i*-th branch, $N_{br}$ is the total number of branches. | [22] |
| | Improvement of volatge profile of network | $\text{OF}=\min\left(\sum_{i=1}^{N_{bus}}\lvert V_{ref}\text{-}V_i\rvert^2\right)$<br>$V_{ref}$ is the nominal voltage, $V_i$ is the operating voltage in the bus *i*. | [23] |
| | Minimization of power fluctuations in distribution system | $\text{OF}=\sum_{m=1}^{M}D_m\left(\sqrt{\sum_{t=1}^{T}(P_s(t)+\overline{P}_s)^2/T}\right)$<br>$P_s(t)$ and $\overline{P_s}$ are the grid input active power at time t and average value of $P_s(t)$ during the time period T, respectively. | [24] |
| | Minimization of fluctations based on voltage sensitivity index | $\text{OF}=\min\sum_{i=1}^{N_{bus}}\left(e^{100\frac{\partial V}{\partial P}}+e^{100\frac{\partial V}{\partial P}}\right)$ | [23] |
| | Loss of power supply probability | $\text{LPSP}=\frac{\sum_{t=1}^{8760}\left(P_{load}(t)+P_{BESS,CH}(t)-P_{supply}(t)-P_{BESS,DCH}(t)\right)}{\sum_{t=1}^{8760}P_{load}(t)}$<br>$P_{load}(t)$ is the power demand at time $t$; $P_{BESS,CH}(t)$ and $P_{BESS,DCH}$ are BESS's charged and discharged power; $P_{supply}(t)$ is the power supply. | [20] |
| Environmental | Minimization of carbon dioxide emissions | $OF=\min(P_t^{grid}*E_m)$<br>$P_t^{grid}$ is the power from utility grid, $E_m$ is the carbon emission rate. | [25] |
| | Minimization of GHG emission from diesel generators | $\text{GHG}_{em}=\sum_{t=1}^{8760}\text{FC}_{dis\ gen}(t)\times\text{EF}_{GHG}$<br>$\text{EF}_{GHG}$ is the total emission factor of diesel generator for greenhouse gasses (kg/L). | [20] |

## *A. Conventional Methods*

Conventional methods used to solve the optimal size and locations of BESS are reviewed in this section. Their advantages and disadvantages are discussed.

*a) Analytical methods:* These methods utilize mathematical models and analytical techniques to find optimal solution to optimization problem. Mathematical models involve setting up numerical equations based on mathematical and theoretical analysis. The accuracy of the analytical method largely depends on the developed model. The advantages of these methods are simple implementation and fast convergence towards the optimum. Analytical methods use some simplification of mathematical models which can affect the accuracy of the solution [26]. An analytical multi-objective index method to determine the optimal power of PV systems and BESS with the aim of reducing total losses and improving the network voltage was used in [27]. An analytical approach was used for simultaneous determination of optimal buses and capacities of RES and BESS in [28]. Objective of optimization was minimization of energy losses and improvement of voltage profiles.

*b) Dynamic programming (DP)* is a type of multi-stage sequential decision procedure. The main disadvantage of DP is that it can be computationally burdensome [26]. Optimal energy management of hybrid system that combines PV systems, wind turbine, diesel generator and BESS was achieved using DP in [29]. Minimization of operation cost and reduction of CO2 emission were optimization goals.

*c) Mixed Integer Linear Programming (MILP)* consists in defining the objective function and various equality and inequality constraints. Variables in the MILP model can be continuous and integer. If the objective function and constraints are a nonlinear problem, they need to be linearized using appropriate linearization techniques to obtain an equivalent linear MILP model. MILP optimization problems are often solved using commercial software such as CPLEX or Gurobi. The main disadvantages of MILP are: the difficulties in applying it to real-size problems, excessive memory requirement and computation time [30]. Optimization approaches based on MILP method for BESSs optimization are proposed in [31], [32], [33].

### *B. Metaheuristic Methods*

Many metaheuristic methods have been developed to mimic some biological, physical or social process. Main advantages of these methods are adaptability, high accuracy rate, less computational time and the ability to solve complex optimization problems [34]. Complex problems include mathematical models where objective function and constraints are highly nonlinear, nonconvex and non-differentiable, with both continuous and discrete variables.

*a) Genetic algorithm (GA):* This algorithm starts with a population of individuals which represents a set of possible solutions of the optimization problem. After series of operation, which include quality evaluation of each individual (based on fitness function, selection, crossover and mutation), new population is made. The genetic algorithm is executed sequentially through a series of iterations until a predetermined criterion for the algorithm termination is met. The best individual from the last generation represents the solution of the optimization problem. Various variants of GA have been developed to enhance its performance. The method that combines GA with linear programing method (GALP) was proposed in [35] for simultaneous determination of optimal number, size, location, and scheduling of BESS. Optimization was performed based on a cost function in which loss reduction and environmental benefits are converted to economic benefits. NSGA (Non-dominated Sorting Genetic Algorithm) is an enhance variant of GA which is used for multi-objective optimizations. The solutions are initially sorted based on their dominance to form a set of non-dominant solutions, namely Pareto front. Solutions in the Pareto front are such that it is not possible to improve one objective without worsening other objectives. Advanced variant of this algorithm, NSGA-II, was applied for optimal sizing of BESS in [36] and [21].

*b) Particle swarm optimization (PSO):* This method was inspired by the behavior of a flock of birds. In PSO, a large number of particles move through the searching space looking for an optimal solution. Each search particle represents a potential solution. In each iteration, the global and local best position of particles are calculated and used to modify their position and direct them towards the optimal solution. PSO method was used in [37] to optimize size and location of BESSs and DGs in order to increase the profit of distribution company. Aiming to minimize power losses, peak demands and costs caused by the voltage deviations in the distribution network, GA and PSO methods were adopted in [38], determining the optimal size and location of BESS and DG. Efficiency comparison of GA and PSO showed that PSO provides better objective value than GA. Also, the execution time of the PSO method is shorter compared to GA. To optimize the size of PV and BESS in grid-connected microgrid, PSO-based method was used in [39]. Minimization of energy costs was selected as objective function. The effectiveness of the PSO-based method was compared with GA. The obtained results showed that PSO algorithm gives a better solution and that the time required to find global point is shorter than GA.

*c) Simulated annealing (SA):* This algorithm is inspired by the cooling process of heated metals in metallurgy. In [40] the optimal BESS size was determined using PSO and SA methods. Minimization of total cost in the microgrid during sudden interruptions in main network was selected as an objective of optimization. It is shown that an optimally sized BESS can effectively stabilize the system and restore the power equilibrium. It is concluded that optimally sized BESS based on PSO, provides faster response during the emergency situation then the BESS sized using SA method. A modified simulated annealing method to solve the problem of determining the optimal size and locations of BESS in DS was applied in [41]. It is shown that the SA method is characterized by a faster convergence towards the optimal solution compared to traditional GA.

*d) Other metaheuristic methods:* Method based on Tabu Search (TS) for optimization of size and locations of BESS and PV systems was proposed in [42]. Ant Colony Optimization (ACO) algorithm is technique inspired by the foraging behavior of an ant colony to find the shortest path to the food. This method was suggested in [43] for optimal sizing of PV systems, wind farms and batteries with the aim of minimizing total annual costs and maximizing system reliability. Optimal size of BESS for improving the reliability of a microgrid was determined using Firefly Algorithm (FA) in [44]. Minimization of total cost, which includes the cost of generation units, exchanged electricity cost, and BESS investment cost, was selected as objective of optimization. The study considered various battery technologies, revealing that lead-acid and Li-ion batteries offer lower overall cost compared to other types. Multi-Objective Modified Firefly Algorithm was used in [19] to find optimal size and the optimal management scheme of the BESS. The performance of this algorithm was compared with the NSGA-II algorithm and it was shown that MOMFA gives more accurate solutions. Metaheuristic optimization methods, such as gray wolf optimizer (GWO), particle swarm optimization (PSO), artificial bee colony (ABC), gravitational search algorithm (GSA) and genetic algorithm (GA) were used to solve the BESS sizing problem in [45]. A comparison on performance of these optimization techniques was carried out and the result showed that GWO gives the best solution.

*e) Hybrid methods:* Each of the mentioned methods has its advantages and disadvantages. Often the good features of two or more different methods are combined with the aim of obtaining a more advanced method. Hybrid method that combines SA and TS method was developed for size optimization of small autonomous power system in [46]. SA method is characterized by fast convergence in the neighborhood of optimal solutions and TS method by the efficiency of finding the optimal solution in the given neighborhood. These advantages were used to form a hybrid method where the solution obtained from the SA method was used as the initial solution for the TS algorithm. In [47] a method based on the SA and PSO algorithm was proposed for determining the optimal capacity of a hybrid EES system consisting of a battery and a supercapacitor. Methodology based on a combination of GA and Constraint Programming (CP) for battery planning and scheduling was applied in [48]. The optimal BESS management scheme was determined in [49] by applying a hybrid algorithm that combines GA and gravity search algorithm (GSA).

### *C. Artificial intelligence-based methods*

This group of methods includes Artificial Neural Networks (ANN), Fuzzy Logic, Reinforcement Learning (RL), and Game Theory. A method based on ANN, for determining optimal BESS size at different locations in distribution networks is presented in [50]. Aiming to determine the optimal scheme for managing BESS, a method based on random search reinforcement algorithm and ANN was developed in [51]. Methods based on Fuzzy Logic for BESS optimization were applied in [52] and [53].

## V. CONCLUSION

Numerous benefits such as voltage stability, power quality enhancement, stability and reliability improvements, power loss reduction and profitability can be achieved with optimal integration and planning of BESS and RES. In grid-scale applications, various types of battery technologies are utilized. Each type of technology has its own characteristics, advantages and limitations, which make it suitable for specific applications. In this paper, a comparison of different battery technologies and their applications in the grid is provided, aiming to offer guidance for technology selection and application strategy development. An overview of methods for optimal placement, sizing and operation was conducted. Methods are categories into three groups: conventional, metaheuristic and artificial intelligence-based. Their strengths and weaknesses are discussed. Conventional methods are easy to implement, but certain approximations of mathematical models can affect accuracy of solution. Metaheuristic methods are characterized by adaptability and efficiency in solving complex multi-objective problems. These advantages make them a popular choice in many optimizations. Although there are various metaheuristic optimization approaches, further improvements, such as hybridizing different algorithms or developing more efficient metaheuristics, are recommended to achieve global optimal solutions.

## ACKNOWLEDGMENT

The authors would like to thank the Ministry of Science, Technological Development and Innovation of the Republic of Serbia for funding the scientific research work, contract no. 451-03-65/2024-03/200155, realized by the Faculty of Technical Sciences in Kosovska Mitrovica, University of Pristina.

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